Titre: Title:	Estimation of health risk impact associated with sustained low pressure events in water distribution systems
Auteur: Author:	Fatemeh Hatam
Date:	2019
Type:	Mémoire ou thèse / Dissertation or Thesis
Référence: Citation:	Hatam, F. (2019). Estimation of health risk impact associated with sustained low pressure events in water distribution systems [Thèse de doctorat, Polytechnique Montréal]. PolyPublie. https://publications.polymtl.ca/3940/

URL de PolyPublie: PolyPublie URL:	https://publications.polymtl.ca/3940/
Directeurs de recherche: Advisors:	Michèle Prévost
Programme: Program:	Génies civil, géologique et des mines

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Estimation of health risk impact associated with sustained low pressure events in water distribution systems

FATEMEH HATAM

Département des génies civil, géologique et des mines

Thèse présentée en vue de l'obtention du diplôme de *Philosophiae Doctor*

Génie Civil

Mai 2019

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Cette thèse intitulée:

Estimation of health risk impact associated with sustained low pressure events in water distribution systems

présentée par **Fatemeh HATAM**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*

a été dûment acceptée par le jury d'examen constitué de :

Benoit BARBEAU, président

Michèle PRÉVOST, membre et directrice de recherche

Manuel J. RODRIGUEZ, membre

Jakobus Ernst VAN ZYL, member externe

DEDICATION

To my beloved parents, Tahereh and Mohsen

and my dear brother, Amir

ACKNOWLEDGEMENTS

First and foremost, I would like to express my utmost appreciation and gratitude to my advisor, Dr. Michele Prevost. Thanks for giving me the opportunity to work on this project at the Chair of drinking water at Polytechnique. I am truly grateful for your continued help and support, while at the same time you gave me the opportunity to pursue my ideas. Thank you for trying to teach me how to connect the theories to practice. I learned so much from you. I really enjoyed all the hours we spent discussing the results and always leaving your office with plenty of great new ideas and feedback. Thank you also for your encouragement and always being so understanding and caring.

I wish to thank all other co-authors of my papers. First, Dr. Marie-Claude Besner who initially suggested me to work on this great subject. Thank you for showing me the way and for all your feedback and help during all those years. I will never forget the weekends that you spent helping me to prepare my proposal and all you taught me. Dr. Gabrielle Ebacher, I am grateful for the opportunity to work closely with you. Thanks for all your thoughtful comments on my articles and always be so encouraging. It was a pleasure for me to work with Dr. Mirjam Blokker for QMRA part of this project. Thank you for your help and sharing your code with us. It was a great experience for me and I learned a lot.

I would like to give special thanks to the Chair staff. Thank you so much Jacinthe, Julie and Yves for always being so supportive, caring and available to help me. Thank you dear Shokoufeh, for all your encouragement, help and being so caring. Thank you so much Laura, for your availability, help and support. Also I would like to thank Manon Latour and Adèle El-Murr for the help with all the administrative work.

Words cannot express the level of gratitude I have for my friends. Thank you Kim, your friendship is invaluable to me. Thank you Evelyne and Sanaz, for always making me feel better and being so encouraging. Thank you so much Milad, Hadis, and Samira for your support from the first day of my PhD journey. Thank you Emile, for introducing me to people from KWR Watercycle Research Institute for initiating a collaboration with them. Also, thank you for the good discussion we had and guiding me with statistical analysis. I would like to thank Emilie, Elise, Laleh, Flavia, Nargess, Margot, Maryam, Jean-Baptiste, Celine, Vanessa, Celso…

Many thanks to Dr. Benoit Barbeau for accepting to be the president of my defense committee. I also learned a lot from him during my PhD. I am grateful to the members of my examination committee Dr. Kobus van Zyl, and Dr. Manuel J. Rodriguez for accepting to review and comment this thesis.

It is not easy to express all the gratitude I have for my family. My dear dad, Mohsen, your help and support during this project was worth more than I can express on paper. Thank you for always encouraging me to push my limits. Thank you for all your wonderful ideas on the modeling part of this project and always being available for my questions. Without your feedback, I could not go over everything that has been done in this project. My beloved mom, Tahereh, thank you for always being available even from a distance. Without your unconditional love and support, I was not able to walk along this long and winding road. My dear brother, Amir, you can always make me feel better, I am very lucky to have you. Thank you for always being so caring and supportive to me.

RÉSUMÉ

Les contaminations dans le réseau de distribution d'eau potable, qu'elles soient intentionnelles ou accidentelles, peuvent avoir un impact négatif sur la santé publique. Cette thèse porte sur la simulation d'intrusions accidentelles dues à des pertes de pression prolongées dans les réseaux. Les distributeur d'eau doivent pouvoir prédire la distribution spatiale et temporelle des contaminants microbiens pendant et après les conditions de pression déficientes (PDC) afin d'identifier les actions correctives appropriées. Des modèles réalistes hydraulique et de qualité d'eau sous conditions PDC, associés à un cadre avancé d'évaluation quantitative du risque microbien (QMRA), peuvent aider les services publics à prendre les mesures appropriées au bon moment pour minimiser le risque d'infection associé à des intrusions accidentelles due à des événements de pression faible / négative.

L'objectif principal de cette recherche est de développer et d'intégrer des concepts réalistes de modélisation de la qualité de l'eau et de l'hydraulique dans un modèle QMRA afin d'améliorer l'évaluation des risques pour la santé publique associés aux événements de pression continue faible ou négative dans les réseaux de distribution d'eau potable. Plus précisément, ce projet visait à: (1) évaluer l'utilisation de l'analyse par la pression (PDA) au lieu de l'analyse traditionnelle par la demande (DDA) pour définir les zones potentiellement à risque d'intrusion / rétro-contamination dans un réseau de distribution de grande taille; (2) développer une méthode combinant à la fois des résultats d'analyse déterminés par la pression et une analyse de la qualité de l'eau multi-espèces (MSWQA-PDA); (3) évaluer l'impact de deux relations pression-demande sur les paramètres hydrauliques et de qualité de l'eau; (4) réduire les incertitudes et améliorer les hypothèses dans la modélisation de l'intrusion, du devenir et du transport accidentels de contaminants; (5) comparer la distribution spatiale et temporelle d'*E. coli* et les zones de pression touchées, résultant de l'intrusion d'eaux usées en l'absence et la présence de divers résidus de désinfectant, et évaluer la possibilité d'émettre un avis sectoriel d'ébullition de l'eau (BWA); (6) étudier dans quelle mesure les conditions de pressions déficientes maintenues causées par la fermeture de stations de traitement de l'eau potable, affectent les résiduels de désinfectant avec et sans l'impact de la demande en oxydant de l'eau d'intrusion; (7) évaluer la probabilité spatiale de détecter *E. coli* à travers le réseau à différentes périodes et (8) évaluer le risque pour la santé publique associé aux événements d'intrusion accidentelle en améliorant un modèle d'évaluation du risque microbien quantitatif disponible.

Dans ce travail, une modélisation de la qualité de l'eau multi-espèces fondée sur la PDA (MSWQA-PDA) est proposée pour prédire l'intrusion d'eau contaminée résultant de pertes de pression prolongées. L'outil développé simule également le devenir et le transport des contaminants et la perte de désinfectant résiduel dans le réseau pendant et après les PDC.

Premièrement, pour vérifier la fiabilité de l'approche présentée (MSWQA-PDA), les conditions de pressions déficients continues sont modélisées en simulant des arrêts prolongés des stations de traitement dans un réseau de distribution d'eau potable de grande taille desservant une population d'environ 400 000 personnes via 1 600 km de conduites. À titre de preuve de concept, de multiples espèces de la qualité de l'eau, notamment l'âge de l'eau, le chlore et le THM, sont modélisées et comparées au scénario de conditions de pressions normales. Les résultats montrent que la simulation DDA surestime les zones exposées à des pressions faibles et négatives, ce qui pourrait donner lieu à des avis préventifs injustifiés. Ces conditions ont généralement causé une diminution des concentrations résiduelles de chlore et, par conséquent, une augmentation des concentrations de THM par rapport aux conditions de fonctionnement normales, et cela même sans prendre en compte l'impact de l'intrusion. Ces différences sont principalement dues aux augmentations de temps de séjour. Les variations sont les plus élevées aux nœuds avec des valeurs de pression plus basses.

Le modèle couplé MSWQA-PDA est ensuite utilisé pour modéliser le devenir et le transport *d'E. coli* résultant de l'intrusion d'eaux usées non traitées suite à des pressions déficientes prolongées (5 heures) en présence de différents types de désinfectant. Les volumes d'intrusion à chacun des 73 sites de fuite ayant des pressions <1 m, sont estimés en tenant compte de l'état des conduites (c'est-à-dire de l'âge et des matériaux) et de la pression résultante d'intrusion calculée à partir de la PDA. Les résultats montrent qu'environ 11% des nœuds sont positifs pour *E. coli* ($\geq$ 1E-06 UFC / L) à tout moment au cours de la période de simulation de 4 jours et en absence de tout désinfectant. Cette valeur diminue à 10% et 1% en présence de 1 mg/L de chloramines et de chlore, respectivement. On constate qu'*E. coli* peut être transporté vers des zones où la pression est plus élevée ($P > 10$ m, sur la base des pressions sous PDC) en fonction de l'effet des résiduels de désinfectant sur les microorganismes. Pour le système chloré (1 mg / L), *E. coli* demeure présent ($\geq$ 10-6 UFC / L) à 119 nœuds 4 heures après le début de l'intrusion, pour ensuite ne persister qu'à 8 nœuds 9 heures après le début de l'intrusion. Cela indique qu'il est peu probable que les événements de contamination soient détectés à l'aide d'un échantillonnage d'*E. coli* à moins que l'échantillonnage ne soit effectué rapidement sur les sites d'intrusion ou à proximité. En présence de chloramines, la probabilité nodale moyenne de détection était supérieure à 0,1 à 166 nœuds aux premier et deuxième intervalles de 5 heures, ce qui indique qu'un échantillonnage à réponse rapide dirigé vers les zones à risque pourrait confirmer efficacement la contamination. Faire correspondre les programmes d'échantillonnage des services publics avec les prévisions numériques correspondantes peut augmenter la probabilité de détecter la contamination. Selon les concentrations modélisées, des volumes d'échantillonnage plus importants peuvent être nécessaires. L'utilisation d'un volume d'échantillon plus important peut prolonger la fenêtre de temps pour effectuer l'échantillonnage après une intrusion, en raison des probabilités plus grandes de détection positive.

Finalement, un nouveau modèle QMRA développé par Blokker et al. (2018) est couplé à un modèle de qualité de l'eau à base de PDA pour évaluer les risque d'infection de *Cryptosporidium* résultant d'une intrusion accidentelle des eaux usées. Pour ce faire, une distribution Poisson du nombre de verres par personne par jour et une distribution log-normale du volume ingéré par verre sont utilisés. Durant les périodes de pression déficiente, l'utilisation moyenne du robinet de cuisine est modifiée en fonction de la disponibilité de la demande calcule à partir des résultats du PDA. Pour tenir compte de l'incertitude des calculs liés à la variabilité comportementale des consommateurs, 200 simulations de Monte Carlo sont réalisées. Le nombre simulé de personnes infectées augmente de 235 fois en fonction des concentrations croissantes de *Cryptosporidium* dans les eaux usées brutes (1 à 560 oocystes/ L) pour une durée d'intrusion de 24 heures. Le nombre maximum de personnes infectées, au cours des 4 jours d'observation, diminue de 64% et 94% pour les scénarios de 10 heures et 1 heure, respectivement, par rapport à une intrusion de 24 heures. La distribution spatiale des risques nodaux pour différentes durées d'événements a montré que cette durée est un facteur clé dans la définition de la délinéation de zones assujetties à une avis préventif. Il est aussi démontré que le fait de ne pas boire de l'eau du robinet lorsque le débit au robinet est très faible (un temps de remplissage de plus de 20 fois plus long) pourrait réduire le nombre de personnes infectées jusqu'à 65% le jour de l'intrusion.

Dans l'ensemble, ce projet de recherche modélise les variations de la qualité de l'eau dues aux pertes de charge prolongées dans les réseaux de distribution d'eau potable. Les résultats de cette étude peuvent être utilisés pour fournir des informations sur l'élaboration et l'amélioration de la réglementation ou des recommandations pratiques pour la gestion du réseau d'eau potable dans des PDC prolongés et minimiser les effets néfastes sur la santé publique.

ABSTRACT

Contamination events in drinking water distribution system, whether intentional or accidental, can adversely affect public health. This study is focused on simulating accidental intrusion events due to sustained pressure losses. Utilities need to understand the spatial and temporal distribution of microbial contaminants during and after pressure deficient conditions (PDCs) to determine adequate remediation actions. Realistic hydraulic and water quality models under PDCs coupled with advanced quantitative microbial risk assessment (QMRA) framework can help utilities to take timely and appropriate action to minimize the infection risk associated with accidental intrusion due to low/negative pressure events.

The main objective of this research is to develop and integrate realistic hydraulic and water quality modeling concepts into a QMRA model in order to improve the assessment of public health risks associated with the occurrence of sustained low/negative pressure events in drinking water distribution systems. On a more detailed level, this project sought to: (1) evaluate the use of pressure-driven analysis (PDA), instead of traditional demand-driven analysis (DDA), to define the zones potentially at risk of intrusion/backflow in a full-scale distribution system; (2) develop a method that combines both pressure-driven analysis results and multi-species water quality analysis (MSWQA-PDA); (3) assess the impact of two pressure-demand relationships on hydraulic and water quality parameters; (4) reduce uncertainty and improve assumptions in modeling accidental intrusion and fate and transport of contaminants; (5) compare the spatial and temporal distribution of *E. coli* and the affected pressure zones, resulting from the ingress of sewage in the absence and presence of various disinfectant residuals and evaluate the possibility of issuing sectorial boil water advisory (BWA); (6) investigate how sustained PDCs, due to major WTPs shutdown, affect the disinfectant residuals with and without considering the ingress demand impact; (7) evaluate the spatial probability of detecting *E. coli* throughout the network at different periods and (8) evaluate the public health risk associated with accidental intrusion events by improving an available quantitative microbial risk assessment model.

In this work, a multi-species water quality modeling based on PDA (MSWQA-PDA) is proposed to predict the ingress of contaminated water resulting from sustained PDCs. The developed tool simulates also the fate and transport of contaminant and the decay of disinfectant across the network during and after PDCs. First, to verify the reliability of the presented approach (MSWQA-

PDA), continuous sustained PDCs are modeled by assuming some major WTP shutdowns in a full-scale drinking water distribution system that serves a population of ~400,000 through 1,600 km of pipes. As a proof of concept, multiple water quality species including water age, chlorine and THM are modeled and compared with the scenario of normal operating conditions. Results show that, DDA overestimate the areas at risk of low and negative pressure, which may lead to unjustified advisories. The simulated continuous PDCs generally resulted in greater chlorine residual loss, and consequently THM augmentation compared to normal operating conditions even without considering the impact of intrusion. This is mainly because of longer residence time. The variations are shown to be higher at nodes with lower pressure values.

As the next step, MSWQA-PDA is applied to model fate and transport of *E. coli* resulting from intrusion of raw sewage due to sustained PDCs of 5 hours in the presence of different types of disinfectant residuals. The intrusion volumes at each of the 73 leakage points, having pressures < 1 m, are estimated by taking into account the state of pipes (i.e. age and materials) and the internal pressure head, calculated from PDA. Results show that, 11% of the nodes experienced positive *E. coli* (≥ 1E-06 CFU/L) at any time during the 4-day simulation period in the absence of any disinfectant. This value decreases to 10% and 1% in the presence of 1 mg/L of chloramine and chlorine, respectively. It is observed that *E. coli* can be transported to areas with higher pressure (P > 10 m, based on pressures under PDCs) according to the efficacy of disinfectant residuals on the intruded microorganisms. For chlorinated system (1 mg/L), positive *E. coli* (≥ 10-6 CFU/L) is found at 119 nodes 4 hours after the start of intrusion rapidly decreasing to 8 nodes 9 hours after the start of intrusion. This indicates that the contamination events are unlikely to be detected using *E. coli* sampling unless sampling is conducted rapidly at or close to intrusion sites. In the presence of chloramine, the nodal mean probability of detection was more than 0.1 in the first and second 5-hour intervals at 166 nodes, indicating that a rapid response sampling directed at the areas at risk could be effective in confirming contamination. Matching the utility sampling schedules with the corresponding numerical predictions can increase the probability of detecting the contamination. Depending on modeled concentrations, larger sampling volumes may be required. A larger sample volume can extend the post intrusion allowable sampling time during which sampling can be performed with a greater likelihood of positive detection.

Finally, a novel QMRA model developed by Blokker et al. (2018) is coupled with water quality calculations based on PDA to assess *Cryptosporidium* infection risk from accidental intrusion of sewage. Poisson and the lognormal distribution for the number of glasses per person per day and ingested volume per glass is used, respectively. For the time of consumption, the average kitchen tap use is modified based on the availability of demand using PDA results. To take into account the uncertainty of the calculations from consumers' behavioral variability, 200 Monte Carlo simulations are performed. The simulated number of infected people increases by 235-fold with increasing concentrations of *Cryptosporidium* in raw sewage from 1 to 560 oocysts/L (fixed intrusion duration: 24 hours). The maximum number of infected people, during the 4 observation days, gets 64% and 94% lower for the scenarios of 10 hours and 1 h, respectively, compared to 24 hour intrusion. Spatial distribution of nodal risks for different event durations illustrated that duration is a key factor in defining the boundaries of BWA. It is shown that, not drinking water from tap with very low-flow (i.e. filling time increase by more than 20 times) could decrease the number of infected people up to 65% on the day of intrusion.

Overall, this research project models the water quality variations due to sustained pressure losses in drinking water distribution systems. Results from this study can be used to provide insight into the development and improvement of regulations or practical recommendations for managing drinking water network under sustained PDCs and minimize the adverse public health effects.

TABLE OF CONTENTS

DEDICATION III

ACKNOWLEDGEMENTS IV

RÉSUMÉ VI

ABSTRACT X

TABLE OF CONTENTS XIII

LIST OF TABLES XIX

LIST OF FIGURES XX

LIST OF SYMBOLS AND ABBREVIATIONS XXVI

LIST OF APPENDICES XXVIII

CHAPTER 1 INTRODUCTION – IMPROVING MODELING TOOLS TO PREDICT WATER QUALITY DUE TO SUSTAINED LOW/NEGATIVE PRESSURE EVENTS 1

CHAPTER 2 LITERATURE REVIEW 4

2.1. Distribution System Deficiencies 4

2.2. Pressure deficient conditions 4

2.2.1. Transient low/negative pressure events 4

2.2.2. Sustained low/negative pressure events 5

2.3. Quantitative microbial risk assessment 6

2.4. Hydraulic simulations: demand-driven analysis vs pressure-driven analysis 8

2.4.1. Pressure-demand relationships 9

2.4.2. Critical Pressure in Water Distribution Systems 12

2.4.3. Approaches to Pressure-Driven Analysis: A General Literature Review 13

2.5. Intrusion of pathogens into distribution systems 16

2.5.1. Intrusion predictions 17

2.5.2. Equation to model fate and transport of pathogens 18

2.5.3. Water quality modeling 19

2.6. Sampling strategies 24

2.7. Critical literature review 26

CHAPTER 3 RESEARCH OBJECTIVES, HYPOTHESIS AND METHODOLOGY 29

3.1 Research objectives and hypotheses 29

3.2 Research methodology 37

3.2.1 Hydraulic analysis under sustained low/negative pressure event 39

3.2.2 Multispecies water quality analysis based on pressure-driven analysis (MSWQA-PDA) 42

3.2.3 Intrusion prediction 43

3.2.4 Fate and transport analysis 44

3.2.5 Quantitative microbial risk assessment 46

CHAPTER 4 ARTICLE 1 – COMBINING A MULTI-SPECIES WATER QUALITY AND PRESSURE-DRIVEN HYDRAULIC ANALYSIS TO DETERMINE AREAS AT RISK DURING SUSTAINED PRESSURE-DEFICIENT CONDITIONS IN A DISTRIBUTION SYSTEM.......... 50

Abstract 51

4.1 Introduction 51

4.2 Methodology 54

4.2.1 Description of the distribution system 54

4.2.2 Pressure-deficient scenarios 55

4.2.3 Pressure-driven analysis 56

4.2.4 Water quality modelling 56

4.3 Results 57

4.3.1 Validating the reliability of the proposed methodology..58

4.3.2 Investigation of hydraulic behavior under scenarios of pressure-deficient conditions 58

4.3.3 Investigation of water quality behavior under pressure-deficient scenarios 62

4.4 Discussion 64

4.4.1 Improving modelling tools towards a better prediction of water quality under pressure-deficient conditions 65

4.4.2 Regulatory and management implications 67

4.5 Conclusion..70

CHAPTER 5 ARTICLE 2 –IMPROVEMENT OF ACCIDENTAL INTRUSION PREDICTION DUE TO SUSTAINED LOW-PRESSURE CONDITIONS: IMPLICATIONS FOR CHLORINE AND *E. COLI* MONITORING IN DISTRIBUTION SYSTEMS 72

Abstract 73

5.1 Introduction 74

5.2 Methodology 76

5.2.1 Description of Simulated Sustained Low-Pressure Event..76

5.2.2 Ingress of Contaminated Water..77

5.2.3 Disinfectant Decay and Microorganism Inactivation..78

5.3 Fate and transport of contaminated water during and after pressure losses...................79

5.4 Results and Discussion..80

5.4.1 Impact of sustained low/negative pressure events on pressure and DSRs.................80

5.4.2 Intrusion volumes to estimate *E. coli* concentration at the intrusion nodes...............81

5.4.3 Behavior of different disinfectants under PDCs and a 5-hour intrusion event 82

5.4.4 Propagation of *E. coli* under different conditions 85

5.4.5 Propagation of *E. coli* based on pressure values under PDCs....86

5.4.6 Source of uncertainties....91

5.4.7 Implications for management strategies....91

5.5 Conclusion....99

CHAPTER 6 ARTICLE 3 –USING NODAL INFECTION RISKS TO GUIDE INTERVENTIONS FOLLOWING ACCIDENTAL INTRUSION DUE TO SUSTAINED LOW PRESSURE EVENTS IN A DRINKING WATER DISTRIBUTION SYSTEM....101

Abstract....102

6.1 Introduction....102

6.2 Methodology....105

6.2.1 Exposure Analysis....106

6.2.2 Calculation of Infection Risk....108

6.3 Results....108

6.4 Discussion....117

6.5 Conclusion....124

CHAPTER 7 ARTICLE 4 –INVESTIGATING THE IMPACT OF SUSTAINED LOW PRESSURE EVENTS ON WATER QUALITY IN WATER SUPPLY NETWORKS USING PRESSURE-DRIVEN ANALYSIS....125

ABSTRACT....125

7.1 Introduction....126

7.2 Methodology....127

7.2.1 Hydraulic analysis....127

7.2.2 Water quality analysis....128

7.3 Results and discussions....129

7.4 Summary and conclusions....134

CHAPTER 8 GENERAL DISCUSSION 136

8.1 What are the proper modeling tools for a more realistic prediction of water quality under sustained pressure-deficient conditions? 140

8.1.1 Why investigate sustained low/negative pressure events? 140

8.1.2 Pressure-driven analysis versus demand-driven analysis 141

8.1.3 Multi-species water quality analysis combined with PDA results 142

8.1.4 How can the developed approach help the existing water distribution modeling community? 143

8.1.5 Improved prediction of contaminant mass rate 144

8.1.6 Improved prediction of disinfectant residuals 146

8.2 Water quality variations due to low/negative pressure events 146

8.2.1 Impact of low/negative pressure events on disinfectant residuals 147

8.2.2 Does disinfectant type affect the contaminant fate and transport through the network?.... 148

8.3 What is the public health risk associated to accidental intrusion under sustained low/negative pressure conditions? 149

8.3.1 QMRA in drinking water distribution systems 149

8.3.2 Investigating the influence of different factors on the infection risk variation 150

8.4 What are the regulatory and management implications of the findings? 152

8.4.1 Can the intrusion events be detected by the standard *E. coli* sampling protocols? .. 152

8.4.2 Do we need a system wide BWA due to low/negative pressure events? 154

8.5 Project contributions 156

8.6 Study limitations and sources of uncertainties 156

CHAPTER 9 CONCLUSION AND RECOMMENDATIONS 159

BIBLIOGRAPHY 164

APPENDICES.. 181

LIST OF TABLES

Table 2.1: Summary of the relationships proposed by different researchers for estimating available flow.....11

Table 2.2. Disinfection decay model presented by different authors;.....23

Table 2.3: Second order three-component system and the simplified one (Uber 2010).....24

Table 3.1. Modeling approach to validate (or invalidate) the research hypothesis and corresponding chapters of the thesis.....34

Table 3.2. Reaction equations and the constant values used in different chapters.....45

Table 3.3. Overview of the simulated scenarios for QMRA analysis.....47

Table 4.1. Hydraulic grade (HG, m) and outflow (Q_{out}, L/s) at each WTP for all 4 scenarios.....55

Table 4.2**.** Average DSR of each zone for scenarios 1 to 4.....59

Table 4.3. Number of nodes experiencing very low pressure for Sc2 to Sc4.....68

Table 5.1. Comparing network hydraulic conditions under normal and pressure-deficient conditions; HG and Q_{out} are hydraulic grade and outflow rate, respectively.....77

Table 5.2. Description of intrusion scenarios.....78

Table 8.1. Overview of the simulated low/negative pressure events and modeled water quality parameters in different chapters.....138

Table A-1 Reaction equations of simulated water quality parameters.....183

Table D-1. Modeling results for network 1 under abnormal condition (pump outage).....198

Table D-2. Modeling results for network 2 under abnormal condition (nodal demand is increased at Junc2).....198

LIST OF FIGURES

Figure 3.1. Flowchart of the model used for infection risk analysis associated with accidental intrusion events under sustained PDCs. 38

Figure 3.2. (a) Location of WTPs (triangles) and the influence zone under normal operating conditions for each of the WTP is demonstrated by different color, (b) distribution of nodal elevation; Node X: location where a fire flow demand of 15,000 L/min is applied (chapter 5). 41

Figure 3.3. Consumption amount using the number of glasses with a Poisson distribution: λ=2.5 in this study (model 2016), and a lognormal distribution (μ=−3.19 en σ=1.485) for the volume per glass (from Blokker et al. (2018)). 48

Figure 3.4. Consumption at kitchen tap use by Blokker et al. (2018) (orange, square); modified kitchen tap use in this study for the residential nodes that have no available demand for consumption based on PDA results at days 1 and 2 for the 10-hour scenario (blue, circle); days 3 and 4 are the same as day 2. 48

Figure 4.1 (a) Location of WTPs (triangles) and approximate boundaries of each influence zone under normal operating conditions (dash-lines); (b) distribution of nodal elevations for each influence zone. 55

Figure 4.2: Flowchart of MSWQA-PDA. 57

Figure 4.3: Comparison between results calculated with the modified .INP file of EPANET and the pressure dependent demand model of WaterGEMS for Sc2: (a) nodal pressures, and (b) pipe flows. 58

Figure 4.4: Comparison of pressure results calculated from PDA (modified EPANET input file) and DDA under pressure-deficient conditions (Sc2, Sc3, and Sc4), and normal reference operating conditions (Sc1) (DDA only). 60

Figure 4.5: Nodal pressure differences between PDA and DDA for pressure-deficient scenarios of (a) Sc3 and (b) Sc4 for different categories of pressure calculated by PDA (modified .INP file) for all the nodes; the proportion (%) of nodes in each pressure category is indicated on top. 61

Figure 4.6: Spatial distribution of pressure using PDA for scenarios 1 to 4 (a, c, b, and d), and using DDA for scenarios 2 and 4 (e, f). 62

Figure 4.7: Comparisons of water quality parameters between normal operation conditions (Sc1) and pressure-deficient conditions (Sc2: WTP 1 and 2 out of service and WTP 3 at 77m) for three categories defined under pressure-deficient conditions: nodes with P > 15m, nodes with P ≤ 15 m (including negative pressure), and nodes with P ≤ 0; n is the number of nodes.....63

Figure 4.8: Differences of computed chlorine residuals between normal operation conditions (NOCs) and pressure-deficient conditions (PDCs) of scenarios 2 to 4 for three categories defined under each scenario-specific pressure-deficient conditions: nodes with P > 15, 0 < P ≤ 15 m, and nodes with P ≤ 0. 64

Figure 4.9: Geographical distribution of areas triggering corrective/preventive actions (in red) for different minimal pressure criteria (0, 5, 10, or 15 m). 69

Figure 5.1. (a) Pressure values during NOCs (15:00), and PDCs (16:00) using both PDA and DDA, and (b) DSR excluding nodes without any demand (469 nodes) during NOCs; Square: Median; *: Mean; Box: 25%-75%; Whisker: Min-Max. 81

Figure 5.2. Distribution of intrusion volumes per node for the 5 hours pressure loss. 82

Figure 5.3. Temporal distribution of disinfectant residuals throughout the network for the nodes with positive *E. coli* at any time during and after the intrusion. No node was positive for *E. coli* without intrusion. Positive nodes with intrusion used for comparison with and without intrusion. For 1 mg/L chlorine (a) without intrusion, Sc5, and (b) with intrusion, Sc3. For 1 mg/L chloramine (c) without intrusion, Sc8, and (d) with intrusion, Sc6. Time intervals on the timeline are not equal. The red boxes show the concentration during PDCs; Square: Median; Box: 10%-90%; Whisker: Min-Max. 84

Figure 5.4. Maximum *E. coli* concentrations for scenarios with chlorine (Sc3, 1 mg/L), chloramine (Sc6, 1 mg/L) and without disinfectant (Sc1). Cyan color represents a concentration of ≤ 1 CFU/100 mL. 85

Figure 5.5. *E. coli* distribution in chloraminated (Sc6) and chlorinated (Sc3) systems at 20:00 of day 1, 01:00 of day 2, and 06:00 of day 2 following intrusion; Intrusion starts at 16:00 of day 1 and lasts for a duration of 5 hours. 86

Figure 5.6. Effect of different chlorine concentrations (0.5, 1 and 2 mg/L) at the outlet of WTPs on maximum *E. coli* concentration estimated over the whole simulation duration, only considering nodes positive for *E. coli* ; *: Median; Box: 25%-75%; Whisker: Min-Max; +: Raw data. 88

Figure 5.7. Effect of different chloramine concentrations (1 and 2 mg/L) at the WTPs on maximum *E. coli* concentration estimated over the whole simulation duration, only considering nodes positive for *E. coli*; *: Median; Box: 25%-75%; Whisker: Min-Max; +: Raw data. 90

Figure 5.8. Mean probability of detecting *E. coli* for sampling volumes of 100 mL (a) to (d) and 1 L (e) to (h) for different periods. 94

Figure 5.9. Box-plot of mean probability of detecting positive *E. coli* during 5 hours for 4 time periods for Sc6 (chloramine, 1 mg/L); each group consists of 2905 nodes, which are the nodes that experience *E. coli* at any time over the whole simulation duration; the y-axis is cut off at 0.2 while the maximum value is 1 for all the box. 96

Figure 5.10. Superposition of pressure map under PDCs (16:00) using PDA on nodes with positive *E. coli* at any time during the simulation (blue circles) (a) in the absence of disinfectant, (b) with chloramine, and (c) with chlorine. 98

Figure 6.1. Flowchart for QMRA of accidental intrusion during sustained PDCs; WL, water level; MO, microorganism. 105

Figure 6.2. Distribution of: (a) nodal pressures for the whole network (30,077 nodes); and (b) demand satisfaction ratios (DSRs) for nodes under pressure-deficient conditions (8578 nodes), excluding the nodes with zero demand. 109

Figure 6.3. Distribution of nodal intrusion flow rates through 93 leak openings under the simulated pressure-deficient conditions. 110

Figure 6.4. Number of infected people corresponding to median and maximum infection risks resulting from a 24-h depressurization; 200 Monte Carlo simulations (consumption events) for each *Cryptosporidium* concentration: 1, 6, 26, and 560 oocysts/L; number of infected people corresponds to the cumulative dose over four days of observation; F(x): probability that the median/maximum number of infected people will be less than or equal to x. 111

Figure 6.5. Impact of consumption volumes and number of glasses per day on the number of infected people corresponding to median infection risk over a four day-period; *Cryptosporidium* concentration = 560 oocysts/L; the x-axis scale is the same between the plots (150 people)....112

Figure 6.6. Comparing the probability distribution of the number of infected people over a four-day period for 200 Monte Carlo simulations for each duration of PDCs: 1, 10, and 24 h; *Cryptosporidium* concentration in sewage = 560 oocysts/L. 113

Figure 6.7. Spatial distribution of nodal risks for three durations of PDCs: 1, 10, and 24 h; *Cryptosporidium* concentration in sewage = 560 oocysts/L; nodes with an infection risk below 1×10^{-3} are drawn in black; infection risks corresponding to consumption events with F(x) = 1 (Figure 6.6) are illustrated....114

Figure 6.8. Number of infected people corresponding to median infection risk for Days 1 to 4 for the scenario of 1 h of PDCs with daily consumption patterns; C_{out} = 560 oocysts/L; 200 Monte Carlo simulations (consumption events) every day. 115

Figure 6.9. Spatial distribution of nodal risk; Days 1–4 for the scenario of 1 h of PDCs with daily consumption patterns; C_{out} = 560 oocysts/L; nodes with infection risk below 1×10^{-3} are drawn in black; infection risks corresponding to consumption events with F(x) = 1 (Figure 6.8) are illustrated....116

Figure 6.10. Probability distributions of the number of infected people during the first day of simulation when people with a DSR null and less than 5% do not drink water from tap; 200 Monte Carlo simulations for each scenario; C_{out} = 560 oocysts/L with 1 h of PDCs with daily consumption patterns....117

Figure 6.11. Number of infected people for different pressure (P) ranges (based on the pressure values under PDCs) on Days 1–4; Infection risks corresponding to the consumption event with F(x) = 1 (Figure 6.8) are illustrated. The event starts at 18:30 on Day 1 for a duration of 1 h. Daily patterns in the hydraulic model. 123

Figure 7.1. Distribution of (a) percentage of DSRs under pressure-deficient scenario when using Tanyimboh for two groups of nodes and (b) nodal DSRs absolute differences between

different PDRs (% ΔDSR=|DSR$_{Tanyimboh}$-DSR$_{Wagner}$|) while performing PDA, for all the nodes. These results exclude nodes with no required demand. 130

Figure 7.2. Comparison of pressure results calculated from PDA (Wagner and Tanyimboh) (modified EPANET input file) and DDA under pressure-deficient conditions and normal operating conditions (NOCs) (DDA). 131

Figure 7.3. Number of nodes at risk of intrusion/backflow based on different minimal pressure criteria and different methods of estimation: traditional DDA and PDA (comparing Wagner and Tanyimboh). 132

Figure 7.4. THM and chlorine concentration under normal and pressure deficient scenario, Tanyimboh equation used while performing PDA. Note: Median; Box: 25%-75%; Whisker: min-max. 132

Figure 7.5. Number of nodes in the network for different ranges of *Cryptosporidium* concentration using Tanyimboh (blue) and Wagner (green) equations. 133

Figure 7.6.(a) distribution of nodal chlorine residual differences between normal (DDA) and pressure deficient conditions (PDA, Tanyimboh) (b) distribution of nodal chlorine residual differences under pressure deficient conditions between Wagner and Tanyimboh equations 134

Figure 8.1. Summary of the research conducted. 137

Figure 8.2. Different types of low/negative pressure events as a function of duration, potential intrusion and resulting risk. 141

Figure A-1 Percentage of demand satisfaction for different pressure-deficient scenarios. 184

Figure B-1. Maximum estimated $Cleak$ at each of the 74 nodes prone to intrusion used for calculating intrusion flow rates. 186

Figure B-2. (a) Pressure values at potential intrusion nodes, and (b) corresponding intrusion flow rates. 187

Figure B-3. Distribution of (a) water age with y-axis limited to 40 hours (b) chlorine (Sc5), and (c) chloramine (Sc8) without considering any intrusion; for all the nodes in the network categorized by pressure values under PDCs (at 16:00) with respect to time; Time intervals are not equal; Square: Median; Box: 10%-90%; Whisker: Min-Max..189

Figure B-4. *E.coli* distribution at 06:00 day 2 in chloraminated system; Concentrations higher than 1 CFU/100mL are demonstrated in red. 190

Figure C-1. Probability of filling a glass or bottle for consumption over the 2 days. Consumption at kitchen tap use (Blokker et al. 2018) (orange, square); modified kitchen tap use for this study for the residential nodes with no available demand for consumption based on PDA results at days 1 and 2 for the 10 hours scenario (blue, circle); days 3 and 4 are the same as day 2. 193

Figure C-2. (a) Geographical distribution of population, and (b) histogram of number of people at each node; Exclude nodes with zero population. 194

Figure C-3. The probability distribution of the number of infected people during 4 days of simulation; 200 Monte Carlo simulations; 1 hour intrusion (a). The spatial distribution of the nodal risk corresponding to consumption event with F(x) =1 (b). Daily pattern in the hydraulic model. 195

Figure C-4. Spatial distribution of pressure using PDA under low/negative pressure event, at 7:00 PM. 196

Figure E-1. (a) Change of water path during PDCs; all the nodes are intrusion nodes (b) Chlorine residuals variation due to PDCs at nodes a and b with and without intrusion (travel time of 77 minutes between nodes). 200

LIST OF SYMBOLS AND ABBREVIATIONS

AVVs	Air Vacuum Valves
BWA	Boil Water Advisory
C_{out}	Concentration of microorganisms outside the pipe
°C	Degree Celsius
DDA	Demand-Driven Analysis
DMA	District Metered Areas
DS	Distribution System
DSR	Demand Satisfaction Ratio
E. coli	*Escherichia coli*
EPS	Extended Period Simulation
GGA	Global Gradient Algorithm
h	Hour
H_{des}	Desired pressure head
HG	Hydraulic Grade
H_{min}	Minimum pressure head
$K_{intrusion}$	Intrusion Decay Constant
K_{normal}	Disinfectant decay rates for water not exposed to intrusion water
MSWQA-PDA	Multi-Species Water Quality Analysis-Pressure-Driven Analysis
NOCs	Normal Operation Conditions
P	Pressure
PDA	Pressure-Driven Analysis
PDCs	Pressure Deficient Conditions
PDFs	Probability Density Functions
PDR	Pressure Demand Relationship
QMRA	Quantitative Microbial Risk Assessment

q_{avl}	Available demand
q_{req}	Required demand
Sc	Scenario
THMs	Trihalomethanes
WTP	Water Treatment Plants

LIST OF APPENDICES

APPENDIX A SUPPLEMENTARY INFORMATION, ARTICLE 1 181

APPENDIX B SUPPLEMENTARY INFORMATION, ARTICLE 2 185

APPENDIX C SUPPLEMENTARY INFORMATION, ARTICLE 3 191

APPENDIX D DISCUSSION ON ISSUES OF REPORTING NEGATIVE NODAL PRESSURE VALUES AS ZERO IN PDA MODELS 197

APPENDIX E IMPACT OF THE CUMULATIVE IMPACT OF INGRESS ON CHLORINE DEMAND DURING EXTENDED PDCS 199

CHAPTER 1 INTRODUCTION – IMPROVING MODELING TOOLS TO PREDICT WATER QUALITY DUE TO SUSTAINED LOW/NEGATIVE PRESSURE EVENTS

The integrity of the drinking water distribution systems is important not only to minimize leakage but also to minimize the risk of contaminants entering into the distribution systems. It is well established that distribution system deficiencies can be a source of waterborne disease outbreaks (Craun et al. 2010, Guzman-Herrador et al. 2015, Hunter et al. 2005, Kirmeyer et al. 2001a, Lindley and Buchberger 2002, Nygard et al. 2007, Payment et al. 1991, Payment et al. 1997). For the period 1971 to 1998 in U.S., 113 outbreaks out of 619 investigated cases (18.1%) were caused by distribution system deficiencies (Lindley and Buchberger 2002). In Quebec, the two epidemiological studies of Payment et al. (1991) and Payment et al. (1997) suggested that deficiencies in the distribution network could lead to an increased burden of gastrointestinal diseases. Pathogen intrusion in water distribution system may result in a decrease of water quality if there is not an adequate disinfectant residual concentration to control the propagation of pathogens from the intrusion points. Three events must occur at the same time to cause pathogen intrusion in distribution system: low/negative pressure, the presence of a source of contamination and a pathway for entry of the contaminated volume. Submerged air valves, cross-connections, faulty seals, faulty joint or leakage points are at risk for entry of untreated water into the drinking water distribution system due to negative or low pressure.

Water utilities need management plans in order to detect and respond to sustained low pressure conditions in order to limit the impact of pressure losses on their customer's health. Realistic and accurate modeling methods under pressure deficient conditions can be a valuable tool for utility managers in decision-making. As mentioned by Besner et al. (2011), the occurrence of adverse pressure conditions can be represented by two types of events: transient low or negative pressure and sustained low or negative pressure events. Transient low/negative pressure events can occur in the network lasting from a few milliseconds to a few minutes. These events have been well documented and were studied through modeling and field investigations, and several guidelines are proposed to prevent these events (Besner et al. 2010b, Boulos et al. 2005, Ebacher et al. 2012, Ebacher et al. 2011a, Gullick et al. 2005, LeChevallier et al. 2011, Walski and Lutes 1994, Yang et al. 2011). Sustained low/negative pressure events have been recorded in the literature (Besner et al. 2007, Besner et al. 2011, Douglas et al. 2018, Kirmeyer et al. 2014) and can become more frequent in decaying infrastructure. The volume of contaminated water ingress into the network is directly influenced by the duration of low/negative pressure events, and consequently adversely affects the level of public health. Therefore, the present work is aimed to concentrate on simulating extended duration low/negative pressure events lasting a few hours.

The use of quantitative microbial risk analysis (QMRA) to assess the microbial risk associated with the intrusion of pathogens in distribution system is challenging. Different factors such as the location of ingress, the contaminant mass rate, the duration of contamination events, the interactions between microorganisms and disinfectant throughout the network, and finally the consumer's behavior all impact the likelihood of contaminated water reaching the tap (Besner et al. 2011). In the last decade, QMRA associated with contamination events due to transient pressure drops, main repairs or intentional contamination has gained more attention (Blokker et al. 2014, Blokker et al. 2018, LeChevallier et al. 2011, Schijven et al. 2016, Teunis et al. 2010, Van Abel et al. 2014, Yang et al. 2011, Yang et al. 2015). However, no study has yet applied QMRA models integrated with realistic pressure-driven analysis (PDA) to assess the probability of infection associated to accidental intrusion due to sustained pressure drops. This can only be achieved by taking into account both the network's response and consumer's behavior during PDCs.

Using PDA rather than demand-driven analysis (DDA) under pressure deficient conditions leads to more realistic hydraulic simulations (Cheung et al. 2005, Siew and Tanyimboh 2012). As water quality parameters depend on hydraulic conditions, a realistic hydraulic simulation (with PDA) is required to be linked with water quality model under pressure deficient conditions. In previous studies, the hydraulic engine for multi-species water quality analysis was based on DDA (Betanzo et al. 2008, Islam et al. 2017, Karamouz et al. 2017, Klosterman et al. 2009, Muray and Adachi 2011, Propato and Uber 2004, Teunis et al. 2010, Tinelli and Juran 2017, Tinelli et al. 2018, Yang and Boccelli 2016). Although useful, these simulations are only valid under normal operating conditions. To the best of our knowledge, all water quality simulation studies under pressure deficient conditions, using PDA, are based on single-species water quality model (Afshar and Mariño 2014, Bashi-Azghadi et al. 2017a, Bashi-Azghadi et al. 2017b, Rasekh and Brumbelow 2014, Seyoum and Tanyimboh 2014, Seyoum et al. 2011, Zafari et al. 2017), except the recent work by Seyoum and Tanyimboh (2017) that modeled chlorine residual, trihalomethanes and haloacetic acids under PDCs for a small network with 380 nodes. In addition, the contaminant mass rate in ingress water was approximated randomly using the existing data or was considered as a fixed parameter for all the intrusion nodes (Besner et al. 2010c, Betanzo et al. 2008, Islam et al. 2017, LeChevallier et al. 2011, Propato and Uber 2004, Teunis et al. 2010). In this study, we estimated node-specific intrusion volume by adjusting the volume for the state of pipes using nodal leakage demand, and the nodal internal pressure value using PDA.

Prior work and this thesis emphasize the need to further develop QMRA models coupled with realistic numerical model calculations. An approach capable of integrating pressure-driven hydraulic simulation results into a multispecies water quality model is proposed. With this approach, the interaction between microorganism and disinfectant residuals under pressure deficient conditions can be considered. These improved models can provide a basis for reevaluating and enhancing statutory monitoring programs to increase the probability of contamination detection. They also offer insights to utility managers for appropriate preventive/corrective actions and timely response to sustained PDCs. Finally, this PhD project addresses several knowledge gaps on assessing the risk associated to accidental intrusion caused by sustained low-pressure conditions by performing several original improvements to various models (hydraulics, intrusion, quality and QMRA).

This thesis is structured in 9 chapters. A review of the state of the literature is presented in Chapter 2. It is followed by the objectives, hypotheses and methodology in Chapter 3. Chapters 4 through 6 represent the research results in the form of published or submitted articles. A published paper in conference proceeding is presented in Chapter 7. Finally, a general discussion is presented in Chapter 8, followed by conclusions and recommendations in Chapter 9.

CHAPTER 2 LITERATURE REVIEW

2.1. Distribution System Deficiencies

Drinking water distribution system is the final barrier for providing safe drinking water to consumers. According to experience records in Canada (Canadian Council of Ministers of the Environment (CCME) 2004), water system infrastructure is subject to a variety of events or threats such as mechanical failures (e.g. pump breakdowns and valves jamming), environmental (e.g. forest fires), power outages, contamination, communication disruption (e.g. failure of automatic signal equipment), etc. Waterborne disease outbreaks are attributed to distribution system deficiencies and their portion has been increased in recent decades (Kirmeyer et al. 2001a, Kirmeyer et al. 2014). Between 1971 and 1998, 18 % of investigated waterborne disease outbreaks (113 out of 619) in the United States were the results of drinking water distribution system deficiencies (Craun and Calderon 2001). Contaminant intrusion or backflow as the result of low or negative pressure events in distribution system can cause water quality problems and consequently lead to adverse health effects (Guzman-Herrador et al. 2015, Lindley and Buchberger 2002). Under these circumstances, appropriate and timely response to contamination events by utilities can minimize public health risks.

2.2. Pressure deficient conditions

The occurrence of adverse pressure conditions in drinking distribution systems can appear in the form of transient or sustained low/negative pressure event. While transient events are short duration events (e.g. few milliseconds to a few minutes) the duration of sustained low or negative pressure is usually in the order of minutes to hours (Besner et al. 2011). Submerged air valves, cross-connections, faulty seals, faulty joint or leakage points are the risk points where untreated water can intrude into the distribution system under pressure deficient conditions. The causes and consequences of each type of event are briefly described below.

2.2.1. Transient low/negative pressure events

Rapid changes in velocity occur when the operational status of flow control component varies (e.g. pump shut down or valve closure). Such rapid changes will impose a pressure wave movement through the system. Different studies have investigated the possibility of ingress of contaminated water into the distribution systems under transient pressure drops using numerical modeling tools or through field studies and practical guidelines are proposed to control these events (Besner et al. 2010b, Boulos et al. 2005, Ebacher et al. 2011a, Gullick et al. 2005, Gullick et al. 2004, LeChevallier et al. 2011, Walski and Lutes 1994). Details toward transient flow concept and the methods of controlling hydraulic transient can also be found in Walski et al. (2003). Some of the causes of transient flow conditions that may lead to pathogen intrusion in distribution systems are as follows (Kirmeyer et al. 2001b): altitude valve closure, opening and closing a fire hydrant, valve operation (opening and closing), air-valve slam, flushing operations, malfunctioning of air release/vacuum valves, malfunctioning of pressure relief valves, booster pump startup and shut down, sudden change in demand, check valve slam, resonance, breaking in a pipeline and losing an overhead storage tank. Isolation and disinfection process may be required at some distance away from the area of the main break as the contamination intrusion does not certainly occur at the point of the main break (LeChevallier 1999). Transient low/negative pressure events were measured by Besner et al. (2010a) installing high-speed pressure transient data loggers in full-scale water systems. Eleven negative pressure events were reported during phase 1 of this study. The cause of these negative pressures was due to power failures at the water treatment plant, repairs of isolated water mains and closure of a transmission main.

2.2.2. Sustained low/negative pressure events

While transient events are short duration events, the duration of sustained low/negative pressure is usually in the order of minutes to hours. The latter event was reported in some distribution systems (Besner et al. 2007, Besner et al. 2011, Douglas et al. 2018, Kirmeyer et al. 2014). With water infrastructure aging, sustained low/negative pressure events are likely to become more common and can be an important source of contaminant intrusion; thus the need for improvement of hydraulic and water quality models under such conditions. Immediately after a pressure drop is reported in the network, preventive/corrective actions are required to protect public health. When the duration of the pressure drop is longer, it is more likely that the utilities are informed about the pressure-deficient conditions through the complaints receive from customers and the pressure monitoring (Erickson et al. 2015). Planned or emergency construction/repair/replacement work, power failures, main break, large scale flushing or high fire-flow water demand by attaching a pump to a hydrant may cause sustained low/negative pressure in distribution systems (Besner et al. 2011, Erickson et al. 2015). During the field measurements done by Besner et al. (2007) and (2010a), the occurrence of sustained low/negative pressure is reported at different locations of the network. Negative pressure lasted between 1 and 37 minutes and pressure below 20 psi lasted up to 20 hours are reported during 3 closures of the transmission main (Besner et al. 2007).

2.3. Quantitative microbial risk assessment

Infection, illness and death can be modeled in microbial risk assessment. The risks of illness and death generally are calculated using infection risk by implementing morbidity or mortality ratios. Infection is the first symptom of exposure to a pathogen. However, in the lack of clinical sign it is difficult to assess infection in humans (United States Environmental Protection Agency USEPA 2012). One common method for evaluation is quantitative microbial risk assessment (QMRA) that has become a useful tool for evaluating the drinking water safety (Smeets et al. 2010, World Health Organisation (WHO) 2006). QMRA consisted of the following steps (United States Environmental Protection Agency USEPA 2012): hazard identification (recognizing the proper microorganism); hazard characterization (the qualitative description of microorganisms' ability or potential to cause harmful effects); exposure assessment and risk characterization.

In spite of the evidence supporting the role of water network in infectious waterborne diseases (Craun et al. 2002, Guzman-Herrador et al. 2015, Lindley and Buchberger 2002), QMRA has been mostly used to only assess the risk of drinking water treatment failures (Schijven et al. 2011, Tfaily et al. 2015, World Health Organisation (WHO) 2016). Employing QMRA model to assess the risk of contamination in water distribution systems is complicated as different parameters such as location, duration and intensity of the event, propagation of contaminated water and the coincidence of a consumption event with passing of contaminants from the tap should be integrated into the model. These requirements are addressed in a conceptual model presented by Besner et al. (2011) to provide a guidance for quantifying the risk from contamination intrusion in the distribution system.

Reviews of the health risk from intrusion in water distribution systems exist (Besner et al. 2011, Hamouda et al. 2018, Islam et al. 2015, Viñas et al. 2019). Most of the current QMRA models have been used to predict the public health risk associated with intentional intrusion, transient events in water distribution system or main breaks (Blokker et al. 2018, Schijven et al. 2016, Teunis et al. 2010, Yang et al. 2011, Yang et al. 2015). Water quality, hydraulic and surge modeling were coupled with Monte Carlo simulations to estimate the average risk of infection and the number of people infected (LeChevallier et al. 2011). Teunis et al. (2010) and Yang et al. (2011) have used the same risk model. The public health risk associated to transient and sustained intrusion events was investigated by Besner et al. (2010c) for a duration of 1 min and 1 hour, respectively. These authors recommended to include pressure driven analysis in future studies to determine the low/negative pressure points instead of demand-driven analysis. The probability of infection resulting from intentional intrusion due to contaminated aerosol droplets inhalation or ingestion of contaminants is investigated, including the consumer behavior (Schijven et al. 2016). In the study done by Blokker et al. (2018), the number of infected people from 1E+4 ingress load of *Cryptosporidium* (1E4 per isolation section volume with average of 3.4 m3) due to breaks in the distribution system was between 1 to ~120 for a single event. In their study the scenarios had been simulated under different hydraulic/water quality conditions (different times of opening valves and contamination locations) in the Monte Carlo simulations.

Usually, standard risk assessment models assume a fixed consumption volume, at a specific hour, per person per day (Besner et al. 2010c, Islam et al. 2017), at fixed times during the day or using randomize times of water consumptions at any time during the day (Besner et al. 2010c, Davis and Janke 2009, Yang et al. 2011), or only one consumption event per day (LeChevallier et al. 2011, Yang et al. 2011). However, there are several studies that used probabilistic models to more accurately simulate the behavior of consumers (Blokker et al. 2014, Blokker et al. 2018, Davis and Janke 2008, 2009, Schijven et al. 2016). Also, Blokker et al. (2018) and Davis and Janke (2009) showed that the time of water intake from the tap, for drinking water purpose, is not necessarily equal to the total consumption time. Blokker et al. (2018) used the kitchen tap use data to better identify realistic consumption times during the day.

2.4. Hydraulic simulations: demand-driven analysis vs pressure-driven analysis

To simulate the hydraulic dynamics of a distribution network, two sets of equations are required. The first set of equations is the conservation of flows for each node in the network and the next is the nonlinear relationship between flow and head loss for each pipe. The energy conservation equation in a steady state condition along hydraulic pipe between node i and j is expressed as follows:

$$\frac{P_1}{\rho_1 g} + \frac{{V_1}^2}{2g} + z_1 + h_{pump,u} = \frac{P_2}{\rho_2 g} + \frac{{V_2}^2}{2g} + z_2 + h_{turbine,u} + h_L \qquad \text{Eq. 2-1}$$

in which $h_{pump,u}$ is head delivered to the fluid by the pump, $h_{turbine,u}$ is the head that is removed from fluid by turbine (it is equal to 0 if there is no turbine in the system), h_L is head loss due to all components of the piping system between points 1 and 2. Hazen-Williams, Darcy-Weisbach, and Chezy-Manning are the most common head loss relationships due to friction that are used in network modeling (Mays 2004).

Flow conservation equation that must be satisfied around all nodes in steady state condition is as follows:

$$\sum_j Q_{ij} - D_i = 0 \quad \text{for } i = 1, \ldots, N \qquad \text{Eq. 2-2}$$

in which D_i is flow demand at node i, N is the number of junction nodes, Q_{ij} is flow in pipe i-j where j is set of nodes directly connected to the node i.

The approaches for simulating the hydraulic behavior in water distribution systems can be classified into two groups: demand-driven analysis (DDA) and pressure driven analysis (PDA). Both of these methods are based on the solution of the energy equation and mass conservation equation. In the demand driven algorithm, while energy and mass conservation equations are solved to calculate nodal heads and link flows, the nodal demands are considered as a fixed parameter in continuity equation. Therefore, this approach lead to unrealistic results under PDCs as it considers that all the nodal demands are met regardless of the nodal pressure values. These results cannot be physically acceptable and are only mathematical results, as in reality the nodal demands cannot be fully satisfied in the case of insufficient nodal pressure (Nyende-Byakika et al. 2012). Therefore, when nodal pressures are not sufficient to supply the full demand, a more realistic approach called PDA is preferred. However, in the majority of network solvers such as EPANET, the demand-driven approach is used and is perfectly adequate to model network hydraulics under normal operating conditions. Pressure deficient condition occurs when the nodal pressure drops below its critical value (see section 2.4.2) due to a failure condition in the system. Examples of such conditions are unplanned pipe outage, insufficient water supply from water sources, pump stations failure, etc.

Several algorithms maybe applied to solve the equations in DDA. Todini (2006) classified the existing solution algorithms presented by the researchers into four groups as: the global gradient algorithm, the linear theory algorithm, the simultaneous loop algorithm, the Newton-Raphson nodal algorithm. The Global Gradient method (GGM) has been established as a robust approach and as the most suitable for fast convergence. This algorithm has been applied in EPANET 2 (Rossman 2000). Wu et al. (2009), Siew and Tanyimboh (2012), Siew and Tanyimboh (2009) and Siew and Tanyimboh (2010b) have applied the improved GGM to consider demands as function of pressures.

2.4.1. Pressure-demand relationships

In a conventional water distribution hydraulic simulation, the demand is assumed as a fixed value that usually comes from field data observations. Recently, by developing pressure driven approach, it has been attempted to compute the demand values in the system as function of nodal head during pressure deficient conditions in the system. Determining an accurate relationship between nodal pressure and demand for a network may require a huge amount of field data, which does not seem to be practical. However, many researchers have attempted to develop some relationships between nodal demand and pressure (Bhave 1981, Fujiwara and Li 1998, Gupta and Bhave 1996, Reddy and Elango 1989, Tanyimboh and Templeman 2004, 2010, Tucciarelli et al. 1999, Wagner et al. 1988). Shirzad et al. (2013) conducted a set of laboratory and field experiments in three points of a real water distribution to measure the discharge from different faucets and their corresponding pressures. These authors were the first to compare different existing PDRs based on measured data.

These authors proposed a new relationship based on the measured data and orifice equation. However, this research reveals the need of more field and/or experimental data to define a suitable function between nodal pressures and demands. Recently, improvement to pressure-demand relationship (PDR) have been proposed by taking into account the impact of the number of orifices that are attached to the hydraulic model node, the number of open orifices and their elevation (Walski 2017, Walski et al. 2019). When demands related to several consumers are aggregated at a node of the hydraulic model, a parabolic relationship may not be applied anymore, because the relationship must be a function of different factors such as consumer location, consumption behavior, plumbing fixtures and headloss in the secondary network (Ciaponi et al. 2014, Gupta 2015). A selection of the proposed relationships and their parameters are shown in Table 2.1.

Table 2.1: Summary of the relationships proposed by different researchers for estimating available flow.

Head-Flow Equation	Parameters to be known	Reference
$q_j^{req} = q_j^{avl}, \quad \text{if } H_j^{avl} \geq H_j^{min}$ $0 < q_j^{avl} < q_j^{req}, \quad \text{if } H_j = H_j^{min}$ $q_j^{avl} = 0, \quad \text{if } H_j^{avl} \leq H_j^{min}$	H_j^{min}	Bhave (1981) Probably the first one who considered the nodal flows and heads at the same time, this method is named as node flow analysis.
$q_j^{avl} = q_j^{req}\left[1 - 10^{b_j\left(\frac{H_j - H_j^{min}}{H_j^{des} - H_j^{min}}\right)}\right]$	b_j, H_j^{min}, H_j^{des}	Gupta and Bhave (1996) Modified Germanopoulos (1985)
$q_j^{avl} = q_j^{req}, \quad H_j \geq H_j^{req}$ $q_j^{avl} = \left(\frac{H_j - H_j^{min}}{H_j^{des} - H_j^{min}}\right)^{1/2} q_j^{req}, \quad H_j^{min} < H_j < H_j^{req}$ $q_j^{avl} = 0, \quad H_j \leq H_j^{min}$	H_j^{min} H_j^{des}	Wagner et al. (1988)
$q_j^{avl} = S_{c_j}(H_j - H_j^{min})^{0.5}$	S_{c_j}, H_j^{min}	Reddy and Elango (1989)
$q_j^{avl} = q_j^{req}, \quad H_j \geq H_j^{req}$ $q_j^{avl} = \frac{(H_j - H_j^{min})^2 (3H_j^{des} - 2H_j - H_j^{min})}{(H_j^{des} - H_j^{min})^3} q_j^{req}, \quad H_j^{min} < H_j < H_j^{req}$ $q_j^{avl} = 0, \quad H_j \leq H_j^{min}$	H_j^{min} H_j^{des}	Fujiwara and Li (1998)
$q_j^{avl} = q_j^{req} \frac{\exp(\alpha_j + \beta_j H_j)}{1 + \exp(\alpha_j + \beta_j H_j)}, \quad \beta_j = \frac{11.502}{H_j^{des} - H_j^{min}}, \alpha_j = \frac{-4..595 H_j^{des} - 6.907 H_j^{min}}{H_j^{des} - H_j^{min}}$	α_j, β_j in the case of existence of field data, otherwise H_j^{des} and H_j^{min}	Tanyimboh and Templeman (2004) Tanyimboh and Templeman (2010) (+)
$Q = a(H_j - e_{min})^b$	a, b, e_{min}	Walski (2017), Walski et al. (2019)

q_j^{avl}: available flow at node j, q_j^{req}: required design demand, H_j^{min}: minimum head at node j, H_j: available nodal head, H_j^{des}: minimum required head at node j, S_{c_j} and b_j are node constants, a: coefficient and is a function of the number of open orifices and their orifice coefficient values, b: coefficient and is a function of orifice elevations, e_{min}: elevation of the lowest orifice.

(+) The values of α_j and β_j are specified using field data for the node in equation. This relationship seems to be the only function that removes the need of extra conditions for $H_j < H_j^{min}$ and $H_j > H_j^{req}$ (Tanyimboh 2008). In the case that no field data is available, these two parameters can be defined as the function of H_j^{min} and H_j^{des} by assuming: $q_j^{avl}(H_j^{des}) = 0.999 q_j^{req}$ and $q_j^{avl}(H_j^{min}) = 0.01 q_j^{req}$.

2.4.2. Critical Pressure in Water Distribution Systems

Critical pressure is the nodal pressure value below which the nodal demand cannot be fully supplied. Actually, the critical pressure is a value that is unique for each node and each network and its exact value must be determined from field measurements. As this task is not often practical, this critical value is usually approximated for the system using existing guidelines. However, this may induce uncertainty in the results when performing PDA.

Several criteria are used to estimate the critical pressure value. The terms threshold pressure, minimum required pressure, and critical pressure are used interchangeably this document. The pressure at any point in the distribution network should never fall below 20 psi across the street when the network is subjected to a maximum daily demand plus fire flow (Ministère de l'environnement du Québec 2002). A minimum pressure of 20 psi must be maintained at ground level at all points in the distribution system under all conditions of flow, while during normal operating condition, the pressure must be approximately 60 to 80 psi and not less than 35 psi (Great Lakes Upper Mississippi River Board of State Public Health and Environmental Managers 2007). Even though acceptable pressure may vary in different systems, they must usually be maintained between 30 psi and 100 psi during normal working conditions (Chase 2000). If the pressure values exceed 100 psi, it is likely to increase water loss through leaks and may also lead to main breaks or plumbing systems damage. Also it is mentioned that a pressure supply of 30 psi is enough for the top floors of multistory buildings. Depending on the characteristics of the water supply system, the minimum pressures may have to be kept higher than 30 psi at specific places in the network. As an example, facilities in some hospitals or industries may require a minimum pressure higher than 30 psi to operate correctly (Chase 2000). Operation of some devices in residential houses may also require specific minimum pressure. As an example most dishwashers require a minimum operating pressure anywhere from 20 to 40 psi (Mays 2004). During emergency cases such as fire flows, the entire system pressure should be kept above 20 psi. Also keeping the system pressure above 20 psi can help to avoid the potable supply being contaminated from cross-connections (Chase 2000).

A survey on the state minimum pressure standards and the practical reaction of the utilities to low/negative pressure events shows that, even though a minimum pressure standard of 20 psi is required for the majority of the states, the delay to issue boil-water advisories and notifying events to state primacy agencies follow different policies (Erickson et al. 2015).

2.4.3. Approaches to Pressure-Driven Analysis: A General Literature Review

Developed approaches to perform PDA can be categorized in (1) methods that involve DDA, (2) and methods that solve the mass and energy conservation equations and the selected PDR at the same time (Sayyed and Gupta 2013). In the following selected approach will be explained in more details.

A semi-pressure-driven approach was developed by Ozger (2003). This method is based on demand-driven analysis using EPANET 2 software. This author was probably one of the first researchers to propose the use of artificial reservoir to model pressure deficient conditions in distribution systems. The strategy of this approach is that the nodal demands are considered as unknown parameters while the threshold pressure is imposed in the system. During semi-pressure-driven analysis (SPDA), the first step is to run the network by demand-driven analysis in order to identify the nodes that cannot supply the full demand due to pressure deficiency. Next the amount of the available flow at these pressure deficient nodes is quantified by the following procedure: (i) new node elevation is set to the original node elevation plus threshold pressure head; (ii) non-zero demand is fixed to zero for all pressure deficient nodes; (iii) artificial reservoir is connected to each pressure deficient node; (iv) artificial tank elevation is set to new node elevation. It should be noted that the reservoir is connected to its junction by an infinitesimally short pipe to avoid head losses. This pipe is defined as a control valve that only allows flow from the junction into the tank. With the above modification, the hydraulics of the networks are solved for the second time. If, after the second simulation, any artificial reservoirs receive more water than the original demand assigned to the node then a new iteration is required. In this case, those artificial reservoirs are removed and the original nodal properties (e.g. nodal elevation and nodal base demand) are restored. While keeping the rest of conditions unchanged, the hydraulic model should be run again. The iteration procedure is continued until all the available flows into artificial reservoirs are less than the original demand. Ozger (2003) applied SPDA for both steady-state analysis and extended period simulation under pressure deficient conditions due to pipe failure. This approach has been used to perform reliability analysis of distribution systems (Ozger 2003, Yoo et al. 2005). The semi pressure driven analysis of Ozger (2003) was then employed to model serious pressure shortfalls in a real network including one reservoir and 22 pipes (Nyende-Byakika et al. 2012).

A methodology named pressure-deficient network algorithm (PDNA) is proposed and implemented into the EPANET hydraulic solver by using artificial reservoirs to model an 8-pipe single source and 14-pipe multiple-source network in the presence of firefighting demand and/or pipe breakage (Ang and Jowitt 2006). As an improvement of the algorithm provided by Ang and Jowitt (2006), a modified pressure deficient network algorithm (M-PDNA) is presented by Jinesh Babu and Mohan (2012) to overcome the drawback of PDNA from the standpoint of topology variation and consequently multiple runs of EPANET. The method was successfully validated to perform extended period simulation by modeling a multiple source pumped network assuming a diurnal change in demands and the performance of M-PDNA was shown by solving a network of 124 pipes. However, Gorev and Kodzhespirova (2013) illustrated that the M-PDNA approaches of Jinesh Babu and Mohan (2012) failed to converge during an extended period simulation under pressure deficient condition using a network example in two different cases. Through a network example, Suribabu and Neelakantan (2011) illustrated that PDNA did not provide reasonable results for some specific pipe isolations and the reason is mentioned to be that in PDNA the pressure is brought to minimum value by obligating the demand to be reduced. While in the case of having no outflow in the critical nodes, this would not be possible. These authors presented a method termed complementary reservoir solution (CRS) that is simpler than PDNA as it requires fewer removals and additions of artificial reservoirs. However, CRS still had the problem of requiring multiple hydraulic run. With CRS, additional flow enters the network through the reservoir even if this is not the case in reality and may cause error, however, Mamizadeh and Sharoonizadeh (2016) proposed some modifications to CRS to overcome this problem. Later, another study proposed an improvement to original CRS to minimize the number of artificial reservoirs that are required to be attached to the nodes with negative pressure head (Suribabua et al. 2017).

The methods that apply artificial reservoirs have some shortcomings such as high computational cost and modification to network topology. It is a tedious approach to apply for the analysis of large networks and for extended period simulation. Wu (2007) mentioned that the computational efficiency will significantly deteriorate during the application of PDNA to large networks due to topology variation and the necessity of refreshing the data of hydraulic model and also reopening the EPANET solver. Non-iterative approaches have been proposed to perform PDA using EPANET 2, in which the artificial elements are attached to all the demand nodes without the need of modifying the topology iteratively (Gorev and Kodzhespirova 2013, Mahmoud et al. 2017, Pacchin et al. 2017, Paez et al. 2018, Sayyed et al. 2014, Sayyed et al. 2015). However, implication of these methods for EPS may still be difficult.

A FORTRAN computer program that uses a globally convergent Newton-Raphson approach to treat PDA that is termed PRAAWDS (Program for the Realistic Analysis of the Availability of Water in Distribution Systems) was applied by Tanyimboh (2008). It was observed that different PDRs (Fujiwara and Li 1998, Gupta and Bhave 1996, Tanyimboh and Templeman 2004, Wagner et al. 1988) have a significant impact on final results. It was also demonstrated that computational time is not increased for PDA compared to DDA. Some researchers (e.g. Giustolisi and Walski (2012)) claimed that PDA is less efficient than DDA from numerical and mathematical point of view, because applying PDRs in PDA complicates the numerical and mathematical process.

An approach for modeling PDA was introduced in which the PDR was integrated in the gradient method. It was shown that this approach can properly model the normal and pressure deficient conditions (Siew and Tanyimboh 2009, 2010a). In these studies, PRAAWDS software was used as a validation reference. Siew and Tanyimboh (2010b) presented an extension of EPANET 2 to model pressure deficient condition by applying Tanyimboh and Templeman (2004) head-flow function. They integrated this function into a gradient method and named it as EPANET-PDX (pressure dependent extension). A real life network was chosen and the pressure deficient condition was generated by causing a pressure shortage for each reservoir in a way that only 22% of the total demand was achieved. Similar results were achieved for EPANET-PDX, PRAAWDS and the feasibility check, so it was concluded that EPANET-PDX models pressure deficient condition accurately. Siew and Tanyimboh (2012) and Seyoum and Tanyimboh (2014) performed additional case studies applying EPANET-PDX. It is observed that EPANET-PDX was robust during the demand satisfaction between zero to 100%. Recently, EPANET-PMX has been developed to combine the advantages of EPANET, EPANET-MXS and EPANE-PDX (Seyoum and Tanyimboh 2017).

A pressure-driven analysis using the existing emitter component within EPANET was proposed by Rossman (2007) to model pressure dependent flows. In 2010, EPANET was modified for pressure-driven demand analysis by Pathirana (2010) who employed emitter modeling of demands. In the current version of EPANET-EMITTER, the user is allowed to define the critical pressure value in the software. However, it is not possible to define various emitter exponent or critical pressure values for different nodes. More details regarding pressure driven analysis, based on emitter formula for the networks with severe topography, can be found in Trifunovic and Vairavamoorthy (2012). OOTEN (Object Oriented Toolkit for EPANET), a code library developed in C and C++, can be applied to modify EPANET's computational engine for specific uses. Cheung et al. (2005) modified the EPANET source code to include PDRs directly into OOTEN. As the values of the minimum and desired heads are required in pressure-driven analysis, the input file must be modified to specify these values. The proposed pressure driven method was applied on two networks to examine the performance of the method under abnormal conditions (fire flow).

An efficient approach of pressure driven model (Wu and Walski 2006) was developed and integrated into the modeling framework WaterGEMS (Bentley 2006) by Wu et al. (2006). The integrated approach was implemented in a real distribution system. In addition, the application of this approach to criticality analysis is demonstrated through the examples. Extended global gradient methods used by Wu et al. (2009) to analyze pressure deficient scenarios can be applied to the case with consideration of different PDR at each node.

2.5. Intrusion of pathogens into distribution systems

Water quality regulations usually require that water entering into the distribution system maintain a predefined minimum disinfectant residual either at the entrance or at end points of the system (Government of Ontario 2003, Ministère du Développement Durable de l'Environnement et des Parcs du Québec (MDDEP) 2005, United States Environmental Protection Agency (USEPA) 2006). Such a disinfectant residual is usually justified to protect from microbiological re-contamination, reduce bacterial regrowth and control biofilm formation. However, depending upon the characteristics of the distributed water, the use of residual disinfection may lead to undesirable side effects such as the excessive formation of disinfection by-products. Therefore, the concentration of disinfectant residual should be determined in consideration of the trade-off between these two issues. Concentrations of disinfectant residual needed to control microbial intrusion events can be determined by applying an accurate hydraulic/water quality model.

2.5.1. Intrusion predictions

Sustained or transient pressure losses can cause contaminant ingress into distribution systems if there is an external source of contamination and a pathway.

Pathways: Submerged air vacuum valve (AVV), faulty joint, main repair sites, cross-connections and leakage points are the potential locations for intrusion during pressure losses. Cross-connections are physical connections between potable and non-potable water source through which a contaminant may enter a drinking water supply. Backflow from buildings into the distribution system, contamination in water tanks, and low pressure in the network are causes of water quality failure reported by Hlavinek et al. (2008) in the networks. A list of backflow incidents can be found in United States Environmental Protection Agency (USEPA) (2001). Field testing done by Schneider et al. (2010) showed that backflow events took place in 1.6% of all meter reads, each month, and in 5% of the homes, affect each year, where backflow-sensing meters had been installed. Water in an air valve chamber presents a risk of contamination, since fecal contamination indicators and enteric viruses have been detected in flooded valve chambers (Besner et al. 2010a). In Canada, after the water is withdrawn by suppliers, ~13% of the water is lost before it arrives to the consumers, however, this value can be higher (20-30%) for other territories (Renzetti and Dupont 2013). This amount of water is mostly lost through pipe leaks, which are representative of the intrusion pathways during pressure losses.

Contamination source outside the pipes: Microbial indicators concentrations in air vacuum valve chambers, groundwater, and runoff water or raw waters/wastewater were measured in previous studies (Besner et al. 2010a, Ebacher et al. 2013, Payment 2003), showing that the detected *E. coli* concentrations were much higher in local wastewater compared to groundwater and valve vault water samples.

Intrusion volume: As field measuring of intrusion volumes is costly and impractical, simulating the potential intrusion volumes and defining the intrusion points, by numerical models is of great importance. The orifice equation used by researchers for this purpose (Besner et al. 2010c, Ebacher et al. 2012, Ebacher et al. 2011b, Gibson et al. 2019, Kirmeyer et al. 2001a, LeChevallier et al. 2011). In these studies the diameter in orifice equation was either directly defined or global leakage rate was applied to all nodes to estimate the intrusion flow rates. Using InfoSurge model, the total intrusion volume of 157 L through 1517 leakage orifices was reported versus the total intrusion volume of 766 L through 11 submerged air vacuum valves, for an intrusion event lasted for ~3 minutes (Ebacher et al. 2010). Some researchers have proposed modifications to the orifice equation to take into account the impact of soil-leak interactions, leak-area variations due to pressure changes, and type of leaks (Clayton and van Zyl 2007, Kabaasha et al. 2018, van Zyl et al. 2017, van Zyl and Malde 2017, Yu et al. 2016). It is shown that variation of round hole area is negligible with pressure changes, while this was not the case for longitudinal slits. In the latter case, a modified orifice equation with leakage exponent varying between 0.5 to 1.5 was proposed (van Zyl et al. 2017). Not considering the impact of soil characteristics outside of pipelines can lead to a conservative intrusion flow rate estimation (Collins et al. 2010).

2.5.2. Equation to model fate and transport of pathogens

For a specific intrusion event, the estimation of the amount of pathogens that an individual may be exposed through drinking tap water requires the simulation of the fate and transport of the microorganisms into the system. The presence and type of disinfectant, the type of pathogen and the organic matter content of the intruded material, attachment/detachment of pathogens from biofilm, and hydraulic conditions are factors that will influence the transport and survival of the microorganisms into the system. Three mechanisms may be used to model water quality: advection, dispersion, and reaction. The advection term describes the particles transport by the bulk motion of flow. The dispersion term model the movement of particles due to molecular diffusion. The reaction term can define the decay, growth, death, adsorption, and consumption rate of the particles. Water quality modeling in water distribution system can be simulated using the advection-dispersion-reaction equation as follows:

$$\frac{\partial}{\partial t}c(x,t)+\frac{\partial}{\partial x}\big(v(x,t)c(x,t)\big)=\frac{\partial}{\partial x}\left(d(x,t)\frac{\partial}{\partial x}c(x,t)\right)+f\big(x,t,c(x,t)\big) \qquad \text{Eq. 2-3}$$

in which $c(x,t)$ is the concentration of a certain species with spatial variable x and time $t \geq 0$, $v(x,t)$ is the flow velocity and $f(x,t,u(x,t))$ counts for reactions between various species. More details on derivation of this equation and numerical solutions for solving this equation can be found in Hundsdorfer and Verwer (2003).

Most of the water quality models apply advection-reaction equation to simulate the concentration of a constituent in the distribution system (Walski et al. 2003). Longitudinal dispersion in pipes is usually neglected with the assumption of completely mixed flow. However, that is only acceptable under turbulent flow conditions. Blokker et al. (2008) reviewed the effect of dispersion on water quality modeling. They mention that the dispersion term cannot be neglected in the case of laminar flow and the contribution of this term in water quality model may be important. There are many other studies documenting the effect of the dispersion term (Lee and Buchberger 2000, Tzatchkov et al. 2002). Tzatchkov et al. (2002) observed that for high and medium velocities, the EPANET advection-reaction model and their proposed advection-dispersion-reaction model gave similar results. While for low velocity condition, their proposed model was more accurate. EPANET's water quality simulator (Rossman 2000) doesn't consider the dispersion phenomenon and models advection transport and reactions in the bulk flow and at the pipe wall.

2.5.3. Water quality modeling

Propato and Uber (2004) quantitatively investigated the vulnerability of distribution systems to microbial intrusions using DDA by assuming deliberate continuous intrusion of *Giardia*, a pathogen resistant to chlorine. These authors were the first who attempted to quantitatively predict the effect of disinfectant residual on microbial intrusion events. Simulation results were expressed as vulnerability curves which showed identical trends in both networks: consumer protection increased with increasing the disinfectant concentrations as well as with applying booster chlorination and free chlorine residual is more effective than combined chlorine. Betanzo et al. (2008) later extended the work by investigating intrusion of *E. coli*, which is more easily inactivated by chlorine. In their simulations, intrusion occurred at a single node of the network and investigated three scenarios to model the fate and transport of pathogens from intrusion event: (i) constant intrusion flow at a specific node, no disinfectant decay, (ii) similar to the first scenario, with the exception for that the intrusion event at that specific node can only take place whenever the pressure is lower or equal to 20 psi, (iii) disinfectant decay modeling was added. Some of the limitations of the simulations presented by Betanzo et al. (2008) are as follows: (i) the dilution of intrusion water is assumed to be less than 1 % to have a first order decay (ii) constant intrusion concentrations of *Giardia/E. coli* are assumed regardless of the system pressure, and (iii) as the pressure of the system at some points goes below 20 psi, the use of a demand driven hydraulic model may cause inaccuracies in simulation and consequently unrealistic estimations of residual disinfectant in the network. Betanzo et al. (2008) concluded that 0.5 mg/L of free chlorine residual in distributed drinking water may be insufficient to control intruded *Giardia*. However, *E. coli* can be inactivated during an intrusion event in the presence of 0.5 mg/L of free chlorine residual. Chloramines as a secondary disinfectant may have negligible benefits for the inactivation of microorganisms from intrusion events (Betanzo et al. 2008, Propato and Uber 2004). There is still debate regarding the protective action of disinfectant residual in the distribution system according to the existing regulations to mitigate the impact of intrusion events in the distribution systems.

In some studies, the concentration of microorganisms is considered constant during the simulations. However this situation can only be accurate and efficient to simulate worst case scenarios where no inactivation of microorganisms occurs such as for *Cryptosporidium* in contact with chlorine or chloramines (Betancourt and Rose 2004). However in other studies, the inactivation of microorganisms is modeled while the disinfectant residual is considered constant, i.e. no disinfectant decay (Betanzo et al. 2008). The interaction between microorganisms and disinfectant cannot be simulated using classical single-species water quality models such as EPANET. To overcome these problems multi-species models such as EPANET-MSX have been developed (Shang et al. 2011). For example, EPANET-MSX software can be used to simulate multi-species interactions such as attachment/detachment of pathogens to/from biofilm, interaction of disinfectant with organic and inorganic matter, and inactivation of microorganisms (Uber 2010). EPANET-MSX facilitated the simulation of multiple interacting species and has been used by a number of authors (Betanzo et al. 2008, Islam et al. 2017, Karamouz et al. 2017, Klosterman et al. 2009, Muray and Adachi 2011, Propato and Uber 2004, Seyoum et al. 2013, Tinelli and Juran 2017, Tinelli et al. 2018, Yang and Boccelli 2016). EPANET-MSX was used to assess the efficacy of disinfectants on virus intrusion associated with low/negative pressure transients by Teunis et al. (2010) and LeChevallier et al. (2011). It should be noted that the hydraulic engine of this software is based on DDA, as in EPANET 2. Recently, Seyoum and

Tanyimboh (2017) modified the source code of EPANET-MSX to provide PDA. Except this recent study, other studies that attempted to model water quality under pressure deficient conditions, using PDA, are based on single-species water quality model (Bashi-Azghadi et al. 2017a, Bashi-Azghadi et al. 2017b, Rasekh and Brumbelow 2014, Seyoum and Tanyimboh 2014, Seyoum et al. 2011, Zafari et al. 2017).

Microbial inactivation model: Haas and Karra (1984a) compared 3 available kinetic models under disinfectant demand free conditions: Chick–Watson, Hom, and Monod model. The equations of these models are as follows:

$$\ln\left(\frac{N}{N_0}\right) = -kC^n t \text{ (Chick–Watson model)} \qquad \text{Eq. 2-4}$$

$$\ln\left(\frac{N}{N_0}\right) = -k'C^n t^m \text{ (Hom model)} \qquad \text{Eq. 2-5}$$

$$\ln\left(\frac{N}{N_0}\right) = \frac{-k_2 C}{C+k_D} * \left[t + \frac{exp{-}k_1 t(C+k_D)-1}{k_1(C+k_D)}\right] \text{ (Monod model)} \qquad \text{Eq. 2-6}$$

where C is disinfectant concentration, N/N_0 is the ratio of microorganism concentration, and k, n and m are empirical constants. Computed combined chlorine and free chlorine were compared with experimental data sets. They observed that, in general, all three models fit the data properly. In a few cases, the Hom and Monod models fitted the data better. However, the authors concluded that applying the simple Chick–Watson model to estimate the inactivation of microorganisms due to free or combined chlorine was generally adequate.

Disinfectant decay model: Most decay model used in water distribution models are first order equations (Betanzo et al. 2008, Islam et al. 2017, Propato and Uber 2004, Teunis et al. 2010). Chlorine consumption is usually divided in two phases. The short term decay phase that usually occurs in the first 4 hours is followed by a much slower decay phase (Jadas-Hécart et al. 1992). As an improvement to first order model, the parallel first order decay model has been used by some researchers. This model assumes two kinetic terms: one for the initial rapid chlorine residual decay and one for the slow and long term chlorine decay. Other relations which proposed to model disinfectant decay are listed in Table 2.2. First and second order models were compared by Boccelli et al. (2003) and the differences between these two models for chlorine decay under re-chlorination conditions were shown. They claimed that the second order model is always better than or provides the same fit as the first order model. The second order model is capable to represent chlorination kinetics more accurately than the first order model. In many cases the parallel first order decay model provides a suitable fit to the existing experimental data (Haas and Karra 1984b, Helbling and Vanbriesen 2009, Warton et al. 2006).

Table 2.2. Disinfection decay model presented by different authors;

Type	Model form and/or Analytical solution	*	Definition of parameters	References
Zero-Order	$\frac{dC}{dt} = -k/r$	1	r=Hydraulic radius of pipe section, k= coefficient rate, C=chlorine concentration	Digiano and Zhang (2005)
First order	$\frac{dC}{dt} = -kC$ $C = C_0 \exp(-kt)$	1	C_0 =initial chlorine, C=chlorine concentration, k= coefficient rate	Fisher et al. (2011); Haas and Karra (1984b)
First-order decay with stable components	$\frac{dC}{dt} = -k(C - C^*)$ $C = C^* + (C_0 - C^*)\exp(-kt)$	2	C^* =portion of the initial chlorine residual which is indefinitely persistent, C=chlorine concentration, k= coefficient rate	Haas and Karra (1984b)
Parallel first-order decay	$\frac{dC}{dt} = -k_1 C\,x, \quad \frac{dC}{dt} = -k_2 C\,(1 - x),$ $C = C_0 x \exp(-k_1 t) + C_0(1 - x)\exp(-k_2 t)$	3	K_1 and k2= coefficient rate, x= chlorine fraction that react with rate of K_1, C_0 =initial chlorine, C=chlorine concentration,	Haas and Karra (1984b) Ramos et al. (2010)
Second order	$\frac{dC}{dt} = -k.C.X$	2	X= concentration of reactant, C=chlorine concentration, k= coefficient rate	Kohpaei et al. (2011)
Parallel second order model	$\frac{dX_{fast}}{dt} = -k_{fast}.C.X_{fast}$ $\frac{dX_{slow}}{dt} = -k_{slow}.C.X_{slow}$ $\frac{dC}{dt} = \frac{dX_{fast}}{dt} + \frac{dX_{slow}}{dt}$	4	X_{fast} and X_{slow} = concentrations of fast and slow reactants with coefficient rate of k_{fast} and k_{slow} respectively	Kohpaei et al. (2011)
Power law decay (nth-order)	$\frac{dC}{dt} = -kC^n$ $C = (kt(n-1) + \left(\frac{1}{C_0}\right)^{n-1})^{-\frac{1}{n-1}}$	2	K and n= adjustable constants, C_0 =initial chlorine, C=chlorine concentration	Haas and Karra 1984c)
Power law decay with stable components (nth-order)	$C = C^* + (kt(n-1) + \frac{1}{(C_0 - C^*)^{n-1}})^{-\frac{1}{n-1}}$	3	K and n= adjustable constants, C_0 =initial chlorine, C^* =portion of the initial chlorine residual which is indefinitely persistent	Haas and Karra (1984b)
Combined first and second order model	$\frac{dC}{dt} = -k_1 C - k_2 C^2$ $\frac{1}{C} + \frac{k_2}{k_1} = (\frac{1}{C_0} + \frac{k_2}{k_1})e^{k_1 t}$	2	K_1 and k2= coefficient rate, C_0 =initial chlorine, C=chlorine concentration	Hua et al. (1999)

*: No. of parameters required to be determined

A theoretical three-species *E. coli* inactivation model was presented by Uber (2010), using EPANET-MSX software. The three-species included in the model were: *E. coli* bacteria, free chlorine and an organic rich matrix (e.g. nutrient broth). They proposed the following second order model for three-component system (Table 2.3).

Table 2.3: Second order three-component system and the simplified one (Uber 2010).

Second order three-component system	**Simplified second order three-component system**
$\frac{dE}{dt} = -k_{e1}CE + k_{e2}BE$	$\frac{dE}{dt} = -k_{e}CE$
$\frac{dC}{dt} = -k_{c1}CE - k_{c2}CB - k_{c3}C$	$\frac{dC}{dt} = -k_{c}CB$
$\frac{dB}{dt} = -k_{b1}BC + k_{b2}BE$	$\frac{dB}{dt} = -k_{b}BC$

Note: E= measure of coliform bacteria in CFU/L, B= organic matrix, in Uber (2010) modeled for an intentional contamination scenario as Tryptic Soy Broth (TSB), in mL TSB/L, C=chlorine concentration in mg/L

The simplified three-species model (free chlorine, *E. coli* bacteria, and a nutrient broth) was applied by Klosterman et al. (2009) to model *E. coli* inactivation in a single pipe. The contaminant injected into the pipe was *E. coli* and Tryptic Soy Broth (TSB). The simulation was done for a single pipe. Later, Karamouz et al. (2017) applied the same equations and constants to model contamination events in a real network. EPANET-MSX was used by Muray and Adachi (2011) to model the inactivation of microorganisms and chlorine decay in the presence of Tryptic Soy Broth (TSB). Laboratory data was used to estimate the model parameters. Two microorganisms, *E. coli* and *B. globigii* spores were studied. Simplified second order model as in Table 2.3 was used in their studies. Estimation of pathogen concentrations may be more complicated than what is considered in most of the models. It should be considered that decay constants in the presence of TSB are not representative of decay in mixed ingress water during intrusion events. In the case of intrusion simulation, it would be more realistic to apply decay constants for the reaction of chlorine with background organics using a two species second-order model, as in Yang and Boccelli (2016).

2.6. Sampling strategies

E. coli analysis is currently used for confirmation of contamination in the distribution system as well as for clearance sampling to confirm that the network is no more contaminated. *E. coli* is a coliform bacteria and the most adopted indicator of contamination by human/animal waste in drinking water. Its presence in the water distribution system can indicate a potential for a serious threat to public health (Federation of Canadian Municipalities (FCM) and National Research Council (NRC-CNRC) 2004). Most coliform bacteria are not harmful, but they come from the same sources as other bacteria and organisms that can cause disease (Centers for Disease Control and Prevention (CDC) 2013). Sampling frequency, distribution of sampling sites and detection limit (volume of sample) are the parameters that can impact the probability of detection (van Lieverloo et al. 2007). Through laboratory studies, some studies showed that larger-volume samples can increase the probability of detecting *E. coli* or total coliform (Hambsch et al. 2007, Hanninen et al. 2003, Hargy et al. 2010).

The prescribed sampling frequency for total coliform monitoring can vary from 1 sample to 480 samples per month for distribution systems serving 25 people and more than 3,960,000 people, respectively (Environmental Protection Agency (EPA) 2013, National Research Council of the National Academies 2006). The locations of sampling should represent various pressure zones and areas that are supplied by different sources and reservoirs (National Research Council of the National Academies 2006). Any total coliform positive sample needs repeat sampling within 24 hours. In the case of total coliform-positive, either for routine or repeat sample, *E. coli* should be measured and if positive the State must be notified by the end of the day (Environmental Protection Agency (EPA) 2013). Any repeat sample with (i) fecal coliform positive, and (ii) total coliform positive following a fecal coliform or *E.coli* positive routine sample is part of an acute violation and a non-acute violation occurs when (National Research Council of the National Academies 2006):

1- > 5% of the samples are total coliform positive during the month, for a system serving > 33,000 people and collecting > 40 samples per month.

2- >1 sample is total coliform positive per month, for a system serving ≤ 33,000 people and collecting < 40 samples per month.

The effectiveness of existing statutory sampling protocols had been investigated by hydraulic model simulations of contamination events (Blokker et al. 2018, van Lieverloo et al. 2007). Blokker et al. (2018) observed that if sampling was conducted 1-4 hours after the repair the at the optimal location, the detection probability increased to 80% compared to ~25% under the statutory Dutch sampling protocol which necessitates a 100 mL sample for *E. coli* analysis to be taken the day after the maintenance. In agreement, van Lieverloo et al. (2007) reported mean detection probabilities of 55–65%, when large parts of the sewage reach reservoirs and 0-13% when contamination does not reach any of the reservoirs. Both studies considered no inactivation for *E. coli* during their simulations, therefore, in reality the detection probability would be even lower in the presence of disinfectant residuals.

2.7. Critical literature review

Events that may lead to sustained low/negative pressure conditions in a distribution system are usually controlled by the following strategies: boil water order, notices not to consume water until return to service, mitigation strategies (e.g. super-disinfection) and installation of temporary networks (Besner et al. 2011). However, some situations may lead to low pressure events of shorter but still significant durations (more than a few minutes), for example during maintenance activities, where the above-mentioned controlling strategies may not be applied. During this type of event, it is possible that intrusion will affect public health. In addition, a delayed response or the application of inadequate preventive/corrective actions can also cause adverse health effects associated with contamination of drinking water due to unplanned extended pressure losses. Most of the existing QMRA models used to evaluate the risk of infection due to intrusion events are related to short transient events, pipe breaks or intentional contamination (Blokker et al. 2018, LeChevallier et al. 2011, Schijven et al. 2016, Teunis et al. 2010, Van Abel et al. 2014, Yang et al. 2011, Yang et al. 2015). Also, the water quality modeling in existing QMRA models is based on demand driven hydraulic simulation. To the best of our knowledge, no studies have yet been conducted to derive a quantitative relationship between public health risk and sustained low/negative pressure events using water quality calculations based on pressure driven analysis and integrating the impact of consumers' behavior during pressure drop on the consumption event.

The other drawback of applying the classical demand driven approach under pressure deficient conditions is that the intrusion flow rate, and consequently the contaminant mass rate cannot be modeled correctly. The reason is that the volume of untreated water that intrudes into the distribution system depends on the internal pipe pressure, while the nodal pressures estimated by DDA are not realistic under PDCs. However, this fact is not considered in most of the studies estimating the contaminant mass rate resulting from intrusion events. Previous studies calculated the concentration of contaminants or the contaminant mass rate at intrusion nodes using random data, a probabilistic model or a fixed value for all the nodes (Besner et al. 2010c, Betanzo et al. 2008, Islam et al. 2017, Propato and Uber 2004, Teunis et al. 2010). Previous researchers that estimated intrusion volume by orifice equation usually applied a fixed diameter to all the potential intrusion nodes or the intrusion volumes were estimated using a global leakage rate (Besner et al. 2010c, Ebacher et al. 2012, Ebacher et al. 2011b, Kirmeyer et al. 2001a, LeChevallier et al. 2011). However, for more realistic simulation, it is recommended that the intrusion volume should reflect the state of pipes (Besner et al. 2011, Ebacher et al. 2012, Gibson et al. 2019). Without this adjustment, the potential intrusion volume would be overestimated at areas of low leakage, while underestimated risks at areas with decaying infrastructure that are more prone to intrusion. Furthermore, studies with calculation of intrusion volumes for extended duration of pressure drops are not available in the literature. The studies that modeled contamination events using EPANET/EPANET-MSX did not consider the impact of intrusion volume on the hydraulic conditions and vice versa. In this study, this simplification will also be addressed.

Recently, Seyoum and Tanyimboh (2017) modified the source code of EPANET-MSX to include PDA and modeled THM and chlorine under continuous sustained PDCs in a small network with 380 nodes. To the best of our knowledge, no study has yet simulated accidental intrusion event due to sustained pressure drops taking into account the interactions between multiple water quality species under sustained PDCs using PDA. Up to now, the studies that modeled contamination events are either based on a single-species water quality model (Blokker et al. 2018, Rasekh and Brumbelow 2015, van Lieverloo et al. 2007), single species water quality model is coupled with PDA (Afshar and Mariño 2014, Bashi-Azghadi et al. 2017a, Bashi-Azghadi et al. 2017b, Rasekh and Brumbelow 2014, Zafari et al. 2017), or multi-species water quality analysis was performed based on DDA (Betanzo et al. 2008, Islam et al. 2017, Karamouz et al. 2017, Klosterman et al. 2009, Muray and Adachi 2011, Propato and Uber 2004, Teunis et al. 2010, Tinelli and Juran 2017, Tinelli et al. 2018, Yang and Boccelli 2016).

Standard hydraulic models based on demand-driven analysis (DDA) do not adequately represent the real hydraulic behavior of distribution networks under pressure deficient conditions. As it has been reported in many studies such as Lee et al. (2016), Siew and Tanyimboh (2012) and Cheung et al. (2005) applying a pressure-dependent analysis (PDA) rather than DDA under pressure deficient conditions lead to more realistic hydraulic simulations. To perform PDA, many studies have proposed some PDRs, compared different PDRs or attempted to improve the existing relationships (Bhave 1981, Cheung et al. 2005, Fujiwara and Li 1998, Gupta and Bhave 1996, Jun and Guoping 2013, Liu et al. 2011, Tanyimboh and Templeman 2004, 2010, Wagner et al. 1988, Walski 2017, Walski et al. 2019). However, finding an appropriate pressure-demand function is a challenging task in the absence of field data, which was the case in all the reported studies. Several studies showed that the choice of PDR affect the nodal pressures and nodal outflows (Cheung et al. 2005, Ciaponi and Creaco 2018, Liu et al. 2011, Yoo et al. 2012). There is no study that has investigated directly the impact of using different PDRs on the water quality in the case of intrusion.

First-order decay model has been generally applied to simulate the decay of chlorine in the case of intrusion (Betanzo et al. 2008, Islam et al. 2017, LeChevallier et al. 2011, Propato and Uber 2004, Teunis et al. 2010). However, this equation does not directly depend on the contaminants concentration and employ a fixed decay constant to all contaminated or non-contaminated zones throughout the network during and after intrusion.

Finally, van Lieverloo et al. (2007) and Blokker et al. (2018) assessed the probability of detecting *E. coli* based on standard monitoring program using the numerical model. However, a single water quality model was used and *E. coli* inactivation was not considered. To the best of our knowledge, there is no study yet that has evaluated the likelihood of detecting *E. coli* in the presence of chlorine residuals due to intrusion events under low-pressure events applying numerical models.

CHAPTER 3 RESEARCH OBJECTIVES, HYPOTHESIS AND METHODOLOGY

3.1 Research objectives and hypotheses

The main objective of this research is to develop and integrate realistic hydraulic and water quality modeling concepts into a QMRA type model in order to improve the assessment of public health risks associated with the occurrence of sustained low/negative pressure events in drinking water distribution systems.

More specifically, the objectives of this project are:

1. Evaluate the use of PDA, instead of traditional DDA, to determine the nodes with low/negative pressure values for defining the zones potentially at risk of intrusion/backflow in a full-scale distribution system;
2. Develop a method to allow combination of both pressure-driven analysis results and multi-species water quality analysis (MSWQA-PDA);
3. Evaluate the impact of two pressure-demand relationships on hydraulic and water quality parameters;
4. Reduce the uncertainty and improve assumptions in modeling accidental intrusion and fate and transport of contaminants under sustained low/negative pressure events of shorter duration lasting few hours;
5. Compare the spatial and temporal distribution of *E. coli* and the affected pressure zone, resulting from the ingress of sewage in the absence and presence of various disinfectant residuals and evaluate the possibility of issuing sectorial BWA following sustained PDCs;
6. Investigate how sustained PDCs due to major WTPs shutdown affect disinfectant residuals with and without considering the ingress demand impact;
7. Evaluate the spatial probability of detecting *E. coli* throughout the network at different periods following an intrusion event resulted from sustained pressure loss

8. Estimate the public health risk associated with intrusion events of *Cryptosporidium* under sustained low/negative pressure by improving the existing quantitative microbial risk assessment model;

The project objectives are derived from the following research hypotheses:

1. DDA cannot correctly define areas prone to intrusion/backflow under pressure-deficient conditions and overestimates the zones potentially at risk of low-pressure.

   <u>Originality</u>: *Even though there are several studies comparing PDA and DDA during pressure losses, an in-depth investigation is conducted to study how the differences in estimated nodal pressures between PDA and DDA can affect the delineation of the zones at risk of intrusion/backflow under different severity of PDCs in a large full-scale network. The extent of the pressure differences between DDA and PDA as a function of pressure values under PDCs is quantified. The use of PDA can avoid unjustified boil water advisories and open the possibility of issuing sectorial BWAs.*

   The hypothesis will be discarded if the spatial distribution of zones at risk of intrusion/backflow does not change using PDA or if the nodal pressure difference is less than 1 m at every node under PDCs.

2. A methodology is required to allow integration of pressure-driven hydraulic analysis and multi-species water quality model for intrusion modeling as the result of sustained low/negative pressure events.

   <u>Originality</u>: *A methodology is proposed which enables to simulate the interactions between multiple water quality species under sustained PDCs using PDA. At the beginning of this project, there was no numerical tool capable of considering the both aspects at the same time. The source code does not require to be modified and the method can be used with any pressure-driven method.*

   The hypothesis can be discarded if the interactions between water quality species can be neglected or if there is no sustained pressure drop in the network.

3. Even slight differences in pressure values (< 1 m) between using different PDRs when performing PDA lead to noticeable differences in potential intrusion volume through leakage points and consequently in the concentration of the intruded microorganisms.

   Originality: *Even though several studies have investigated the impact of using different pressure-demand relationships on the pressure and total available demand, but there is no information about the impact on water quality. During modeling intrusion through leakage points resulted from sustained PDCs, the computed intrusion volume and contaminant concentration are compared using the Tanyimboh and the Wagner relationships while performing PDA.*

   The hypothesis will be discarded if the nodal pressures are the same between using Wagner and Tanyimboh relationships or if the difference in total intrusion volumes is less than 10%.

4. The effect of nodal pressure head inside the network and leak characteristic must be incorporated in the calculation of contamination mass rate at each intrusion node.

   Originality: *In existing studies, some simplified assumptions are made when modeling intrusion. Improvements are proposed in the presented project to include (a) a systematic calculation of nodal intrusion volume, based on differentiation of pressure outside and inside of the water main under PDCs and leakage demand during normal condition at each node, and (b) the impact of intrusion volume on hydraulic behavior and vice versa and consequently its effect on nodal contaminants mass rate.*

   The hypothesis may be refuted if the intrusion volume variations from different intrusion nodes are less than 10%.

   A secondary hypothesis should be also considered: the chlorine decay constant must be increased selectively based on the existence of contamination, in the case of using nth-order decay model.

   Originality: *Improvement is proposed in the presented project to include the dependency of disinfectant decay at different locations on the presence of contamination when using first-order decay model.*

The hypothesis may be refuted if all the pipes are contaminated during and after intrusion events.

5. Disinfectant residuals can prevent widespread propagation of contaminants throughout the network and confine *E. coli* CFUs to lower-pressure areas compared with the scenario of no disinfectant residual.

   Originality: *There is no study available modeling accidental intrusion considering interaction between microorganism and disinfectant residual as the results of sustained PDCs using pressure-driven hydraulic analysis. This allows investigating the propagation of contaminants based on nodal pressure under depressurization. In addition, it opens the possibility of issuing sectorial BWA based on hydraulic and water quality simulation results.*

   This hypothesis may be refuted if disinfectant residuals do not confine the propagation of E. coli to lower-pressure areas.

6. Losses of chlorine residual as the result of sustained PDCs, resulting from WTP shutdowns, are due to ingress demand and less so because of increasing water age, outlasting the duration of low-pressure event.

   Originality: With the help of the presented approach (MSWQ-PDA) and improved assumptions, chlorine variations during and after sustained PDCs of few-hours can be modeled to estimate the role of water age variations and ingress demand on the changes, and assess the time that it takes for the residuals to reach the predicted values before the pressure losses.

   This hypothesis may be refuted if the median chlorine concentration of the affected nodes with intrusion demand decreases by less than 0.1 mg/L than without intrusion, and if the chlorine residuals reach the normal level immediately after the pressure is back to normal.

7. The probability of detecting *E. coli* by standard sampling protocols is almost nil for contamination confirmation and clearance following accidental intrusion events.

   Originality: *No study has yet assessed the probability of detecting E. coli in the presence of disinfectant residuals resulting from intrusion events due to PDCs using numerical models.*

The simulation results can be applied to improve the sampling strategies in terms of timing, location and volume of sample for confirmation and clearance of intrusion events

This hypothesis may be refuted if the probability is high enough (> 50%) that standard sampling protocols or improved sampling can be conducted in chlorine or chloraminated system to detect intrusion events by E. coli sampling.

8. Coupling QMRA with water quality calculation based on pressure-driven hydraulic analysis is essential when assessing the infection risk associated with the accidental intrusion events due to sustained PDCs. The impact of consumers' behavior on the infection risk is not negligible

   <u>Originality</u>: *No other study conducted QMRA coupled with water quality model calculation based on PDA to quantify the microbial infection risks resulted from accidental intrusion through leakage points due to sustained pressure drop. The impact of consumers' behavior such as volume of consumption and number of times that one fills a glass should also be considered when assessing the probability of infection from the consumption of drinking water from the tap.*

   This hypothesis may be discarded if there is no significant (< 20%) change in the number of infected people when taking into account the behavioral variability within each consumer at each day using Monte Carlo simulation as well as if the number of intrusion nodes (P < 1 m) for both PDA and DDA are the same

A summary of the modeling approach for each of the hypothesis, the expected results and the corresponding chapter of the thesis is demonstrated in Table 3.1.

Table 3.1. Modeling approach to validate (or invalidate) the research hypothesis and corresponding chapters of the thesis.

Hypothesis	Scale	Modeling approach	Expected results	Chapter
1. DDA cannot correctly define areas prone to intrusion/backflow under pressure-deficient conditions and overestimates the zones potentially at risk of low-pressure.	Modeling	PDA performed by WaterGEMS. Modified EPANET input file used for negative pressure.	Hydraulic parameters during sustained PDCs by PDA. Potential intrusion volume. Impact of pressure criteria on the areas at risk of low/negative pressure.	Chapter 4 Chapter 7
2. Pressure-driven hydraulic analysis must be combined with a multi-species water quality model to account for the interactions between microorganism and disinfectant residual for intrusion modeling as the result of sustained low/negative pressure events.	Modeling	Developed MSWQA-PDA approach by modifying INP file based on PDA results using MATLAB to be used by EPANET-MSX for water quality analysis.	An approach that enables multi-species water quality analysis under sustained PDCs. Application to a large real network with hourly variations of parameters.	Chapters 4 to 7
3. Even slight differences in pressure values (< 1 m) between using different PDRs when performing PDA lead to noticeable differences in potential intrusion volume through leakage points and consequently in the concentration of the intruded microorganisms.	Modeling	MSWQA-PDA was applied to investigate the impact of using two different pressure-demand relationships (Wagner and Tanyimboh) on the hydraulic and water quality results.	Difference between pressure head, number of intrusion nodes and intrusion volume, demand satisfaction ratio, and *Cryptosporidium* concentration between using different pressure demand relationships.	Chapter 7

Table 3.1. Modeling approach to validate (or invalidate) the research hypothesis and corresponding chapters of the thesis (continued).

Hypothesis	Scale	Modeling approach	Expected results	Chapter
4. The effect of nodal pressure head inside the network and leak characteristic must be incorporated in the calculation of contamination mass rate at each intrusion node, and the chlorine decay constant must be increased selectively based on the existence of contamination, in the case of using nth-order decay model.	Modeling	Estimating intrusion volume by orifice equation at each node. The leakage constant at each node is adjusted based on the nodal leakage demand and pressure head of the calibrated model under normal conditions reflecting the state of pipes. Intrusion volume defined as negative demand in the model and the modified INP file is regenerated using the adjusted PDA hydraulic results. Selectively increase the chlorine decay rate in the first order model based on the presence of the conservative fictitious species defined in the model.	Adjusted hydraulic conditions considering intrusion volume. An exclusive nodal intrusion volume and contamination mass rate corresponding to hydraulic parameters of that node under low/negative pressure event. Areas subjected to increased chlorine decay due to intrusion as a function of time based on tracer monitoring.	Chapter 5 Chapter 6
5. Disinfectant residuals can prevent widespread propagation of contaminants throughout the network and confine *E. coli* CFUs to lower-pressure areas compared with the scenario of no disinfectant residual.	Modeling	Applying the modeling approaches presented for hypotheses 3 and 4.	Spatial and temporal distribution of *E. coli* throughout the network in the absence and presence of different types and concentrations of disinfectant residual. Determine the pressure zones under PDCs that can be affected by *E. coli* during and after the intrusion events.	Chapter 5

Table 3.1. Modeling approach to validate (or invalidate) the research hypothesis and corresponding chapters of the thesis (continued).

Hypothesis	Scale	Modeling approach	Expected results	Chapter
6. Losses of chlorine residual as the result of sustained PDCs, resulting from WTP shutdowns, are due to ingress demand and less so because of increasing water age, outlasting the duration of the low-pressure event.	Modeling	Applying the modeling approaches presented for hypotheses 3 and 4.	Impact of sustained PDCs on chlorine and chloramine concentration variation without and with intrusion-associated demand.	Chapter 5
7. The probability of detecting *E. coli* by standard sampling protocols is almost nil for contamination confirmation and clearance following accidental intrusion events.	Modeling	Using the water quality results of MSWQA-PDA and a Poisson distribution to estimate the probability of detecting *E. coli* based on sampling volumes of 100 mL and 1 L.	Distribution of the mean probability of detecting positive *E. coli* nodes during the 5-hour intervals from the start of intrusion up to 20 hours.	Chapter 5
8. Coupling QMRA with water quality calculation based on pressure-driven hydraulic analysis is essential when assessing the infection risk associated with the accidental intrusion events due to sustained PDCs. The impact of consumers' behavior on the infection risk is not negligible.	Modeling	An advanced QMRA model is linked with water quality calculations based on PDA.	Impact of *Cryptosporidium* concentration, duration, volume, time of consumption, dose-response relationship, on infection risk from accidental intrusion due to PDCs Spatial distribution of event risk and daily risk	Chapter 6

3.2 Research methodology

The modeling approach can be classified into five main parts:

1) Identification of potential intrusion nodes, intrusion volumes, and demand availability at the nodes experiencing low-pressure conditions using pressure-driven hydraulic analysis (hypotheses 1-3);
2) Developing a technique that enables multispecies water quality analysis based on pressure-driven analysis (MSWQA-PDA) (hypothesis 2);
3) Prediction of accidental intrusion through leakage points (hypothesis 4);
4) Characterization and simulation of the fate and transport of pathogens from the pathways of entry across the network (hypothesis 4 to 7);
5) Using QMRA to assess the impact of intrusion of pathogenic microorganisms due to sustained PDCs on public health (hypothesis 8).

A framework of the proposed approaches to intrusion modeling, fate/transport of contaminants, and QMRA analysis of water distribution system due to substandard pressure conditions is illustrated diagrammatically in Figure 3.1. A summary of each step is described in this chapter. More details on the developed methodology (MSWQA-PDA), intrusion modeling and fate and transport of multiple species are presented in Chapter 4, Chapter 5, and Chapter 7. Quantitative microbial risk assessment model that is used to predict the infection risk of intrusion through leak openings during pressure drops is described in more details in Chapter 6.

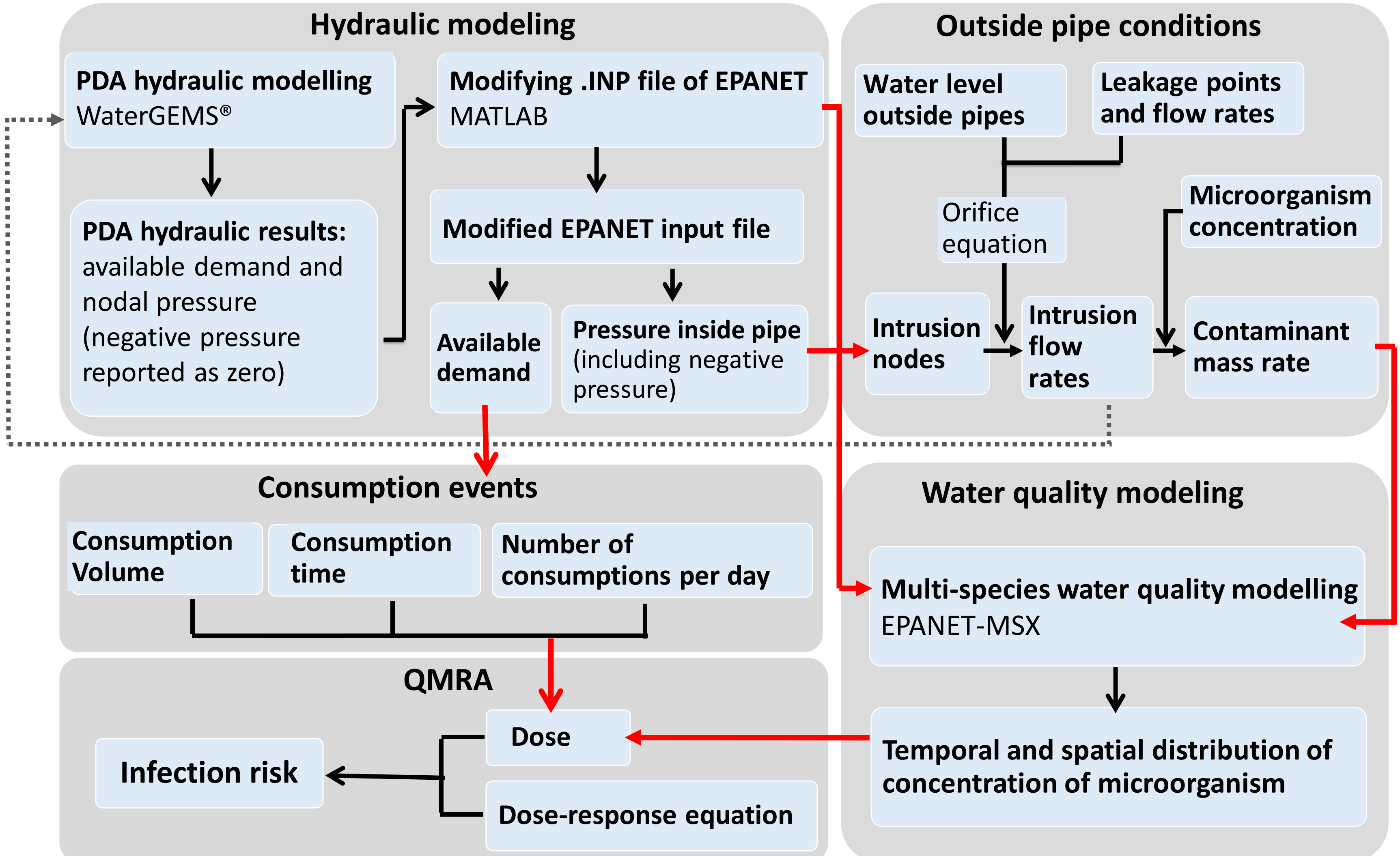


Figure 3.1. Flowchart of the model used for infection risk analysis associated with accidental intrusion events under sustained PDCs.

3.2.1 Hydraulic analysis under sustained low/negative pressure event

To simulate hydraulic of the network during substandard pressure conditions, pressure-driven hydraulic analysis is used in this study and the results are compared with DDA. PDA is more reliable to simulate water network under low/negative pressure conditions than traditional DDA, which considers a fixed demand at the nodes regardless of the adequacy of nodal pressure for supplying all the required demand.

3.2.1.1 Pressure-driven hydraulic analysis

The hydraulic analysis of the drinking water distribution system is carried out using WaterGEMS (Bentley Systems 2014) software because of its ability to perform PDA. When applying PDA, an extra equation that is the relationship between pressure and demand should be implemented in the model. The selection of pressure-demand relationships (PDRs) is a challenge when performing PDA and can lead to some uncertainty in the absence of field data. The impacts of using two different PDRs are investigated on the hydraulic and water quality results: Tanyimboh and Templeman (2004, 2010) and Wagner et al. (1988) in Chapter 7. The PDR can be described more by a parabolic equation at a withdrawal point (faucet). However, if the demand at each node of the distribution system corresponds to several consumers and taps, which is the case for the studied network, other elements such as the configuration and head loss of the secondary network and locations of consumptions must be considered when selecting an appropriate PDR (Ciaponi et al. 2014, Gupta 2015). The equation suggested by Tanyimboh and Templeman (2004, 2010) was used throughout the rest of the simulations according to the literature and due to lack of field data for the studied network. In the PDRs, the desired pressure head, which is the value below which the nodal demand can only be satisfied partially, is considered to be 15 m (21 psi) at all nodes. It is assumed that no demand can be supplied if the nodal head is lower than the elevation of the node. The equations, parameters and the assumptions are explained in more details in Chapter 4 and Chapter 7.

3.2.1.2 Characteristics of the Distribution System and Scenarios of Pressure-Deficient Conditions

A large full-scale water distribution system with more than 30,000 nodes, and three water treatment plants (WTPs) was selected to be evaluated under sustained low/negative pressure events and to test the performance of the proposed modeling approach. The network serves nearly 400,000 residents across around 1,630 km of pipes in Laval (Quebec-Canada). The pipe materials include cast iron, ductile iron, prestressed concrete and PVC, which consist 41%, 35%, 10% and 8% of the total pipe length, respectively. There is no storage tanks or pump stations in the water network and the whole network is hydraulically interconnected. Therefore, the influence zone corresponding to each WTP under normal operating conditions (Figure 3.2) can be affected by any change in the hydraulic conditions.

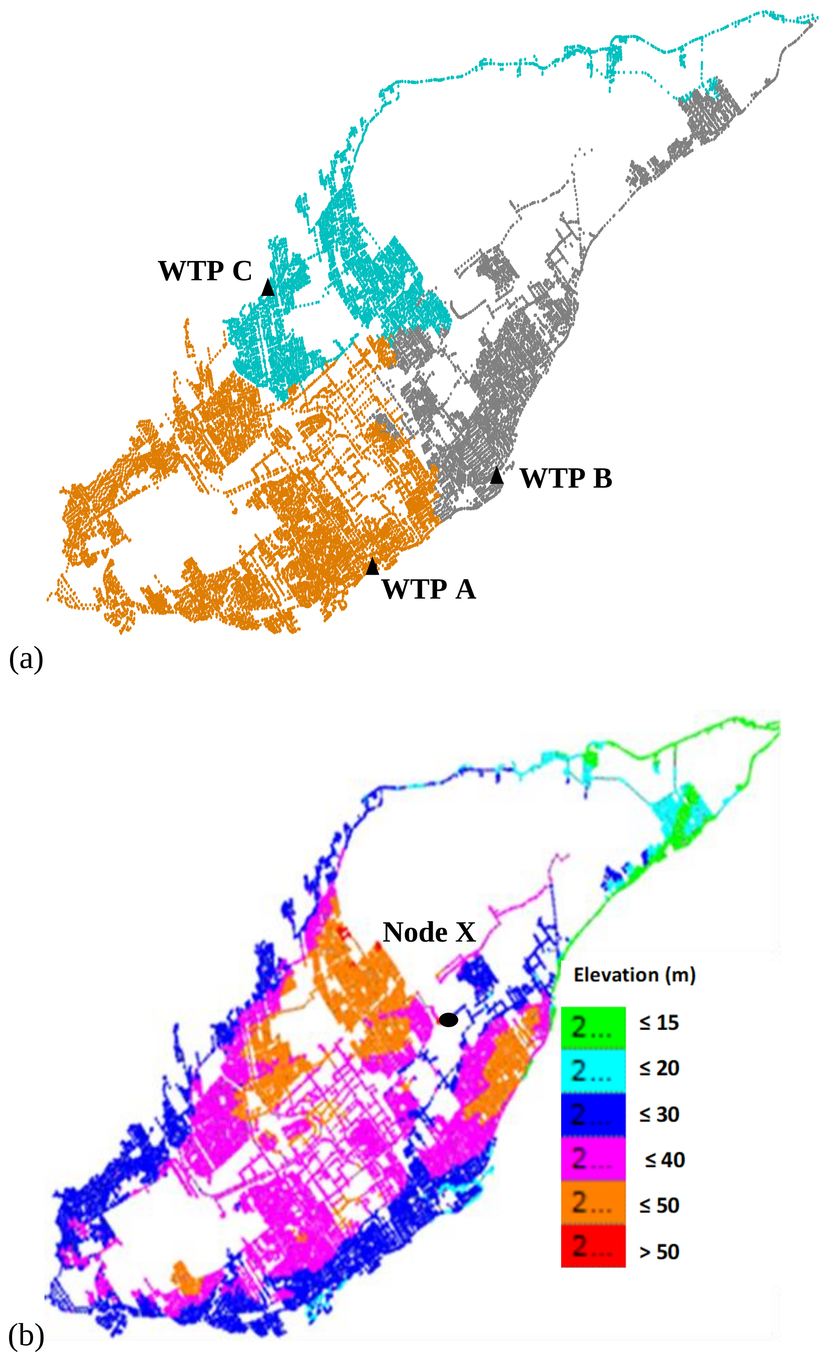


Figure 3.2. (a) Location of WTPs (triangles) and the influence zone under normal operating conditions for each of the WTP is demonstrated by different color, (b) distribution of nodal elevation; Node X: location where a fire flow demand of 15,000 L/min is applied (chapter 5).

Different scenarios of hypothetical sustained PDCs are simulated in the following chapters while all are based on major shutdown of one or two of the WTPs. To evaluate and test the proposed approach and to illustrate its efficacy on real systems first continues PDCs with different intensities are simulated in Chapter 4 and Chapter 7 and water quality results are compared with the scenario of normal operating conditions. Then, the methodology is applied to model shorter duration low/negative pressure events (1, 5, 10, or 24 hours) in Chapter 5 and Chapter 6.

3.2.2 Multispecies water quality analysis based on pressure-driven analysis (MSWQA-PDA)

3.2.2.1 Modifying the input file of EPANET

EPANET-MSX as a multi-species water quality model is selected for the simulations to model the interactions between pathogens inactivation, disinfectant decay, and the chlorine demand of different types of contamination matrices. The command-line version of EPANET-MSX is used in this study. For command line execution of EPANET-MSX, the original EPANET function library (epanet2.dll), epanetmsx.exe, MSX file and the input file of EPANET should be placed in the same directory as the application's executable file (Shang et al. 2011). However, EPANET-MSX engine is based on demand-driven hydraulic analysis, which is not realistic to be used for modeling water quality under sustained PDCs. To overcome this limitation, a technique is presented in which the input file of EPANET is modified by incorporating the computed available demands under pressure-deficient conditions with the help of the developed MATLAB program. A feasibility check (Ackley et al. 2001) was performed to verify the reliability and accuracy of the proposed methodology and validate the content of the modified EPANET input file. The presented methodology has been tested for large full-scale network with up to 30,000 nodes for time-varying hydraulic parameters equal and longer than 1 hour. More details regarding the proposed technique can be found in Chapter 4.

3.2.2.2 Low and Negative Pressure Values

During simulations, it is observed that negative pressure values were reported as zeros by WaterGEMS V8i (SELECTseries 5) (Bentley Systems 2014), the latest version available at the beginning of this project. Determining the value of negative pressures at these nodes was an important issue in this project for estimating the intrusion volume by orifice equation. To overcome this problem, we proposed to use the pressure values results from the modified .INP file of EPANET, by which the negative values were calculated (Figure 3.1). At the same time, we reported this issue to the Bentley technical support and they fixed it after a while in one of their next versions of WaterGEMS. However, for this project, the same procedure proposed at the beginning of the project is continued in the simulations.

3.2.3 Intrusion prediction

Three conditions must exist simultaneously at a node to allow intrusion to occur: (i) existence of pathway, which is defined based on the existence of leakage demand at the node, (ii) force to drive intrusion, which is determined based on the differences between internal and external pressure head on pipe, and (iii) presence of contamination source, which is assumed to exist everywhere around the pipes. The pressure values calculated from pressure-driven hydraulic analysis are used to define areas prone to intrusion during low/negative pressure events and to calculate the intrusion flow rates at each node. We assumed a pressure head outside the pipe of 1 m across the distribution system, within the range of the water table above the pipe in the studied network (Ebacher et al. 2013).

In order to produce contaminant mass rate values that are node-event-specific, the nodal potential intrusion volume is adjusted by nodal leakage demand and internal pressure head under normal operating conditions. With this adjustment, the intrusion potential would be more representative of areas of low leakage (low intrusion potential) and areas with decaying infrastructure prone to intrusion (high intrusion potential). The calibrated network model with daily demand patterns under normal operating conditions is used to estimate the leakage constant at each node and at each hour of the day. For simplicity, and to be conservative in our analyses, the maximum value of leakage constant during the day at each node is applied to estimate the intrusion flow rate under PDCs. More details on calculating the leakage constant and intrusion flow rate can be found in Chapter 5. Due to the issue that we observed in the PDA model of WaterGEMS, when the intrusion flow rates were directly implemented at the intrusion nodes, we propose to assign the negative demand to an artificial node that is connected to the intrusion node with a short pipe having negligible head loss. This is to address the issue of the negative demand implemented at the node that was used by the model to first supply the nodal demand, even if the nodal pressure value was

≤ 0 and PDA model was used. After implementing the intrusion volume in the model as a negative demand, the impact of intrusion volume on hydraulic behavior and vice versa is then considered, details are presented Chapter 5.

3.2.4 Fate and transport analysis

The EPANET-MSX software utilizes a Lagrangian transport approach to solve the advection-reaction equation. The model assumes that the mixing of fluid at pipe junctions is instantaneous and complete. The effect of axial dispersion is neglected in the model. The reaction equations used in this study are listed in Table 3.2. Regarding the THM modeling, chlorine demand in the bulk flow was only considered while both bulk and wall demand were considered in the model. To provide more realistic results from the widely used nth-order kinetic model (here 1st order for chlorine and 2nd order for chloramine, Table 3.2) in the case of intrusion events, we have proposed a simple technique to apply different decay constants in contaminated ($K_{intrusio}$) and non-contaminated zones (K_{normal}). The contaminated areas can be changed in time based on the presence or absence of a conservative fictitious species, which is injected into the distribution system at the intrusion nodes. Because of some limitations that exist in the software, we notice some issues during intrusion modeling. Because of the initial chlorine demand (0.088 mg/L) that is implemented at the intrusion node during intrusion events, the chlorine value gets negative at the intrusion node if the chlorine concertation at that node is less than 0.088 any time during intrusion. To avoid mistakenly calculating *E. coli* concenrtations, due to negative values of chlorine at the intrusion nodes, the chlorine concentration is set to zero in the Chick-Watson model (Table 3.2), if it has a negative value. Even though we tried to overcome this limitation, it remains important to address these shortcomings in future improvements of numerical hydraulic/quality models when used for intrusion simulation. We also noticed that, even if the chlorine residual becomes negative at an intrusion node, the initial demand is not transferred to the next nodes; however, in reality the chlorine demand is transferred to the downstream nodes.

Extended period simulation (EPS) is used to perform hydraulic and water quality analysis. For water quality simulation the model is run for a while under normal operation conditions to allow water quality (water age and disinfectant residuals) reaching equilibrium conditions. The simulation time and hydraulic and water quality time steps are defined in each chapter based on the simulated scenarios.

Table 3.2. Reaction equations and the constant values used in different chapters.

Parameter	Reaction	Constant values	Chapter
Water age	$R = k_1$ (zero-order reaction)	k_1=1	Everywhere
Chlorine[a]	$\frac{dC}{dt} = -kC$ (first-order reaction)	$k = k_b + k_w$, k_b=0.02 h-1 (0.48 day^{-1}), k_w=0.01 h^{-1} (0.24 day^{-1})	Chapter 4 Chapter 7
THM[b]	$THM = K_{tc}(C_0 - C) + THM_0$	$C_0 = 1.5$ mg/L $K_{tc} = 41$ µg/L per mg/L free Cl_2	Chapter 4 Chapter 7
E. coli[c]	$\frac{dP}{dt} = -k_p CP$ (Chick-Watson model)	k_p= 246 (L/mg · h), chlorine, 10℃ k_p=0.99 (L/mg · h), chloramine, 10℃	Chapter 5
Chlorine[d]	$\frac{dC}{dt} = -k'C$	Contaminated zone: k'=$K_{intrusion}$=0.24 h^{-1} Non-contaminated zone: k'=K_{normal}=0.055 h^{-1} Initial chlorine demand of the ingress water: 0.088 mg/L	Chapter 5
Chloramine[e]	$\frac{dC}{dt} = -k''C^n$	Contaminated zone: k''=$K_{intrusion}$=0.11 $(\text{mg } Cl_2 \cdot h/L)^{-1}$ Non-contaminated zone: k''=K_{normal}=0.012 $(\text{mg } Cl_2 \cdot h/L)^{-1}$ No initial chlorine demand	Chapter 5

Note: R: the instantaneous rate of reaction, k_1: the reaction rate coefficient, k_b: the bulk decay constant (h^{-1}), k_w: the wall decay constant (h^{-1}), k: the overall decay constant (h^{-1}), THM_0: the initial THM concentration at t=0, C_0: the initial chlorine concentration at t=0, C: the chlorine concentration (mg/L), and K_{tc}: an indicator of the THM productivity of the water (µg/L of THM per mg/L of free chlorine), P: the *E. coli* concentration (CFU/L), k_p: the inactivation constant (L/mg · h), k': the chlorine decay coefficient (h^{-1}), k'': the chloramine decay coefficient (L/mg · h), n: assigned a value of 2. (a) Brown et al. (2011); (b) Boccelli et al. (2003), (Hua 2000); (c) Betanzo et al. (2008); (d) (LeChevallier et al. 2011, Yang et al. 2011).

The probability of finding an *E. coli* during sampling is calculated based on the spatial and temporal concentrations calculated by the water quality model, the probability of not detecting *E. coli* is calculated using a Poisson distribution, and the probability of detecting positive is then calculated as: 1- probability of not detecting *E. coli*. Poisson function is a simple model that can express the distribution of suspended particles. The probability of finding *k* particle can be calculated as follows (Teunis et al. 2004):

$$P(k;\mu) = \frac{e^{-\mu}\mu^k}{k!} \quad \text{Eq. 3-1}$$

in which μ is sample volume multiplied by concentration of particles.

3.2.5 Quantitative microbial risk assessment

In this project, a QMRA model is coupled with water quality calculations based on PDA results. Dr. Mirjam Blokker from KWR Watercycle Research Institute provided us the MATLAB code for the QMRA model which was previously used to assess the microbial risk of repairs of part of the drinking water network of the town Zandvoort serving 4,347 people (Blokker et al. 2018). We customized this MATLAB code to asses the risk of accidental intrusion events as the result of hypothetical sustained low/negative pressure events for the studied network by coupling the QMRA model with the PDA.

Exposure analysis is one of the main steps in calculating the infection risk using QMRA models. As illustrated in Figure 3.1, the exposure analysis predicts the dose by taking into account the concentrations computed from the numerical model and the probability of coinciding the water intake from the tap with the passage of contaminants through that node.

In this study, sewage is considered as the external source of contamination. The risk of *Cryptosporidium* infection associated with intrusion events due to sustained low/negative pressure events is then assessed. More details on the calculation of contaminant mass rates and fate/transport can be found in Chapter 5. The calculated concentrations at each time step for all the 30,077 nodes are saved in an excel file and the data are imported into MATLAB as the input of the exposure analysis. The reported time step for the concentrations is 1 hour in all the scenarios.

The network is modeled for 4 days from the onset of intrusion. Therefore, the ingested dose for each person corresponds to 4 days of observation. However, reporting the risk for each day individually can also be beneficial for further assessment. For this purpose, the QMRA model is run for only one day, using the temporal *Cryptosporidium* concentration related to the desired day from water quality model and the modified kitchen tap use corresponding to that specific day, to be able to calculate the dose of each day, separately, for each people. To evaluate the impact of various parameters in estimating the *Cryptosporidium* infection risk, 23 scenarios are simulated

(Table 3.3). A detailed description of the assumptions used for each scenario can be found in Chapter 6.

Table 3.3. Overview of the simulated scenarios for QMRA analysis

Duration	Time	Demand pattern	Daily risk or event risk
24 hours	From 00:00 (day1) to 00:00 (day 2)	Constant peak hour	Event risk (4 days): **a. Concentration of *Cryptosporidium*:** 1, 6, 26, and 560 oocysts/L **b. Volume per day:** Lognormal distribution, 300 mL, 500 mL, and 1 L **c. Number of glasses per day:** Poisson distribution, 1, 3, and 10 times **d. Infection risk:** maximum, median
10 hours	From 14:00 to 00:00	Constant peak hour	Event risk (4 days)
1 hour	From 06:30 to 07:30	Constant peak hour	Event risk (4 days)
1 hour	From 06:30 to 07:30	Daily pattern	Event risk (4 days) Day 1 Day 2 Day 3 Day 4 Day 1 with DSR of 5 % instead of zero

In exposure analysis, to take into account the uncertainties concerning the consumers' behavioral variability in estimating the dose 200 Monte Carlo simulations are performed. Consumer's behavior in the current study is defined as: (i) time of consumption during the day, (ii) number of glasses, and (iii) volume per glass.

For each person, the number of glasses per day is estimated using a Poisson distribution and for the volume per glass lognormal distribution is applied using the data from Blokker et al. (2018) (Figure 3.3). As the boundary, minimum and maximum volume per person per day were set to 0 and 4.2 L (Blokker et al. 2018). Other scenarios with constant volumes and number of glasses per person per day are simulated to investigate the sensitivity of infection risk (Table 3.3). The Dutch kitchen tap use from Blokker et al. (2018) is modified based on the demand availability during PDCs obtained from PDA to be used as the consumption time during the day. Figure 3.4 shows both patterns for scenario of 10 hours for days 1 and 2. More details can be found in chapter P3.

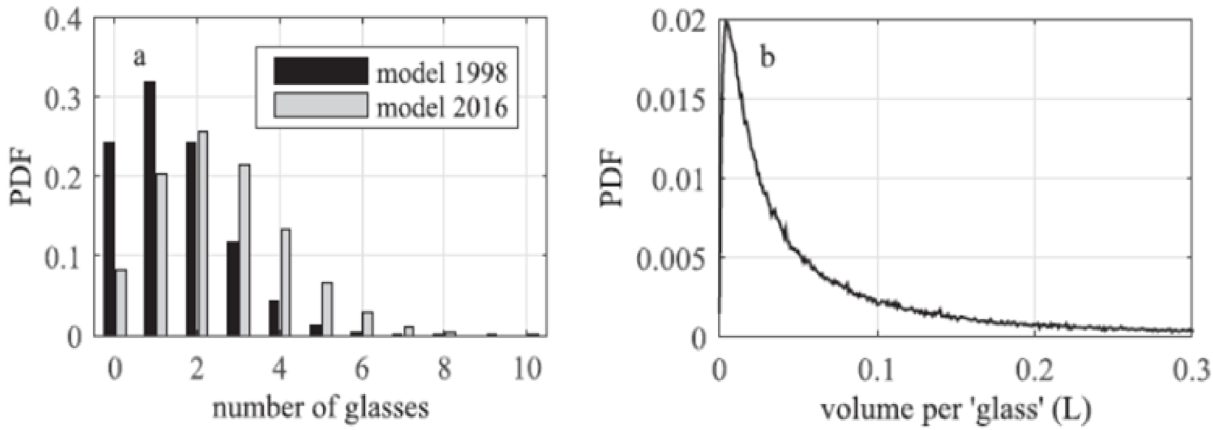


Figure 3.3. Consumption amount using the number of glasses with a Poisson distribution: λ=2.5 in this study (model 2016), and a lognormal distribution (μ=−3.19 en σ=1.485) for the volume per glass (from Blokker et al. (2018)).

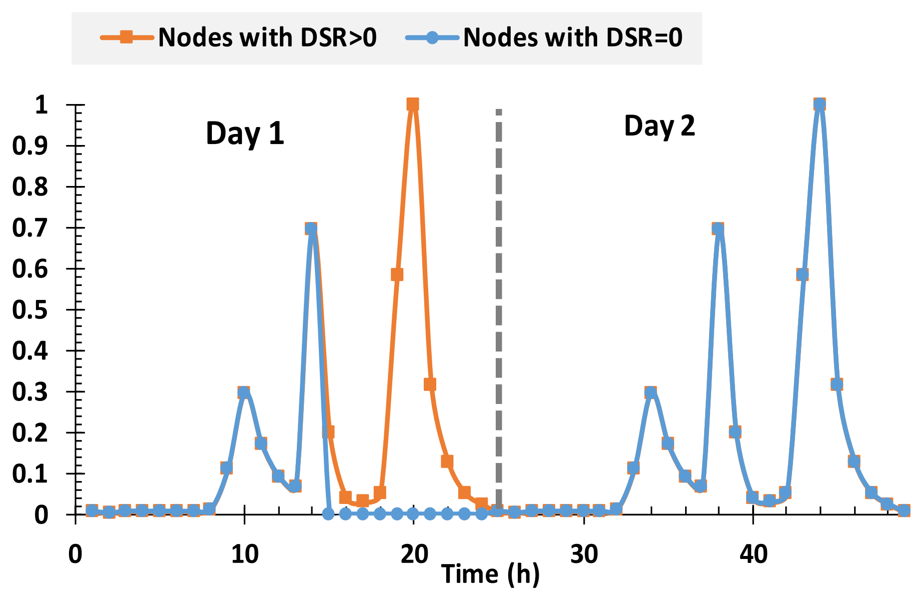


Figure 3.4. Consumption at kitchen tap use by Blokker et al. (2018) (orange, square); modified kitchen tap use in this study for the residential nodes that have no available demand for consumption based on PDA results at days 1 and 2 for the 10-hour scenario (blue, circle); days 3 and 4 are the same as day 2.

Dose-response analysis is carried on to predict the probability of infection using the estimated dose from exposure analysis. In their model, Monte Carlo simulation is done with 10,000 parameter

(α, β) pairs (Teunis et al. 2010) and a set of dose-response relationships is achieved. Then, the median (50th percentile) and maximum (100th percentile) dose-response relationships are selected to calculate the median and maximum infection risk, respectively. This method reduces the computational cost of dose-response analysis (Blokker et al. 2018). More details regarding the dose-response model used in this study can be found in (Blokker et al. 2014, Blokker et al. 2018).

CHAPTER 4 ARTICLE 1 – COMBINING A MULTI-SPECIES WATER QUALITY AND PRESSURE-DRIVEN HYDRAULIC ANALYSIS TO DETERMINE AREAS AT RISK DURING SUSTAINED PRESSURE-DEFICIENT CONDITIONS IN A DISTRIBUTION SYSTEM

With pipeline infrastructure ageing and system renewal activities, sustained pressure losses in drinking water distribution systems may become more frequent. In this chapter, a methodology that enables multi-species water quality analysis based on pressure-driven analysis is proposed. To evaluate the capability of the developed approach, multiple water quality parameters (water age, chlorine residual, and THMs) under continuous pressure-deficient conditions were simulated in a full-scale water distribution system (30,077 nodes). Variations of water quality under the simulated pressure-deficient conditions are compared to normal operating conditions for different groups of nodes, which are categorized according to the nodal pressure values during pressure losses. The extent of the pressure differences between DDA and PDA and their impact on the estimation of the zones at risk of low pressures is also presented. This paper was published in *Journal of Water Resources Planning and Management* in 2018. Supplementary information is presented in Appendix A.

COMBINING A MULTI-SPECIES WATER QUALITY AND PRESSURE-DRIVEN HYDRAULIC ANALYSIS TO DETERMINE AREAS AT RISK DURING SUSTAINED PRESSURE-DEFICIENT CONDITIONS IN A DISTRIBUTION SYSTEM

Fatemeh Hatam[1], Marie-Claude Besner[2], Gabrielle Ebacher[3], Michèle Prévost[1]*

[1]NSERC Industrial Chair in Drinking Water, Department of Civil, Geological and Mining Engineering, Polytechnique Montréal, CP 6079, Succ. Centre-ville, Montréal (Québec), H3C 3A7, Canada
[2]R&D Engineer, Water Service, City of Montreal, Montréal, QC, Canada H3C 6W2
[3]Technical Engineer, Environment Service, Drinking Water Division, City of Laval, QC, Canada, H7V 3Z4
[*]Corresponding author, E-mail address: fatemeh.hatam@polymtl.ca, Tel.: 514 340-4711 ext. 2983

Abstract

Realistic numerical models can assist in managing pressure losses in water distribution systems, which is a challenge for water utilities. This paper presents a methodology for simulating the impact of sustained low/negative pressure events on hydraulic and water quality parameters. The developed methodology enables Multi-Species Water Quality Analysis based on Pressure-Driven Analysis (MSWQA-PDA). This approach has been applied to a large full-scale water distribution system model to evaluate its capability. The spatial variation of water age, chlorine residual, and trihalomethanes (THMs), under normal and sustained low/negative pressure conditions is investigated. Generally, poorer water quality was observed under pressure-deficient conditions compared to normal operating conditions, especially at nodes reaching lower pressure values. The results confirm that under significant sustained low/negative pressure events, demand-driven analysis cannot correctly identify the zones at risk of low and negative pressure, which may lead to unjustified boil water advisories (BWA) for some customers.

KEYWORDS: Water distribution system; Demand-driven analysis; Pressure-deficient conditions; Pressure-driven analysis; EPANET-MSX; Water quality

4.1 Introduction

Two analysis methods exist for predicting the hydraulic behavior of water distribution systems: demand-driven analysis (DDA) and pressure-driven analysis (PDA). The demand-driven algorithm solves the mass and energy conservation equations to calculate nodal heads and pipe flows. In DDA, demand values are considered constant, while in the pressure-driven approach, the actual nodal demands are considered as unknowns and vary with the nodal pressure values. Many researchers have demonstrated that the use of PDA rather than DDA provides more realistic results under pressure-deficient conditions (Cheung et al. 2005, Liserra et al. 2014, Siew and Tanyimboh 2012).

Several methods have been proposed to perform PDA. These methods are generally classified in two categories (Sayyed and Gupta 2013, Siew and Tanyimboh 2012). The first category includes approaches that involve DDA such as in the studies by Ozger (2003) and Ang and Jowitt (2006). For example, Ozger (2003) developed a semi-pressure-driven approach based on iterative use of demand-driven analysis and artificial reservoirs to model pressure-deficient conditions. The other category of approaches simultaneously solves the mass and energy conservation equations and the selected Pressure Demand Relationship (PDR) (Giustolisi and Laucelli 2011, Siew and Tanyimboh 2012, Wu et al. 2009).

Several PDRs have been proposed in the literature to perform PDA (Fujiwara and Li 1998, Gupta and Bhave 1996, Tanyimboh and Templeman 2004, Wagner et al. 1988). When modelling low pressure events using PDA, the selection of a specific PDR over another may lead to some differences in the computed pressure values and available demands (Cheung et al. 2005, Liu et al. 2011). Gupta and Bhave (1996) compared several existing PDRs and concluded that the relationship from Wagner et al. (1988) was more representative of the network behavior in their study. Several existing PDRs were also evaluated by Shirzad et al. (2013) through field experiments in some locations of a real water distribution system by measuring the discharge from different faucets and their corresponding pressures. These authors concluded the data measured at the faucets was best described by the orifice and Wagner et al. (1988) equations. Vairagade et al. (2015) investigated PDRs at different nodes of a skeletonized network using the WaterGEMS® software and pressure-dependent analysis. Each primary node in the reduced network was representative of a secondary network. These authors concluded that the Tanyimboh and Templeman (2010) relationship better describes the PDR at the nodes of this skeletonized network. While the PDR at a withdrawal point such as a faucet behaves like a parabolic relationship, the governing PDR at a node, where demands of a secondary network representing several consumers are lumped, depends on different factors such as the locations where consumption occurs, the configuration and head loss of the secondary network and indoor plumbing systems (Ciaponi et al. 2014, Gupta 2015). However, finding an appropriate PDR is a challenging task in the absence of field data.

Some commercial software packages enable PDA. However, this capability is not available in the standard publicly available version of the EPANET 2.0 software (Rossman 2000). Although not publicly available, EPANET-PDX has been developed by modifying the source code of EPANET to enable PDA through the application of the head dependent gradient method (Siew and Tanyimboh 2012). Seyoum et al. (2011) verified the accuracy of EPANET-PDX by applying the calculated actual nodal demands as new demands in EPANET 2.0. The new nodal heads were identical to the calculated values from EPANET-PDX. This verification procedure is called feasibility check (Ackley et al. 2001).

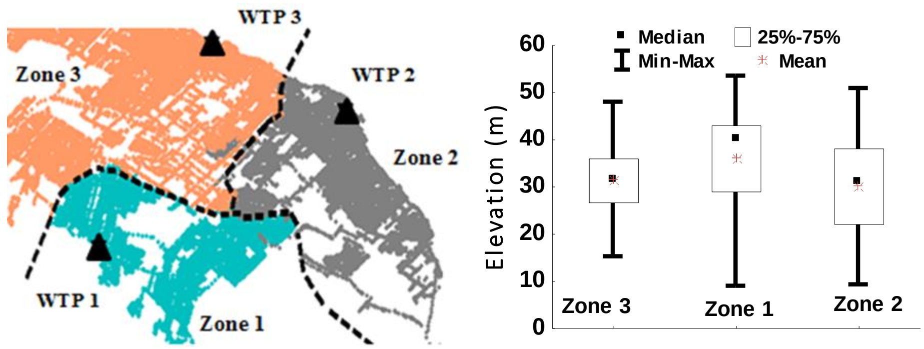
Simulation of water quality in a distribution system is usually performed based on DDA results and commonly involves a single-species water quality model (as in EPANET 2.0). Although useful, single-species models are unable to simulate the interactions between two or more species (such as chlorine and *E. coli*). This may become a limitation if this type of analysis is required. In 2007, USEPA released the Multi-Species Extension of EPANET (EPANET-MSX) which is a DDA-based model. As water quality parameters depend on hydraulic conditions, a realistic hydraulic simulation with PDA should be linked with water quality modelling to assess the impact of pressure-deficient conditions on water quality. In recent years, very few studies have combined PDA and water quality modelling due to existing limitations in most water quality and hydraulic modelling tools, being either a single-species water quality model or hydraulic engine based on DDA. The EPANET-MSX software has the ability to consider any number of multi-species interactions and may be used to simulate processes such as attachment/detachment of pathogens to/from biofilm, interaction of disinfectant with organic and inorganic matter, and inactivation of microorganisms (Uber 2010). A prototype of this software was used by Betanzo et al. (2008) and Propato and Uber (2004) to model intrusion events in distribution systems. They were able to simulate the simultaneous inactivation of microorganisms and disinfectant decay. However, because EPANET-MSX is based on DDA, it may not accurately simulate low/negative pressure conditions. The commercial software market is rapidly evolving and the latest version of WaterGEMS now proposes multi-species analysis based on the EPANET-MSX model (Bentley Systems 2014). Seyoum and Tanyimboh (2014) and Seyoum et al. (2013) applied EPANET-PDX to perform water quality modelling under pressure-deficient conditions. However, as EPANET-PDX considers single-species water quality modeling, interactions between species could not be modeled. The coupling of PDA and single species water quality analysis in simulation-optimization models by Rasekh and Brumbelow (2014) has been proposed to assist in operational decision making during contamination events.

This study presents a methodology for modelling hydraulic behavior and water quality in a network under sustained low/negative pressure conditions. The developed methodology, which is referred as Multi-Species Water Quality Analysis based on Pressure-Driven Analysis (MSWQA-PDA) throughout this paper, allowed us to incorporate the advantages of both a multi-species water quality model (EPANET-MSX) and PDA. As a proof of concept, spatial variations of water quality species, including water age, chlorine residual, and THMs, are simulated throughout a full-scale distribution system under different sustained low/negative pressure scenarios. Simulation outputs such as nodal Demand Satisfaction Ratios (DSRs), spatial clustering and number of nodes considered at risk of low/negative pressure are also investigated. It is hypothesized that the use of a more realistic tool, as described and applied in this study, can help better define areas prone to intrusion/backflow, which may need corrective/preventive actions in the case of pressure loss events.

4.2 Methodology

4.2.1 Description of the distribution system

The studied distribution system has three water treatment plants (WTPs) and serves a population of about 400,000. The all-pipes hydraulic model of the network includes 30,077 nodes and a total pipe length of about 1,600 km. There are no storage tanks or pump stations in the water network. The average daily demand is approximately 210,000 m^3/day. The whole network is hydraulically interconnected, yet each WTP supplies water to different areas (or influence zones) of the distribution system under normal operating conditions (Figure 4.1(a)). Therefore, the supply area of each WTP can vary if pressure-deficient conditions occur in the network. Zones 1, 2 and 3 include 24 %, 28 %, and 47 % of the total nodes, respectively. Because of the control system architecture of high lift pump stations at the three WTPs, the hydraulic model of the water utility uses reservoirs with variable head to simulate pump operation rather than individual pump curves and operation routines. Figure 4.1 (b) shows the distribution of nodal elevations in each of the three influence zones.



(a) (b)

Figure 4.1 (a) Location of WTPs (triangles) and approximate boundaries of each influence zone under normal operating conditions (dash-lines); (b) distribution of nodal elevations for each influence zone.

4.2.2 Pressure-deficient scenarios

For this proof of concept, hypothetical sustained and significant pressure-deficient conditions were achieved by simulating the shutdown of two WTPs with only one WTP remaining for the supply of the complete distribution system. Three pressure-deficient scenarios were simulated by varying the available head at the supplying source (Table 4.1). Hydraulic and water quality results from these scenarios were compared to normal operating conditions (first scenario, Sc1). In the second scenario, the water head at the only online WTP (WTP 3) remains the same as normal. In scenario 3, it is assumed that the water head is lower at WTP 3, for example due to malfunctioning of the pumping system in response to increased discharge. The fourth scenario is based on the assumption of the flexibility of the pumping system at the only online WTP (WTP 3) to produce higher head to compensate for the shortage of supply caused by the failure of the other two WTPs.

Table 4.1. Hydraulic grade (HG, m) and outflow (Q_{out}, L/s) at each WTP for all 4 scenarios.

Scenarios	WTP 1		WTP 2		WTP 3	
	HG	Q_{out}	HG	Q_{out}	HG	Q_{out}
Sc1	76	716	75	701	77	1354
Sc2	-	0	-	0	77	2367
Sc3	-	0	-	0	63	2084
Sc4	-	0	-	0	88	2549

In order to verify the validity of the proposed modelling approach, and for simplicity, continuous sustained pressure-deficient conditions are considered throughout the whole simulation duration for this first application of the presented methodology. A constant demand of 239,414 m^3/day is applied throughout the simulations as well. This demand corresponds to peak hour consumption in the studied distribution system.

4.2.3 Pressure-driven analysis

In this study, the commercial software WaterGEMS® is used to model the hydraulic behavior of the network. This software incorporates a pressure-driven analysis tool based on the modified Global Gradient Algorithm (GGA), as formulated by Wu and Walski (2006) and Wu et al. (2006). Wu et al. (2009) have applied this modified GGA to a large-scale water distribution system under a critical pipe outage. More details on the modified GGA solution can be found in WaterGEMS manual (Bentley Systems 2014).

In this software, relationship between pressure and demand can be defined as either a power function or a pressure-demand piecewise linear curve. In this paper, the Tanyimboh and Templeman (2004, 2010) equation is selected as the PDR to be used in the pressure-driven algorithm (hereafter referred to as the Tanyimboh equation). More details about this equation and the choice of parameters are included in the Supplemental Information. In this work, it is assumed that when the nodal head above the ground level is less than 15 m (desired pressure head), the flow is considered as partially supplied. Also, no demand is supplied for nodes with head lower than the nodal elevation. The DSR for a node is the ratio of the available demand (under pressure-deficient conditions) to the required demand at that node. The DSR for each supply zone is calculated by dividing the sum of the available demands by the total required demand within the zone.

4.2.4 Water quality modelling

Multi-species water quality modelling is performed using the EPANET-MSX software (Shang et al. 2011). More details about this software are provided in the Supplemental Information. To simulate the water quality behavior of the studied network, an extended period simulation (EPS) of 480 h was carried out to reach the equilibrium conditions of water quality parameters. The water quality results were then reported for the last hour. As water quality modelling in EPANET-MSX is based on demand-driven analysis, a MATLAB program was developed to modify the input file of EPANET (.INP) by incorporating the computed available demands under pressure-deficient conditions. This modified .INP file is then used by EPANET-MSX for water quality modelling under pressure-deficient conditions in the all-pipes network which, in this case includes more than 30,000 nodes and 33,252 pipe segments. This methodology is referred as MSWQA-PDA and the flowchart is illustrated in Figure 4.2. A feasibility check (Ackley et al. 2001) was performed to validate the content of the modified .INP file. In this regard, the nodal heads and pipe flows calculated from the .INP file generated by MATLAB should be identical with the results from the pressure-driven algorithm. The pressure dependent demand model of WaterGEMS V8i (SELECTseries 5) was found to report the negative nodal pressure values as zero. However, the generated EPANET input file allows for the calculation of the negative pressure magnitude for these nodes, as shown in Figure 4.2, which is another advantage of the presented technique.

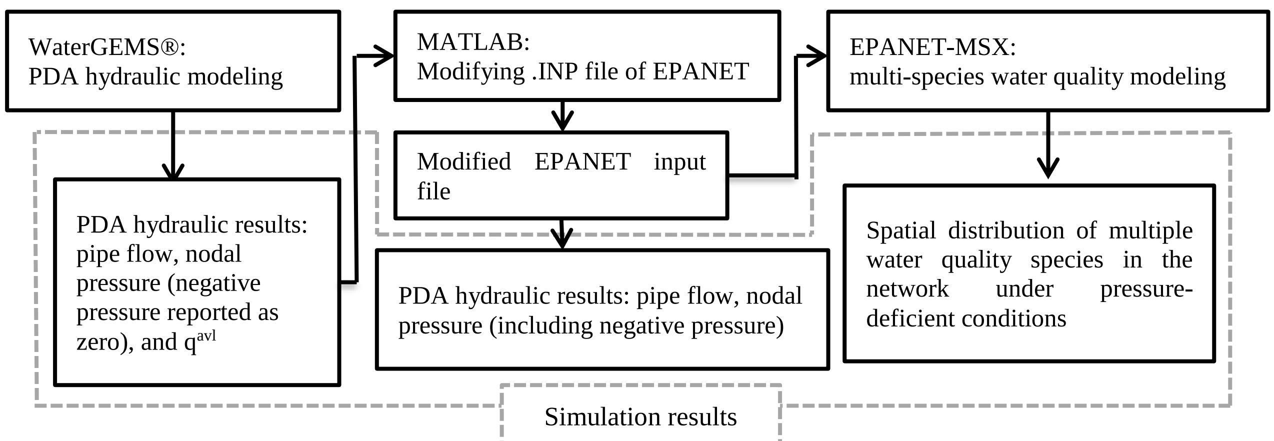


Figure 4.2: Flowchart of MSWQA-PDA.

For the purpose of this demonstration, three water quality parameters were selected for multi-species water quality analysis: water age, chlorine residual, and THM formation. Although some of these parameters may not be directly related to pressure-deficient conditions, they were selected for the sake of simplicity and to validate the efficacy of the modelling approach developed. The reaction equations and the constant values used to simulate water quality are included in the Supplemental Information (Table A-1).

4.3 Results

In the studied distribution system, under normal operating conditions (Sc1), WTPs 1, 2, and 3 supply 26%, 25%, and 49% of the total demand, respectively. To demonstrate the application of the proposed modelling approach, simulations were performed under normal operating and sustained low pressure conditions (Table 4.1). Significant pressure-deficient conditions (Sc2, Sc3, and Sc4) were created by the shutdown of WTPs 1 and 2. Under the simulated conditions, results indicate that WTP 3, which has the largest capacity, can provide 85 %, 75 %, and 92 % of the total required network demand in scenarios 2, 3, and 4, respectively.

4.3.1 Validating the reliability of the proposed methodology

As a first step, because the modified .INP file is used by EPANET-MSX to perform water quality analysis, the reliability and accuracy of this file were verified. To do so, the results from the modified .INP file of EPANET were compared with those from the pressure-driven algorithm. Identical values of flow and pressure (zero and positive pressures) ensure that the generated modified .INP file is reliable (Figure 4.3). Comparison results for the second scenario are illustrated, but the same trend is obtained for other scenarios. As can be seen in Figure 4.3 (a), the generated modified .INP file of EPANET allows for the calculation of negative pressure values, while WaterGEMS V8i reports those as zero.

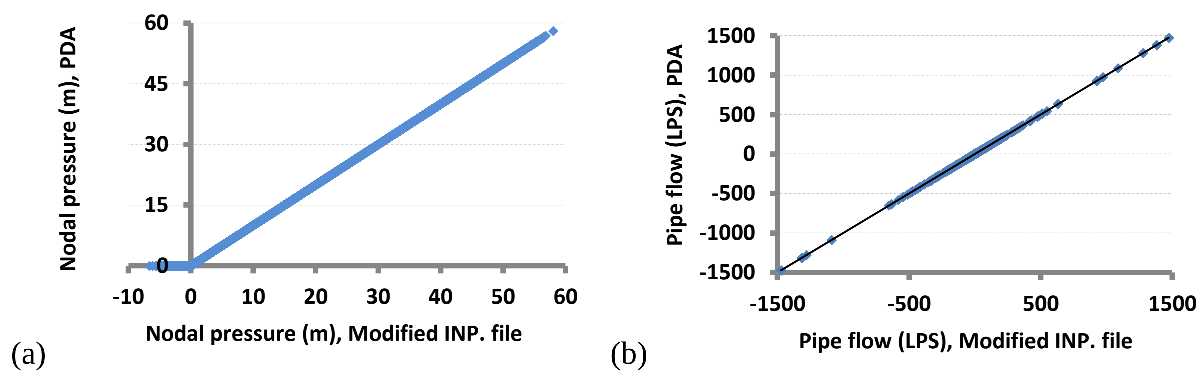


Figure 4.3: Comparison between results calculated with the modified .INP file of EPANET and the pressure dependent demand model of WaterGEMS for Sc2: (a) nodal pressures, and (b) pipe flows.

4.3.2 Investigation of hydraulic behavior under scenarios of pressure-deficient conditions

Impact of pressure-deficient conditions on satisfaction of required demand

The average DSR of each zone is indicated in Table 4.2, for scenarios 1 to 4. As expected, under normal operating conditions (Sc1), all demands are satisfied. For all other scenarios, where the water is only supplied by WTP 3, meeting the required demand especially for zones 1 and 2, which are located further from WTP 3 becomes challenging at some nodes. The DSR is related to the hydraulic grade maintained at WTP 3. Under the studied pressure-deficient conditions, zone 2 is globally better fed by WTP 3 as compared to zone 1, reflecting network topology and the average nodal elevation in each zone (Figure 4.1 (b)). Statistics related to the distribution of percentage of demand satisfaction for different pressure-deficient scenarios are shown in Figure A-1 in Appendix A.

Table 4.2**.** Average DSR of each zone for scenarios 1 to 4.

Scenarios	**Demand Satisfaction Ratio (%)**			
	Zone 1	**Zone 2**	**Zone 3**	**Total**
Sc1	100%	100%	100%	100%
Sc2	59.2%	85.9%	99.2%	85.4%
Sc3	38.0%	72.4%	96.5%	75.2%
Sc4	75.3%	94.4%	99.7%	92%

Comparison of pressure values from DDA and PDA

Statistics related to the distribution of nodal pressure values (median, maximum, minimum, mean, 25th and 75th percentiles) for different scenarios are illustrated in Figure 4.4. Pressure values obtained from PDA and DDA are compared for each zone. As expected, for the first scenario, the calculated pressure values were the same using the PDA or DDA tool. As the lowest possible gauge pressure of water at 20ºC is -10.1 m (i.e. cavitation head), the extent of the unrealistic underestimation of pressure values by DDA under pressure-deficient conditions is obvious. Pressure values from the PDA model were above -10.1 m in all zones for all the pressure-deficient scenarios. In the second scenario, the median pressure values obtained by DDA and PDA are, respectively, 37 m and 39 m for zone 3 (DSR: 99 %), -1 m and 16 m for zone 2 (DSR: 86 %), and -11 m and 8 m for zone 1 (DSR: 59 %) (Figure 4.4).

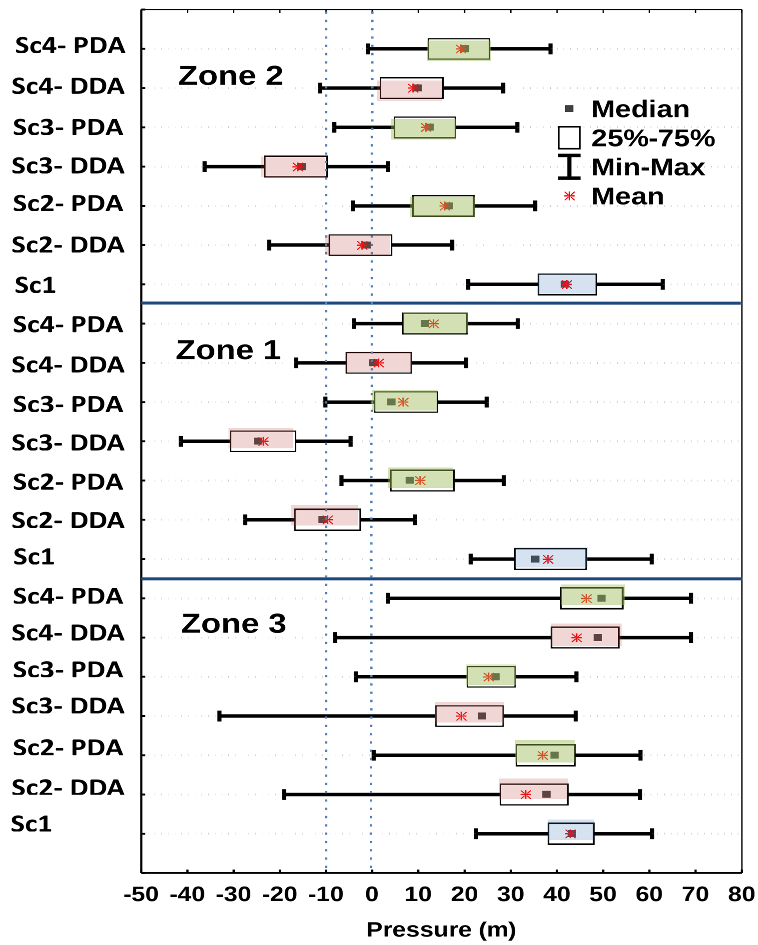


Figure 4.4: Comparison of pressure results calculated from PDA (modified EPANET input file) and DDA under pressure-deficient conditions (Sc2, Sc3, and Sc4), and normal reference operating conditions (Sc1) (DDA only).

As expected, Figure 4.5 shows that the extent of the difference of nodal pressure (ΔP) estimated by DDA and PDA decreases with increasing values of pressure estimated by PDA. The extent of the differences is clearly driven by the severity of the pressure-deficient conditions. Indeed, the differences for Sc3 with only 75% of DSR are much larger than for Sc4 with a DSR of 92%. Even though the ΔP is generally lower for the groups of nodes with higher pressure, no specific minimal pressure can be determined after which PDA and DDA estimates would converge for all nodes.

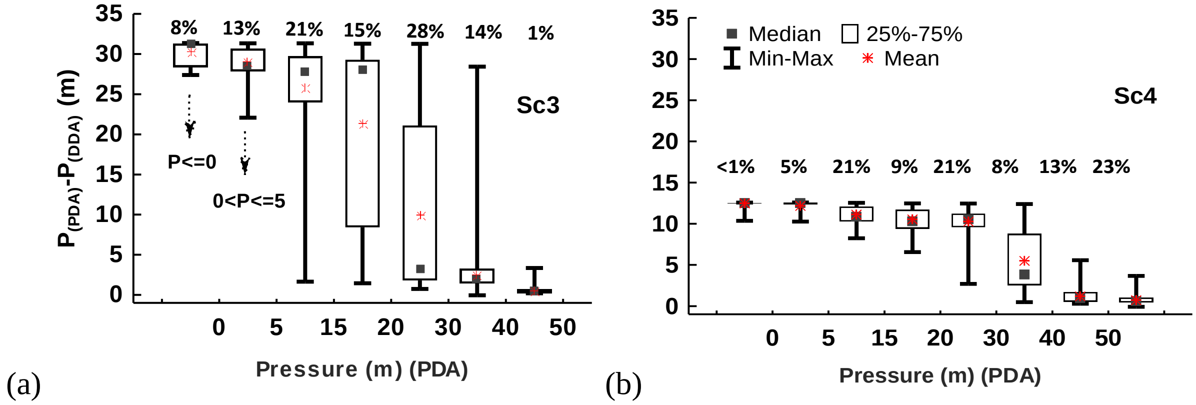


Figure 4.5: Nodal pressure differences between PDA and DDA for pressure-deficient scenarios of (a) Sc3 and (b) Sc4 for different categories of pressure calculated by PDA (modified .INP file) for all the nodes; the proportion (%) of nodes in each pressure category is indicated on top.

Spatial distribution of negative and low pressure areas under pressure-deficient conditions

The spatial distribution of areas of most interest for low pressure is illustrated in Figure 4.6. Figure 4.6 (a) shows normal operating conditions, which are equivalent for DDA and PDA, with all nodes maintaining pressures above 21 m. Pressure maps of scenarios 2 to 4 (Figure 4.6 (b) to (d)) show that the extent of the area affected by low and negative pressures depends on the hydraulic grade maintained at the only online WTP. Figure 4.6 (e) and (f) show the spatial distribution of pressure values simulated by DDA under two of the pressure-deficient scenarios (Sc2 and Sc4). The extent of the zones with negative pressure is largely overestimated when compared to the PDA results, in line with the difference in computed pressures by the two methods (Figure 4.4). Therefore, DDA cannot correctly identify the zones which are prone to backflow and/or intrusion under the significant simulated pressure-deficient conditions.

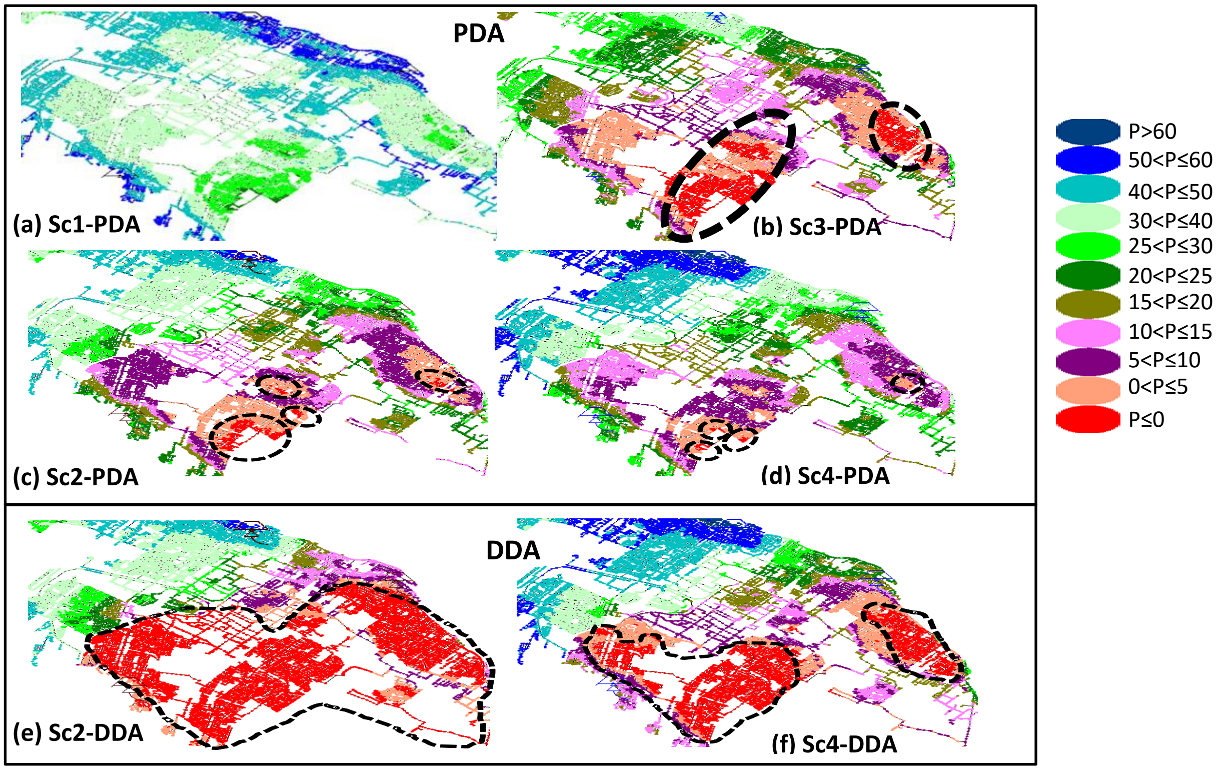


Figure 4.6: Spatial distribution of pressure using PDA for scenarios 1 to 4 (a, c, b, and d), and using DDA for scenarios 2 and 4 (e, f).

4.3.3 Investigation of water quality behavior under pressure-deficient scenarios

To illustrate the impact of low pressure events on water quality, the simulated water age, chlorine residual and THM concentration for Sc2 are compared with the values corresponding to normal operating conditions (Sc1) (Figure 4.7). Three categories defined under pressure-deficient conditions of Sc2 are used for comparison: nodes with pressure (a) more than 15 m, (b) less than or equal to 15 m including negative pressure, and (c) less than or equal to zero. For nodes with P>15 m (20,470 nodes, 68%), median and 75th percentile water age reached 12 and 26 h during Sc2, as compared to 12 and 19 h under normal operating conditions, respectively (Figure 4.7(a)). As the pressure at the nodes under pressure-deficient conditions decreases, statistical parameters (median, 75th and 95th percentiles) related to water age for nodes with P $\leq$ 15 m (9607 nodes, 32%) reach higher values: they go from 9, 14, and 27 h under normal operating conditions to 19, 29, and 68 h under pressure-deficient conditions, respectively. These differences are increased even more for nodes with zero or negative pressure (585 nodes, 2%). Chlorine residuals at nodes with P ≤ 15 m also showed considerable variations between pressure-deficient and normal operating conditions: medians decreased from 1.2 to 0.8 mg/L, and 25th percentiles decreased from 1 to 0.6 mg/L (Figure 4.7(b)). These differences are even more important for nodes with zero or negative pressure where the median chlorine concentration is decreased from 1.2 to 0.5 mg/L. THM concentration generally increased under pressure-deficient conditions as a result of increased water age and chlorine consumption, especially at the nodes with lower pressures (Figure 4.7(c)). The correlation between water age, chlorine residual, and THM concentration obeys a logical trend for all pressure categories.

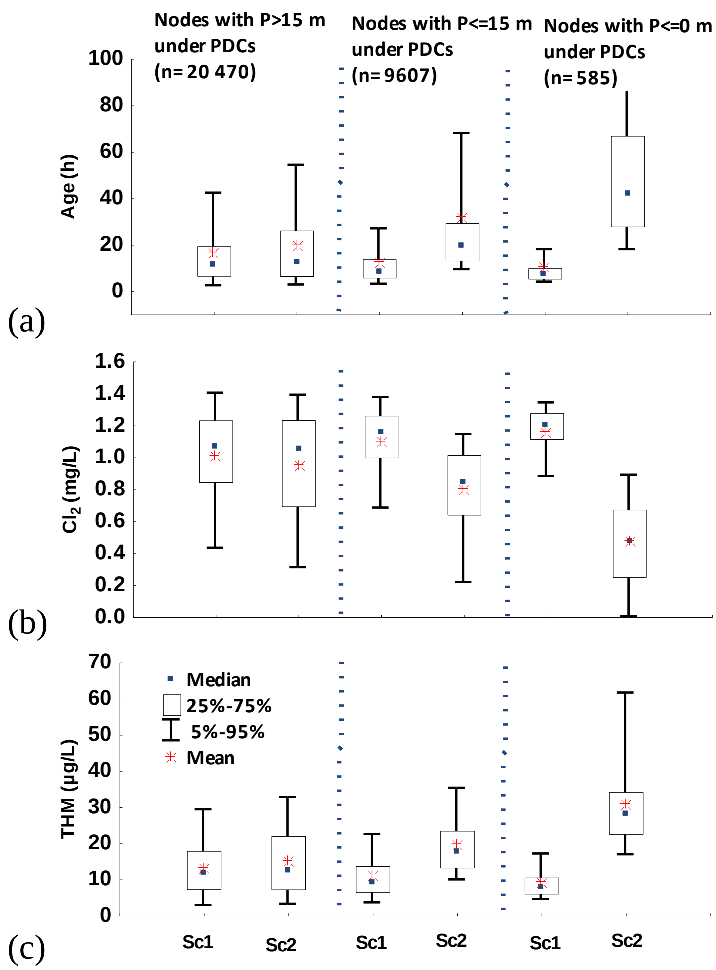


Figure 4.7: Comparisons of water quality parameters between normal operation conditions (Sc1) and pressure-deficient conditions (Sc2: WTP 1 and 2 out of service and WTP 3 at 77m) for three categories defined under pressure-deficient conditions: nodes with P > 15m, nodes with P ≤ 15 m (including negative pressure), and nodes with P ≤ 0; n is the number of nodes.

Similar trends as shown for Sc2 was observed for water quality parameters in other pressure-deficient scenarios (Sc3 and Sc4). Figure 4.8 shows that the range of differences in chlorine residuals between pressure-deficient conditions and normal operating conditions (Sc1) generally increases for group of nodes with lower pressure under the three pressure-deficient scenarios (Sc2 to Sc4). The median of these differences in chlorine residuals for Sc2 to Sc4 were 0.0 for nodes with P > 15, 0.3 mg/L for nodes with 0 < P ≤ 15, and varied between 0.6 to 0.8 mg/L for nodes with P ≤ 0.

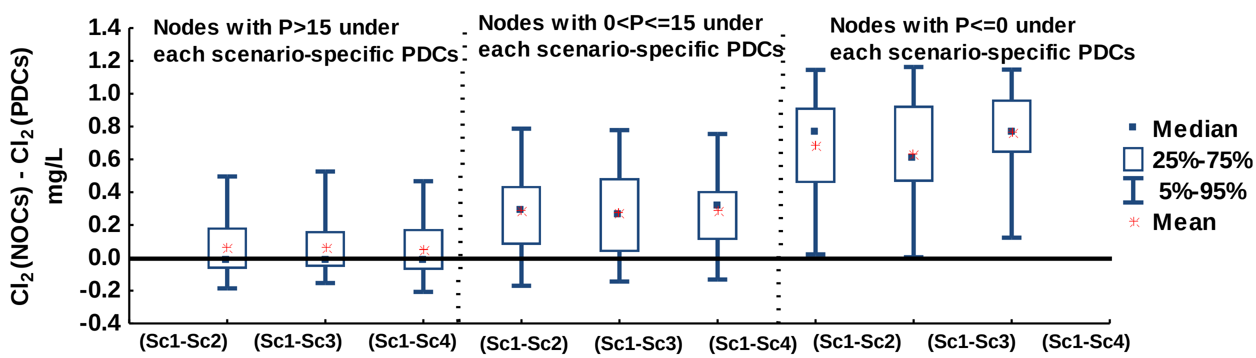


Figure 4.8: Differences of computed chlorine residuals between normal operation conditions (NOCs) and pressure-deficient conditions (PDCs) of scenarios 2 to 4 for three categories defined under each scenario-specific pressure-deficient conditions: nodes with P > 15, 0 < P ≤ 15 m, and nodes with P ≤ 0.

4.4 Discussion

Adverse pressure conditions in distribution systems may take the form of transient or sustained low/negative pressure events. Modelling and field investigations of distribution systems have shown that transient low and negative pressures can be common, ranging in duration from few milliseconds to a few minutes (Besner et al. 2010b, Ebacher et al. 2012, Ebacher et al. 2011a, Gullick et al. 2005) leading to the introduction of guidelines to prevent these events (Boulos et al. 2005, LeChevallier et al. 2011). The potential for intrusion of contaminated water during transients has been evaluated through field investigations and modelling (Ebacher et al. 2013, McInnis 2004, Teunis et al. 2010, Yang et al. 2011) and a framework to assess the associated potential public health risk proposed (Besner et al. 2011).

With water infrastructure aging and intensified system renewal activities, sustained pressure-deficient conditions in distribution systems may become more common. Sustained low/negative pressure events were measured by Besner et al. (2007) and (2010a) during construction work on a transmission main (400 mm). Low pressure (< 20 psi) lasting up to 20 hours was recorded at some sites. In order to identify appropriate utility management response to protect public health, these events should be better characterized in terms of intensity, duration and spatial distribution. A methodology consisting of an innovative combination of PDA results and multi species water quality model capable to conduct this evaluation is proposed.

4.4.1 Improving modelling tools towards a better prediction of water quality under pressure-deficient conditions

In DDA, demand values are considered fixed parameters in the continuity equation, and satisfaction of these demand values under pressure-deficient conditions may lead to unrealistically low nodal pressure values. PDA is more realistic as it calculates the available nodal demand as a function of nodal pressure. Also, DDA cannot predict the nodes with unsatisfied demand during a system failure.

As expected, the comparison of the distribution of estimated nodal pressures (Figure 4.4) reveals that the differences between DDA and PDA are most pronounced in areas where demand satisfaction is lowest. Demand satisfaction ratio was lowest in zone 1 (38.0-75.3%) than in zone 2 (72.4-94.4%), whereas zone 3 hardly experienced unsatisfied demand (96.5-99.7%) (Table 4.2). These results confirm that system managers cannot rely on DDA to model pressure-deficient conditions, especially in the case of very low and negative pressures, and that PDA should be used to identify areas with critical pressure loss across the distribution system.

The pressure underestimation by DDA was not only observed at nodes with low pressure (≤ 15m) as computed by PDA, but also at nodes with pressures up to 50 m, although smaller differences were generally observed for higher pressure nodes (Figure 4.5). The intensity of the pressure-deficient conditions also impacts the range of these differences. Yet, no minimal pressure in the pressure range tested (≤ 70m) could be identified above which pressure results from both approaches (DDA and PDA) would converge for all nodes and scenarios. These differences in estimated nodal pressures directly influence the delineation of the areas at risk of intrusion and backflow in the distribution system. Finally, whether DDA (under normal operating conditions) or PDA is used, proper calibration and validation are needed. In the case of PDA, the selection of a proper pressure demand relationship should be addressed.

A hydraulic feasibility check (Ackley et al. 2001) of flow and pressure was conducted by using results of the modified EPANET input file and WaterGEMS (Figure 4.3). Such verification is warranted not only to validate the reliability of the generated modified INP. file but also to determine whether or not negative pressures reported as zero have an impact on the other hydraulic results. Negative pressures reported as zero can lead to apparent total head reversal observations for PDA. Lee et al. (2015) argue that their PDA used tool produces unacceptable results as they observed flow direction from a node with lower total head to a node with higher total head under pressure-deficient conditions in a small model distribution system. However, this observation was likely caused only by the fact that negative pressures were not reported in the PDA model used. The pressure dependent demand model of WaterGEMS (V8i SELECTseries 5) used in this study was also found to report negative nodal pressure values as zero pressure. Such a limitation was addressed in the proposed approach by calculating the negative pressure values using the generated modified EPANET input file (Figure 4.2). As illustrated in Figure 4.3, the negative pressures reported as zero in WaterGEMS do not have any impact on the hydraulic calculations of pipe flows and positive nodal pressures and is only a reporting issue.

Water quality modelling in a distribution system is commonly limited to a single-species with demand-driven hydraulic analysis. However, a multi-species water quality model is required to simulate the interactions between two or more species. Moreover, a realistic hydraulic analysis, such as PDA, must be combined with water quality modelling to enable simulating the impact of low/negative pressure events on water quality. The presented technique (MSWQA-PDA) allows applying a multi-species water quality model (i.e. EPANET-MSX) to an all-pipes model of a large full-scale distribution system under different severe hypothetical sustained low/negative pressure conditions. As a proof of concept for multi-species water quality modeling, variations of water age, chlorine residual, and THM concentration were modeled and compared for normal and pressure-deficient conditions throughout the network.

The results show the importance of integrating a realistic hydraulic analysis (i.e. PDA) with a multi-species water quality analysis, providing a step forward towards more accurate and reliable management strategies and consequently reducing public health risk under sustained pressure-deficient conditions. The proposed methodology can be used without modifying the source code and can contribute to the future development of open source software combining multi-species analysis and PDA. It should be noted that further efforts are needed to provide more reliable numerical models capable to consider and predict water quality changes more accurately in water distribution systems. For example, under unsteady conditions, the impact of flow reversals and biofilm re-suspension on turbidity and chlorine decay must be investigated.

4.4.2 Regulatory and management implications

The delineation of zones at risk for intrusion and backflow relies on the identification of distribution system zones at risk for low and negative pressures. For each system, these zones should be defined by setting the minimum acceptable threshold pressure that reflects the risk of backflow from the connected buildings. The minimal pressure that should be maintained in distribution systems has been lengthily debated, and guideline reference values vary in their tolerance of low but positive pressures. When pressures decrease below 14 m (20 psi), during main breaks, it is not uncommon for the water utility to issue a boil water advisory because of the possibility of system contamination from cross-connections (Mays 2000). Erickson et al. (2015) surveyed the existing standards and guidelines addressing low/negative pressure events in the United States. The authors report that, although the majority of the interviewed agencies have guidelines for issuing a BWA for zero or negative pressure events, this is not the case for low positive pressures. Only two of the eleven interviewed states always recommended issuing a BWA for low pressure between 0 to 14 m. In this context, nodes with negative pressure ($P \leq 0$m) are considered part of the highest risk zone justifying a BWA, and nodes with low but positive pressure ($0 < P \leq 15$ m) are considered as susceptible location to intrusion/backflow which may lead to corrective/preventive actions in the network. For the studied distribution system, the number of nodes susceptible to intrusion/backflow varies considerably for different minimal pressure criteria (0, 5, 10 or 15 m) as shown in Table 4.3. This clearly demonstrates the need to select an appropriate pressure criterion to evaluate the risk of low pressure. For example, in scenario 2, the number of nodes prone to intrusion/backflow varies from 585 (2%) to 9,607 (32%) when considering different minimal pressure criteria (0, 5, 10 or 15 m) (Table 4.3). The number of nodes at risk also varies with the pressure loss scenario (Sc2 to Sc4). The number of nodes triggering a BWA ($P \leq 0$ m) varies from 2472 (8 %) to 103 (< 1 %) by changing the hydraulic grade at the only working WTP (Table 4.3). Even a small number of nodes prone to intrusion/backflow may impact public health, depending on the vulnerability of the supplied customers, the intrusion rate, and the contamination level. Although the minimal pressure triggering corrective/preventive actions is a most critical criterion when defining the extent of the zone at risk, guidance remains poorly defined. Furthermore, the actual response should also be based on online field pressure monitoring with adequate number and suitable location of monitoring sites.

Table 4.3. Number of nodes experiencing very low pressure for Sc2 to Sc4.

Scenario	**Cause of low/negative pressure event**	**Number of nodes**			
		P ≤ 0 m	**(P ≤ 5 m)**	**(P ≤ 10 m)**	**P ≤ 15 m**
Sc2	Shutdown of two WTPs	585 (2%)	3,250 (11%)	7,131 (24%)	9,607 (32%)
Sc3	Shutdown of two WTPs and loss of pressure head at the remaining WTP	2,472 (8%)	6,528 (22%)	9,193 (31%)	12,722 (42%)
Sc4	Shutdown of two WTPs and increased pressure head at the remaining WTP	103 (<1%)	1,470 (5%)	4,422 (15%)	7,773 (26%)

Negative and low pressure zones are significantly reduced in this distribution system when the PDA modelling approach is used (Figure 4.6). Besides the number of nodes affected by low or negative pressures, the boundaries of a BWA zone depend on the spatial clustering of these nodes. Figure 4.9 illustrates the extent of areas which may require corrective/preventive actions for different minimal pressure criteria. As the criteria for minimal pressure increases, the spatial dispersion of the low-pressure nodes across the system is such that the definition of a system wide BWA area may become unavoidable. The possibility of issuing sectorial BWAs is an important issue for utilities wishing to limit the impact of pressure losses on their customers.

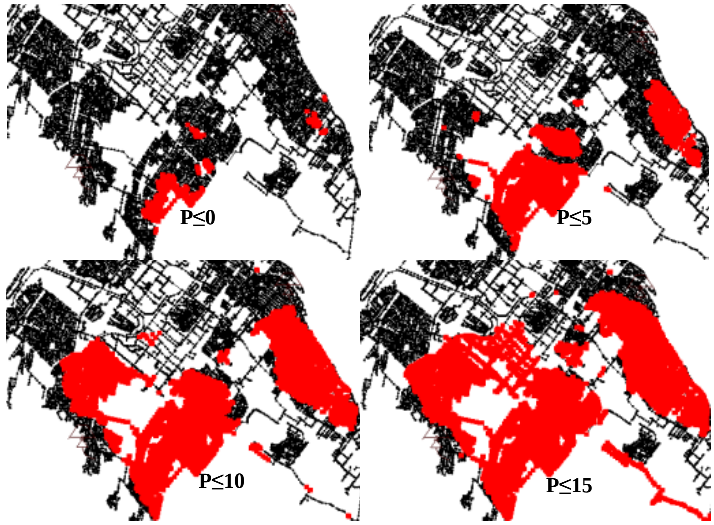


Figure 4.9: Geographical distribution of areas triggering corrective/preventive actions (in red) for different minimal pressure criteria (0, 5, 10, or 15 m).

Although hydraulic modelling using PDA is a useful tool, other factors should also be considered by water utility managers to justify issuing a BWA or corrective/preventive actions, including the duration of the low or negative pressure, measurements from online pressure monitors, the presence of vulnerable populations (hospitals, schools, day care centers, etc.), residual disinfectant concentrations at the time of pressure loss, fate and transport of contaminants, the number of stories of buildings in low pressure areas, the zoning (ex. industrial), and the presence of backflow prevention devices.

Water quality variations during sustained low pressure events in distribution systems can be related to changes in the hydraulic conditions of the system (i.e. nodal pressures and pipe flow rates), and also to contamination from intrusion/backflow into the distribution system. In this study, the focus was put on the first issue. In the case of unsteady flow conditions, the variation of disinfectant residual concentrations due to biofilm re-suspension and scouring of corrosion products caused by flow reversals is also another factor to be investigated. Generally, results show poorer water quality (water age, Cl_2 and THM) for the simulated sustained pressure-deficient scenarios compared to normal operating conditions. These differences are generally higher for nodes with negative pressure ($P \leq 0$) or low/negative pressure ($P \leq 15$) compared to nodes with pressure above 15 m (Figure 4.8). These water quality variations were only due to changes in the hydraulic parameters such as flow direction, flow rate, and head loss. This means that, besides the higher risk of intrusion or backflow due to pressure drop in some areas of the network, the protection provided by chlorine residuals also decreases, when compared to normal operating conditions. This loss of chlorine is of particular interest as the residual disinfectant is usually considered as the last barrier against pathogen (mostly bacterial and viral) intrusion. In this study, THM formation was used to demonstrate the capability of the presented technique to simulate multiple species in a single run under pressure-deficient conditions. The results showed that the increase in THM concentrations was not a major concern.

4.5 Conclusion

A methodology that enables multi-species water quality analysis based on pressure-driven analysis (MSWQA-PDA) was developed by modifying the EPANET input file. The main advantage of this methodology is the simultaneous modelling of multiple water quality parameters, and hydraulic conditions during sustained low/negative pressure conditions. The proposed approach does not require modifying the source code and can also communicate with other existing pressure-dependent approaches. To the best of the authors' knowledge, this is the first application of a multi-species water quality model to a large full-scale network (more than 30,000 nodes and 1,630 km of pipes) under sustained pressure-deficient conditions based on a pressure-driven approach.

The simulated sustained pressure-deficient scenarios showed that models based on DDA will overestimate the zones at risk of low pressures, potentially leading to unjustified boil water advisories. Responding competently to depressurization is an important challenge for water utilities and health authorities. Therefore, a realistic hydraulic analysis (i.e. PDA) is required to achieve more reliable results.

The critical pressure value triggering corrective/preventive actions has been the subject of much debate. This critical pressure value (0, 5, 10, or 15 m) directly influences the number of nodes subject to corrective/preventive actions and their spatial clustering zones under BWA. In the studied distribution system, the selection of a higher pressure threshold limits the potential for a sectorial BWA.

Water quality parameters (water age, chlorine residual and THM concentration) were generally poorer under the simulated pressure-deficient scenarios compared to normal operating conditions, especially at nodes with lower pressure values. This shows the importance of using enhanced modelling tools which can combine both pressure-driven analysis and multi-species water quality simulations.

Although such results were observed for continuous sustained pressure-deficient conditions, the next step will consist in using the MSWQA-PDA approach to simulate low/negative pressure events lasting a few hours. Microbial intrusion should also be integrated to the model to take advantage of the full potential of the developed approach.

ACKNOWLEDGEMENTS:

This research was funded by the NSERC Industrial Chair on Drinking Water at Polytechnique Montréal. The participating utility gratefully provided data and information of the distribution system model. The authors are also grateful to Bentley Systems for their technical support and providing academic access, with unlimited pipes version, to the utility model.

CHAPTER 5 ARTICLE 2 –IMPROVEMENT OF ACCIDENTAL INTRUSION PREDICTION DUE TO SUSTAINED LOW-PRESSURE CONDITIONS: IMPLICATIONS FOR CHLORINE AND *E. COLI* MONITORING IN DISTRIBUTION SYSTEMS

Appropriate numerical models can provide a basis to redefine the current *E. coli* sampling protocols. In this chapter, intrusion of contaminated water due to sustained pressure losses lasting a few hours and fate and transport of *E. coli* through the network are simulated using the developed approach (MSWQA-PDA). This technique allows for simultaneous consideration of the interactions between *E. coli* and disinfectant residuals and the impact of water quality variations due to hydraulic changes under sustained PDCs, using realistic PDA. The results can offer timely actionable information to utilities and improve sampling strategies in terms of location, timing, and volume of samples. The results also provide insight into propagation of *E. coli* throughout the network based on pressure values under PDCs and issuing sectorial boil water advisories. This paper was submitted in *Journal of Water Resources Planning and Management*. Supplementary information is presented in Appendix B.

IMPROVEMENT OF ACCIDENTAL INTRUSION PREDICTION DUE TO SUSTAINED LOW-PRESSURE CONDITIONS: IMPLICATIONS FOR CHLORINE AND *E. COLI*

Fatemeh Hatam[1], Marie-Claude Besner[2], Gabrielle Ebacher[3], Michèle Prévost[1]*

[1]NSERC Industrial Chair in Drinking Water, Department of Civil, Geological and Mining Engineering, Polytechnique Montréal, CP 6079, Succ. Centre-ville, Montréal (Québec), H3C 3A7, Canada
[2]R&D Engineer, Water Service, City of Montreal, Montréal, QC, Canada H3C 6W2
[3]Technical Engineer, Environment Service, Drinking Water Division, City of Laval, QC, Canada, H7V 3Z4
[*]Corresponding author, E-mail address: fatemeh.hatam@polymtl.ca, Tel.: 514 340-4711 ext. 2983

Abstract

Low/negative pressure events that increase the risk of contaminant intrusion may take place in distribution systems and may become more common in ageing infrastructure. Guidance of whether to issue an advisory after loss of pressure is based on the duration and extent of pressure loss and is accompanied by *E. coli* monitoring obligation. In this paper, the limitations of *E. coli* monitoring to detect intrusion is demonstrated using a conservative 5-hour pressure loss and considering intrusion of raw sewage. In low/negative pressure areas (P < 1 m), 74 nodes were prone to intrusion. Volumes of intrusion are adjusted as a function of the pipe internal pressure and an adjusted leakage constant. Ingress of contaminated water and fate and transport of *E. coli* throughout a 30,077 nodes distribution system are simulated using a realistic pressure-driven hydraulic model coupled to a multi-species water quality model (EPANET-MSX). Spatial and temporal distribution of contamination shows that contamination can be transported to higher-pressure zones with the extent of propagation depending on the efficacy of disinfectant residuals to inactivate intruded microorganisms. For chlorinated distribution system the limited positive nodes show the challenge of any confirmation of contamination unless conducted during the intrusion at or downstream of the intrusion sites. In chloraminated system, a larger number of nodes (2905 nodes) experienced *E. coli* over the simulation duration compared to chlorinated system (166 nodes), increasing the likelihood of detecting contamination. The nodal mean probability of detection was > 0.1 in both the first and second 5-hour intervals at 166 nodes. Larger sampling volumes (1 L versus 100 mL) provides greater sensitivity: it extends the period and increases the number of sites where samples can be collected with a higher probability of positive detection. These observations question whether extending *E. coli* sampling after 15 hours is informative without using larger sampling volumes. Overall, numerical predictions can guide utilities to optimal locations for both confirmation and clearance sampling. Large volume sampling at at-risk nodes identified by advanced numerical models provide greater credence in negative results to manage boiling advisories.

KEYWORDS: Sustained pressure deficient conditions; Intrusion; E. coli detection; Chlorine; Multi-species water quality simulation; Pressure-driven analysis;

5.1 Introduction

Pressure and disinfectant residuals in distribution systems (DSs) are the final barrier for protecting the public health against microbial contamination. Ingress of contaminated water due to network deficiencies can cause water quality issues and health problems (Craun et al. 2010, Lindley and Buchberger 2002). Sampling locations and/or sensor placements to monitor water quality in the network can be optimized to increase the probability of detecting a contamination event (He et al. 2018, Khorshidi et al. 2018, Ohar et al. 2015, Zhao et al. 2016). However, as sensors are parameter-dependent and may not be deployed everywhere, numerical models are required to optimize monitoring and response during and after pressure deficient conditions (PDCs). Therefore, improving the accuracy and reliability of hydraulic and water quality models to simulate intrusion and the propagation of contaminants throughout the DSs is essential.

Intrusion events in DSs can be classified into two types: accidental and intentional. Simulation of accidental intrusion due to low/negative pressure events requires a PDA, in place of the traditional demand-driven analysis (DDA). In the PDA, the available demand at each node is calculated as a function of nodal pressure using different methodologies (Ang and Jowitt 2006, Giustolisi and Laucelli 2011, Paez et al. 2018, Siew and Tanyimboh 2012). A detailed literature review on pressure-driven approaches and existing pressure-demand relationships can be found elsewhere (Hatam et al. 2018a).

The water quality model used to simulate the fate and transport of contamination should be based on a realistic hydraulic analysis of PDCs (i.e. PDA). DDA has been used for the management of contamination events and optimization modeling along with single-species water quality modeling (Baranowski and LeBoeuf 2006, Shafiee and Berglund 2017). Rasekh and Brumbelow (2014) and Zafari et al. (2017) proposed optimization models based on PDA and single-species water quality simulations (using EPANET) to minimize the adverse effects of contamination. Besner et al. (2011) discussed challenges related to estimation of public health risk associated with contamination resulting from PDCs. With the Multi-Species Extension of EPANET (Shang et al. 2011), multi-species interactions including interaction of disinfectant with organic and inorganic matter, inactivation of microorganisms, and attachment/detachment of pathogens to/from biofilm can be considered (Uber 2010). Some studies have applied EPANET-MSX to model contaminant intrusion events in the DSs considering the inactivation of microorganisms and disinfectant decay

(Betanzo et al. 2008, Islam et al. 2017, LeChevallier et al. 2011, Propato and Uber 2004, Teunis et al. 2010, Yang and Boccelli 2016). However, as for EPANET 2, EPANET-MSX is a DDA based model that is less accurate to model fate and transport of contaminants under sustained PDCs.

Using the numerical model, van Lieverloo et al. (2007) and Blokker et al. (2018) evaluated the probability of detecting *E. coli* with standard monitoring program and they observed that the detection probability was low. It should be noted that *E. coli* inactivation was not considered in these studies. The possibilities to improved sampling strategies (location, timing and volume) are required to be further investigated in the presence of disinfectant. For a more realistic simulation of accidental ingress and propagation of contaminated water under sustained pressure losses, a multi-species water quality model should be combined with PDA. Recently, EPANET-MSX has been coupled to pressure-driven hydraulic analysis results by Seyoum and Tanyimboh (2017) and Hatam et al. (2018a) using different approaches to model THM and chlorine under continuous sustained PDCs. The latter approach was used to simulate the transport of the non-reactive *Cryptosporidium* under continuous PDCs (Hatam et al. 2018b). To the knowledge of the authors, no study so far has investigated fate and transport of contaminants by simultaneously accounting for (1) the interactions between microorganism and disinfectant residuals, and (2) the effect of hydraulic conditions under sustained pressure losses applying a realistic hydraulic analysis (i.e. PDA).

Pressure within a pipe is one of the key factors determining intrusion locations and contaminant concentration at the entry points. Intrusion flow rates are driven by the pressure differential between the outside and inside of a water main. Contaminant concentrations have been considered using different approaches. Teunis et al. (2010) have calculated virus concentrations at intrusion nodes based on local water flow, random intrusion volume, random negative pressure duration and random sewage concentration. Besner et al. (2010c) have generated a possible range of contaminant mass rates using a probabilistic model, considering the pressure head values inside and outside the pipe as a triangular probability distribution function. Propato and Uber (2004) simulated intrusion events considering a constant mass flow rate of pathogens downstream of each intrusion node. Finally, Betanzo et al. (2008) assumed constant microorganism concentrations based on concentrations reported in sewage with a specific dilution factor into pipe water (10%), without considering the nodal pressure values impact on intrusion flow rate.

In this paper, a methodology to estimate node-specific contaminant mass rate at nodes prone to intrusion is proposed. For the simulated sustained PDCs, the potential nodal intrusion volume is tuned adjusting the leakage constant of each node based on the nodal leakage demand (representing pipe age and type of materials) and application of the nodal pressure inside the network, using PDA results. Then, the fate and transport of *E. coli* resulting from the ingress of sewage caused by sustained PDCs lasting 5 hours is modeled in a large full-scale DS with 30,077 nodes. The results from coupling of EPANET-MSX to PDA provides insight into the fate of *E. coli* with estimates of disinfectant decay and microorganism inactivation. Results are then interpreted to reevaluate and improve sampling strategies (location, timing, and volume sample) during and after intrusion events for various disinfectant residual scenarios (no residual, chlorine, and chloramine).

5.2 Methodology

5.2.1 Description of Simulated Sustained Low-Pressure Event

The modeled network includes 30,077 nodes, three WTPs and a total pipe length of about 1,600 km. Under normal operation conditions (NOCs), each WTP supplies water to a specific area of the system. However, as the entire network is hydraulically interconnected, the influence zone of each WTP is modified when changes in hydraulic conditions take place. More information on the characteristics of the network can be found in Hatam et al. (2018a). The sustained PDCs correspond to a combination of the shutdown of one of the WTPs for a 5-hour period and a fire flow demand of 15,000 L/min at one point (Table 5.1). Flow rates of the remaining WTPs were increased to some extent to compensate the shutdown of WTP1 as described in (Hatam et al. 2018a). For simplicity of analysis, the demand is considered to be constant (239,414 m^3/day) corresponding to the peak hour consumption. The hydraulic model of the studied system is built such that total demands at each node are classified as residential, industrial, commercial, institutional, municipal, and leakage. To allow water quality (disinfectant residuals) reaching equilibrium conditions, the model is run for 10 days under NOCs using the extended period simulation. The PDCs are simulated from 16:00 to 21:00 of day 11^{th} (Table 5.1).The model is then run for three additional days to investigate the spatial and temporal distribution of contamination throughout the network.

Table 5.1. Comparing network hydraulic conditions under normal and pressure-deficient conditions; HG and Q_{out} are hydraulic grade and outflow rate, respectively.

Pressure conditions	**NOCs**		**PDCs (5 hours)**	
	HG (m)	Q_{out} (L/s)	HG (m)	Q_{out} (L/s)
WTP1	76	716	-	-
WTP2	75	701	65	856
WTP3	77	1354	77	2028
Fire Flow	-		15,000 L/min	

5.2.2 Ingress of Contaminated Water

The following hypotheses are used to model contaminant intrusion: (i) the size of the entry pathway is proportional to the leakage demand assigned to a node, (ii) the pressure differential between internal and external pressure heads is obtained through PDA. The pressure head on all pipes is assumed equal to 1 m, based on the range of the water table head above the pipes in the studied network (Ebacher et al. 2013), and (iii) a contamination source (sewage) is assumed to exist everywhere around all pipes. To calculate the intrusion flow rate (Q_i (m^3/s)) the orifice equation ($Q_i = (C_d A)_i \sqrt{2g(H_{ext} - H_{int_i})}$) is used. To calculate intrusion flow rate, H_{int_i} is the pressure head inside the pipe at node i (m) under PDCs calculated using PDA. In this study, $(C_d A)_i$ are calculated using the corresponding leakage flow rate at time t ($Q_{leakage_{i,t}}$) in the calibrated model under NOCs:

$$C_{leak_{i,t}} = (C_d A)_{i,t} = Q_{leakage_{i,t}} / \sqrt{2g(H_{int_{i,t}} - H_{ext})} \qquad \text{Eq. 5-1}$$

in which $C_{leak_{i,t}}$ is the leakage constant, $H_{int_{i,t}}$ is the pressure head inside the pipe at node *i* at time *t*, under NOCs, H_{ext} is the pressure head outside the pipe (m), A is the orifice area (m^2), C_d is the coefficient of discharge (unitless), and *g* is the gravitational acceleration (m/s^2). Using the network model with daily demand patterns, C_{leak} is calculated at each node and at each hour over a 24-hour period. For the sake of simplicity and to be conservative, the maximum value of C_{leak} at each node during this period is used for computing the intrusion flow rate during the PDCs period (Figure B-1).

The external source of contamination selected here is raw sewage assumed to be leaking from adjacent sewer mains. *E. coli* was selected for simulation, as it is the reference indicator organism for confirmation and clearance of contamination in DSs, is abundant and is inactivated to various degrees by disinfectants. A concentration of 1.6E06 CFU/100 mL in the local sewage was used (Payment et al. 2001). The contaminant mass rate at each intrusion node is calculated by multiplying the concentration of microorganisms outside the pipe (C_{out}) by nodal intrusion flow rate. The intrusion flow rates are implemented by assigning a negative demand to an artificial node connected to the intrusion node using a short pipe with negligible head loss. The impact of intrusion volumes on the pressure values and DSRs is considered by adding the intrusion flow rates to the PDA model and solving the hydraulic model again. The modified INP file of EPANET is then regenerated based on these hydraulic results. The intrusion flow rates can be recalculated using the recent pressure values to investigate the impact of possible pressure variations on the intrusion flows. Another iteration may be needed if larger intrusion flow rates (such as backflow from cross connections or submerged air vacuum valves) enter the system, although this is not the case here.

Several intrusion scenarios (Table 5.2) are simulated to investigate the impacts of disinfectant residual type and concentration on the fate and transport of *E. coli*. The intrusion duration is assumed to be equal to the duration of the low/negative pressure event. Contaminant propagation is simulated for 3 days after PDCs are over.

Table 5.2. Description of intrusion scenarios.

Scenario	Disinfectant type	Disinfectant Concentration (mg/L)	Contaminant
(1)	No disinfectant	0.0	Sewage- *E. coli*
(2)	Chlorine	0.5	Sewage- *E. coli*
(3)	Chlorine	1.0	Sewage- *E. coli*
(4)	Chlorine	2.0	Sewage- *E. coli*
(5)	Chlorine	1.0	No intrusion
(6)	Chloramine	1.0	Sewage- *E. coli*
(7)	Chloramine	2.0	Sewage- *E. coli*
(8)	Chloramine	1.0	No intrusion

5.2.3 Disinfectant Decay and Microorganism Inactivation

To simulate chlorine decay the simple first-order model is used and for chloramine, the second-order model is applied. The Chick-Watson model is applied for the inactivation of *E. coli* (Betanzo et al. 2008). The inactivation constant (k_p) is considered 246 and 0.99 ($\mathrm{L/mg \cdot h}$) for chlorine and chloramine at 10°C, respectively, by assuming that k_p is reduced by half for every 10°C decrement in temperature (Betanzo et al. 2008). Based on data obtained from disinfectant decay experiments for a 0.1% wastewater intrusion with total organic carbon levels ranging from 4.6 to 54 mg/L (LeChevallier et al. 2011, Yang et al. 2011), the initial chlorine demand of the ingress water was set to 0.088 mg/L and no initial demand is considered in the case of chloramine. For chlorine, the decay constants with and without intrusion are set to 0.24 and 0.055 h^{-1}, respectively, and for chloramine, these values are set to 0.11 and 0.012 $(\mathrm{mg\,Cl_2 \cdot h/L})^{-1}$, respectively. The higher disinfectant decay constant value (identified as $K_{intrusion}$) is only applied to pipes that receive intrusion materials as determined by a conservative tracer. For a more accurate estimation of disinfectant residuals while using the nth-order decay model, a conservative fictitious species is assumed to be injected into the network at the intrusion nodes. Contrary to *E. coli*, this species is transported into the system without any decay and is only used to determine zones, at each time step, for which $K_{intrusion}$ will be applied in the decay model. For simplicity, a constant $K_{intrusion}$ value is applied to these pipes regardless of the variation in dilution of entering sewage. For the remaining pipes in the network, the disinfectant decay rates set for water not exposed to intrusion water (K_{normal}) is used. In this study, if negative chlorine concentrations are computed at intrusion nodes from the initial chlorine demand, the chlorine concentration is considered as zero in the analysis. The probability detecting *E. coli* is calculated using a Poisson distribution (Teunis et al. 2004).

5.3 Fate and transport of contaminated water during and after pressure losses

Fate and transport of ingress *E. coli* throughout the network, in the absence and presence of disinfectant residuals, and the propagations of conservative fictitious species is then simulated using a multi-species water quality analysis based on PDA by employing the approach presented in Hatam et al. (2018a). Previously, the methodology (MSWQA-PDA) was applied to model continuous PDCs (Hatam et al. 2018a, b). In this study, the capability of MSWQA-PDA approach to consider time-varying parameters (with hourly variations) such as pumping regimes at water treatment plants (WTPs) is illustrated by applying it to simulate intrusion events due to low/negative pressure events lasting a few hours. More details on the methodology can be found in supplemental materials and Hatam et al. (2018a).

5.4 Results and Discussion

5.4.1 Impact of sustained low/negative pressure events on pressure and DSRs

Pressure values during NOCs (at 15:00) and sustained PDCs (at 16:00) are illustrated for different groups of nodes in Figure 5.1 (a). The nodes are categorized based on their pressure values during PDCs to better visualize the differences. Median pressure values calculated by DDA and PDA are, respectively, -4.6 and 0.3 m for the first group of nodes ($P \leq 1$ m, 74 nodes), whereas closer values (35.0 and 35.8 m) are obtained for the group of nodes with $P > 15$ m (25,168 nodes). The results show that DDA underestimates the pressure values when modeling pressure losses, especially for nodes with low-pressure values ($P < 15$ m), which agrees with a previous study (Hatam et al. 2018a). This can lead to unreliable overestimation of the areas prone to intrusion as well as incorrect estimation of intrusion volumes potentially entering the system. As an illustration, the number of nodes with pressure less than 1 m (considered as prone to intrusion in this study) increases to 1156 nodes when using DDA, as compared to 74 nodes using PDA.

About 16% of nodes, excluding the nodes with no demand during NOCs (469 nodes), experience pressure less than or equal to 15 m (Figure 5.1 b). During the studied PDCs, 25% of these nodes experience a DSR between 0 and 56%, and the 75th percentile is 99%. Defining the nodes with partial demand satisfaction is important for customers, but even more so in terms of ensuring adequate fire flows. For the studied event, the node where a fire demand (15,000 L/min) was assigned for 5 hours had a DSR of 99% with a pressure of 12 m during PDCs.

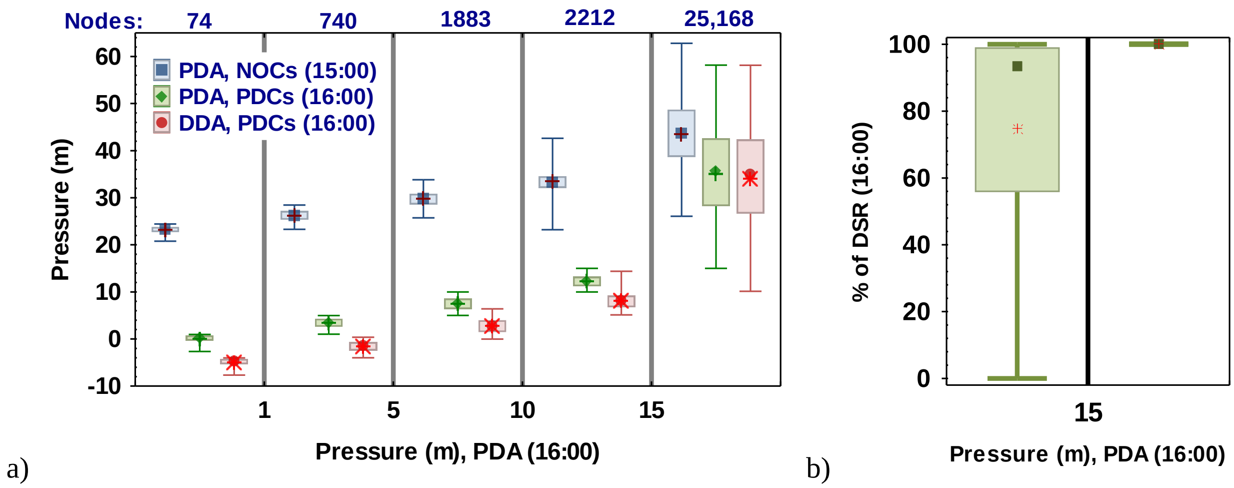


Figure 5.1. (a) Pressure values during NOCs (15:00), and PDCs (16:00) using both PDA and DDA, and (b) DSR excluding nodes without any demand (469 nodes) during NOCs; Square: Median; *: Mean; Box: 25%-75%; Whisker: Min-Max.

5.4.2 Intrusion volumes to estimate *E. coli* concentration at the intrusion nodes

PDA showed that 74 nodes had an internal pressure less than 1 m. Intrusion flow rates have been computed at 73 of these nodes as one node had no leakage demand assigned in the model (translating into no intrusion pathway). The corresponding pressure values and intrusion flow rates for the nodes identified as experiencing potential ingress are illustrated in (Figure B-2). The total volume of ingress water for the 5-hour pressure loss is 1,909 L through the 73 leakage orifices. Distribution of intrusion volume through these nodes is illustrated in Figure 5.2. For half of the nodes the intrusion volume is less than 17 L, while the maximum value reaches 119 L. Duration of event is an important factor that affects intrusion volume. To the knowledge of the authors, studies computing intrusion volumes for long duration of PDCs are not available in the literature. This makes it difficult to compare the order of magnitude of intrusion volumes. For a shorter event duration, a smaller total intrusion volume of 157 L for a 3-minute event through 1,517 leakage orifices was reported in the same DS (Ebacher et al. 2010).

Given the extent of the intrusion volumes obtained under the modeled scenario, the impact of the intrusion volumes on the network hydraulic, was considered by adding the intrusion flow rates into the PDA model. The adjusted PDA hydraulic results were used to regenerate the modified INP file of EPANET. The adjusted pressure values obtained from the modified INP file differed only slightly (less than 0.004 m), with no need for additional iterations. The intrusion flow rates (Figure

5.2) can then be used to calculate the contaminant mass rate at each intrusion node. Consequently, the concentration of *E. coli* at each intrusion node can be obtained based on the severity of PDCs, assumptions regarding leakage magnitude, contaminant concentration outside the pipe, and water table submergence, the upstream flow rates, and water quality conditions.

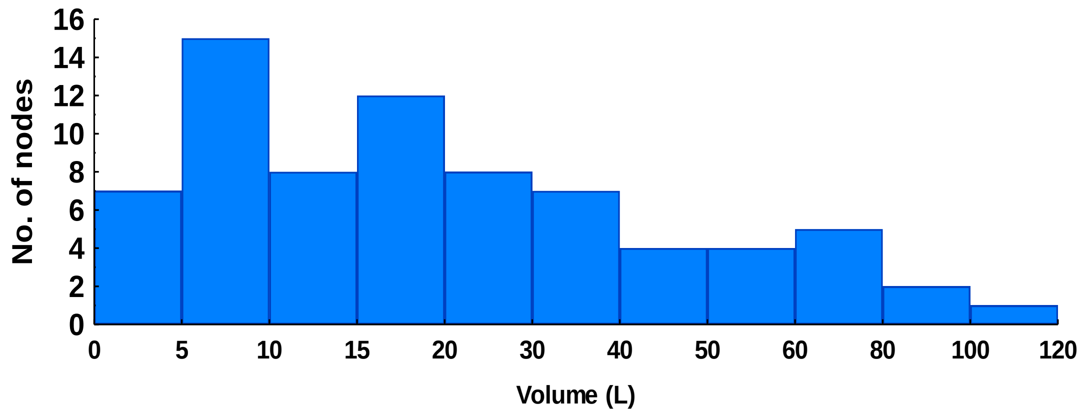


Figure 5.2. Distribution of intrusion volumes per node for the 5 hours pressure loss.

5.4.3 Behavior of different disinfectants under PDCs and a 5-hour intrusion event

The impact of the contaminated water ingress on disinfectant residual concentrations is illustrated in Figure 5.3. For clarity, results are only illustrated for the nodes with positive *E. coli* during any time over the whole simulation period for intrusion scenarios 3 and 5 (Figure 5.3 (b) and (d), respectively). The results for disinfectant residuals at these same nodes in the absence of intrusion are also presented in Figure 5.3 (a) and (c) allowing for a comparison of chlorine concentrations with and without intrusion. For the case of chlorine without intrusion, chlorine residuals remain higher than 0.4 mg/L at nearly 90% of nodes at any time before and after PDCs (Figure 5.3, a). After the ingress of contaminated water, chlorine concentrations at these nodes decrease with half of the nodes experiencing residuals lower than 0.4 mg/L for 5 hours, and less than 0.1 mg/L for 2 hours (Figure 5.3, b). It is interesting to note that a 5-hour intrusion event leads to sustained and significant chlorine losses outlasting the PDCs. The sharp decrease in chlorine concentrations with intrusion can be explained by: (1) the effect of the immediate chlorine demand (0.088 mg/L) applied to the 73 nodes with intrusion (2) the increased chlorine decay rates applied to the areas with conservative fictitious species, and (3) the rises in water age (described on Figure 5.3, a).

With chlorine, a relatively small number of nodes were found to be positive for *E. coli* ($\geq 10^{-6}$ CFU/L) with a maximum of 166 nodes at any time. It should be noted that an accuracy of 6 decimals is used to report species concentration in EPANET-MSX. As expected, at nodes positive for *E. coli*, chlorine residual losses are higher than for chloramines (Figure 5.3, b and d). The median chloramine residuals remained high (0.7 $\mathrm{mg/L}$) even after the intrusion event, reflecting the absence of immediate demand and the lower rate constant of 0.11 $(\mathrm{mg\,Cl_2 \cdot hour/L})^{-1}$ associated with ingress as compared to chlorine (0.24 h^{-1}). Regardless of the higher residuals, the inactivation of *E. coli* was also slower than for chlorine reflecting the lower inactivation rate constant. During the whole simulation period, more *E. coli* positive nodes (2,905) were observed, as compared to 166 nodes for chlorine. In contrast to chlorine, chloramine decay is not a critical factor as the limited inactivation reflects the slower kinetics of this disinfectant requiring higher CT values as compared to chlorine. The trend here agrees with previous studies investigating contamination by *Giardia* or viruses in the presence of chlorine and chloramine (LeChevallier et al. 2011, Propato and Uber 2004, Yang et al. 2011). Figure B-3 shows the distribution of water age and chlorine residual without the influence of ingress water considering all 30,077 nodes. Median water age generally increases at nodes with pressure $\leq$ 15 m, resulting in decreases in chlorine residuals that persist after the end of PDCs, decreasing the protection at nodes most vulnerable to contamination.

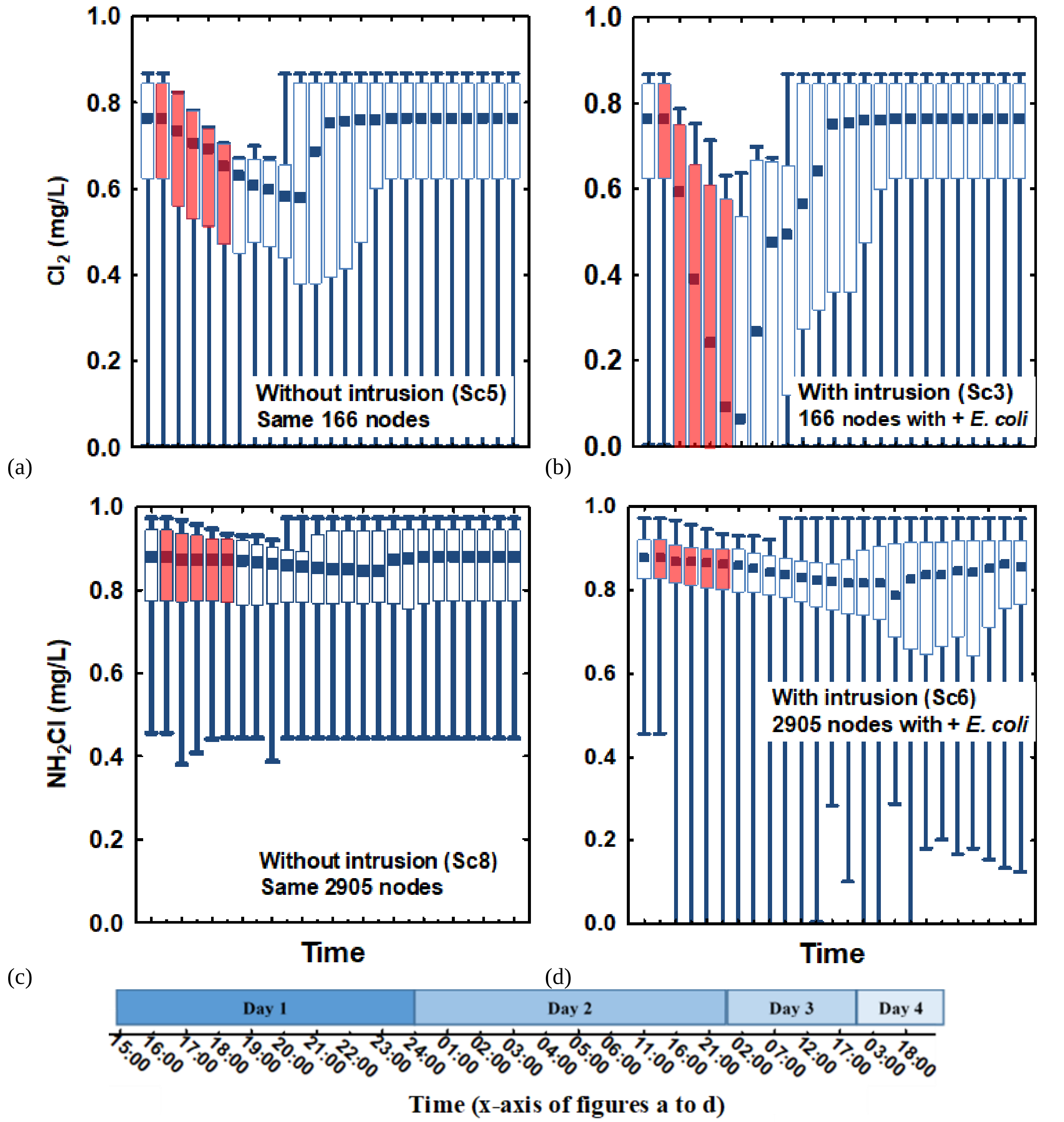


Figure 5.3. Temporal distribution of disinfectant residuals throughout the network for the nodes with positive *E. coli* at any time during and after the intrusion. No node was positive for *E. coli* without intrusion. Positive nodes with intrusion used for comparison with and without intrusion. For 1 mg/L chlorine (a) without intrusion, Sc5, and (b) with intrusion, Sc3. For 1 mg/L chloramine (c) without intrusion, Sc8, and (d) with intrusion, Sc6. Time intervals on the timeline are not equal. The red boxes show the concentration during PDCs; Square: Median; Box: 10%-90%; Whisker: Min-Max.

5.4.4 Propagation of *E. coli* under different conditions

As expected, the presence of chlorine residuals in the network limits the widespread propagation of *E. coli* downstream of the intrusion nodes, to a maximum of 166 nodes at any time during the 4-day simulation. Within that timeframe, the extent of areas positive for *E. coli* at any time is larger (2,095 nodes) in the chloraminated system as compared to the chlorinated system (Figure 5.4). As expected, the no disinfectant scenario shows an even larger contamination area (3,287 nodes) and increased *E. coli* concentrations. These results suggest that, in the case of a chlorinated system, the detection of an intrusion event can be a difficult process unless sampling is conducted during peak *E. coli* concentration at nodes, which is highly unlikely.

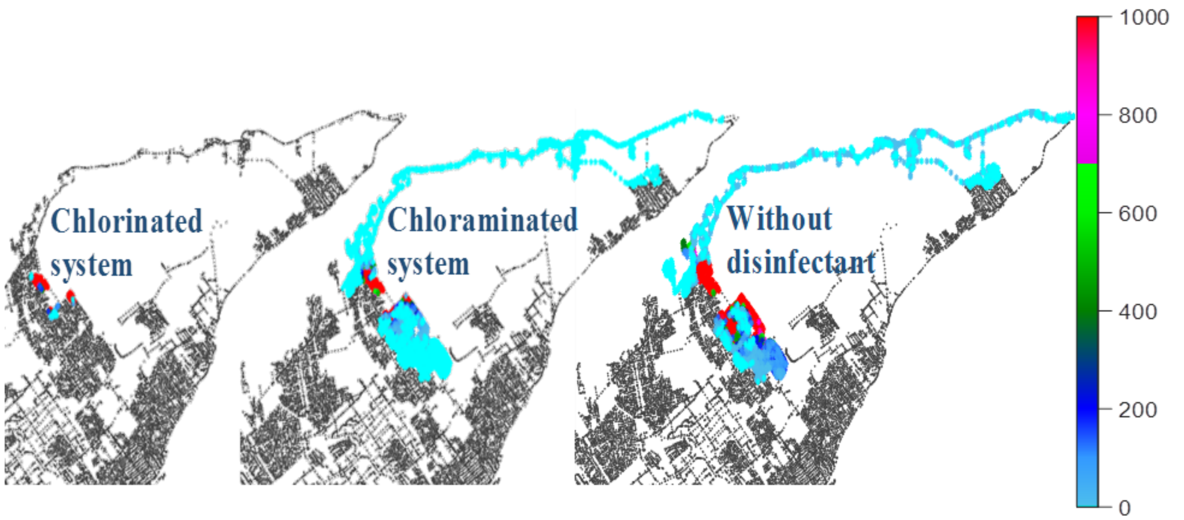


Figure 5.4. Maximum *E. coli* concentrations for scenarios with chlorine (Sc3, 1 mg/L), chloramine (Sc6, 1 mg/L) and without disinfectant (Sc1). Cyan color represents a concentration of ≤ 1 CFU/100 mL.

Figure 5.4 does not inform on the temporal shifts in the distribution of *E. coli* across the network nor on the duration of positivity for *E. coli* at any given node. Figure 5.5 summarizes the temporal propagation of *E. coli* in chloraminated and chlorinated systems. For both disinfectants, 4 hours after the start of intrusion (20:00 day 1), the concentrations are high (up to 1.6E06 CFU/100 mL) at and near the intrusion nodes, reflecting the conservative scenario of undiluted wastewater present around the pipe. The number of nodes positive for *E. coli* is greater in the chloraminated system (192 nodes) as compared to the chlorinated system (119 nodes). *E. coli* are transported to areas farther away albeit at lower concentrations, as shown by results after four and nine hours after the intrusion event (Figure 5.5). After nine hours, 826 nodes remain positive for *E. coli* with 72 % (593 nodes) experiencing low expected concentrations of *E. coli* (≤ 1 CFU/100 mL in cyan). The closer examination of the breakdown of these low concentrations reveals that concentrations in 314/826 (38%) of nodes positive for *E. coli* are very low (≤ 0.01 *E. coli*/100 mL) (Figure B-4). With chlorine, few nodes remain positive (8 and 2 nodes after four and nine hours, respectively).

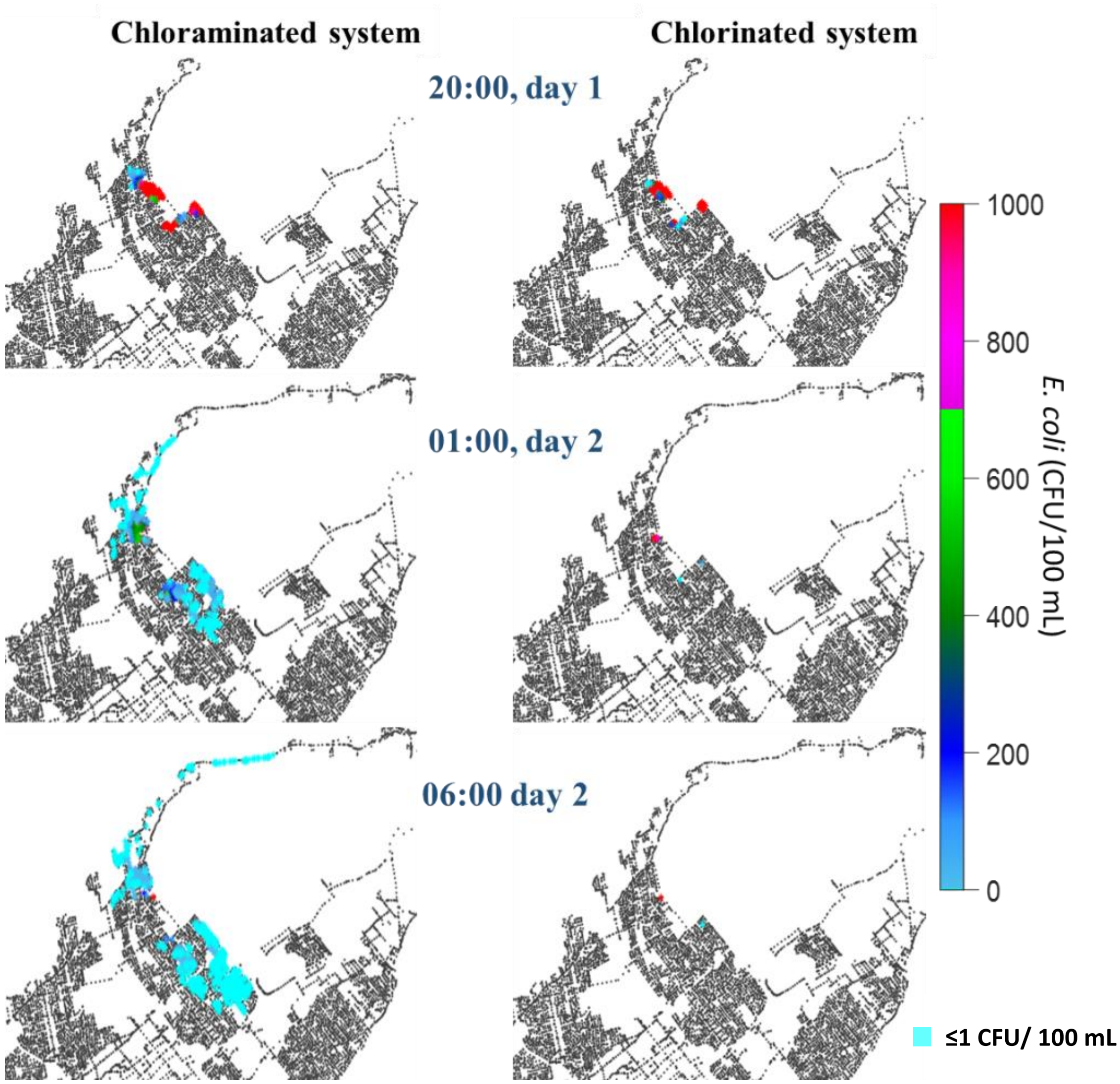


Figure 5.5. *E. coli* distribution in chloraminated (Sc6) and chlorinated (Sc3) systems at 20:00 of day 1, 01:00 of day 2, and 06:00 of day 2 following intrusion; Intrusion starts at 16:00 of day 1 and lasts for a duration of 5 hours.

5.4.5 Propagation of *E. coli* based on pressure values under PDCs

The effect of different chlorine concentrations on the propagation of contamination is illustrated in Figure 5.6. The nodes are grouped into six intervals based on their maximum *E. coli* concentration against their respective pressure values under PDCs. Maximum *E. coli* concentrations at the intrusion nodes (P < 1 m) are higher than 100 CFU/ 100 mL for all scenarios (Sc2 to Sc4). By increasing chlorine concentration from 0.5 to 1, and then to 2 mg/L, the number of nodes with positive *E. coli* is decreased from 228 to 166, and 101, respectively. Over the simulation duration in these scenarios, *E. coli* reached nodes that had maximum pressure values of 11, 8, and 5 m under PDCs, respectively. Higher chlorine residuals therefore contribute to restrain the impact of a contamination by limiting the propagation of *E. coli* into the system, confining it into lower pressure areas (defined based on the pressure values under PDCs) in the case of intrusion during PDCs.

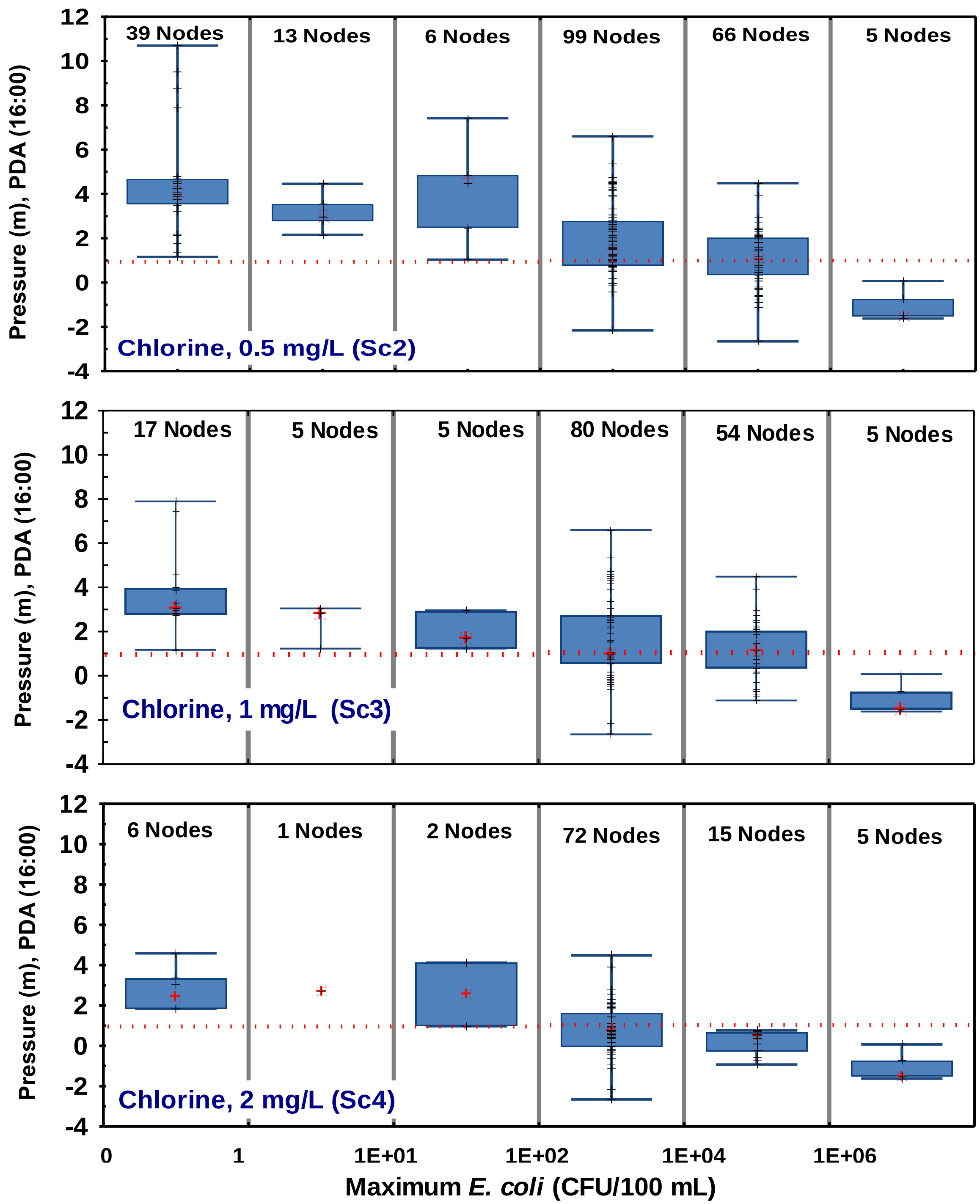


Figure 5.6. Effect of different chlorine concentrations (0.5, 1 and 2 mg/L) at the outlet of WTPs on maximum *E. coli* concentration estimated over the whole simulation duration, only considering nodes positive for *E. coli* ; *: Median; Box: 25%-75%; Whisker: Min-Max; +: Raw data.

In the case of a chloraminated system (Sc6 and Sc7), the number of nodes with positive *E. coli* is higher than in a chlorinated system for the same 5-hour intrusion event (Figure 5.7, a and b). Over the simulation duration in these scenarios, *E. coli* reached nodes with pressures up to 40 m (defined based on pressure values under PDCs). In the absence of a disinfectant residuals in the system (Figure 5.7, c), the absence of inactivation leads to an even wider propagation and higher concentrations in line with the spatial distribution of maximum *E. coli* observed in Figure 5.4.

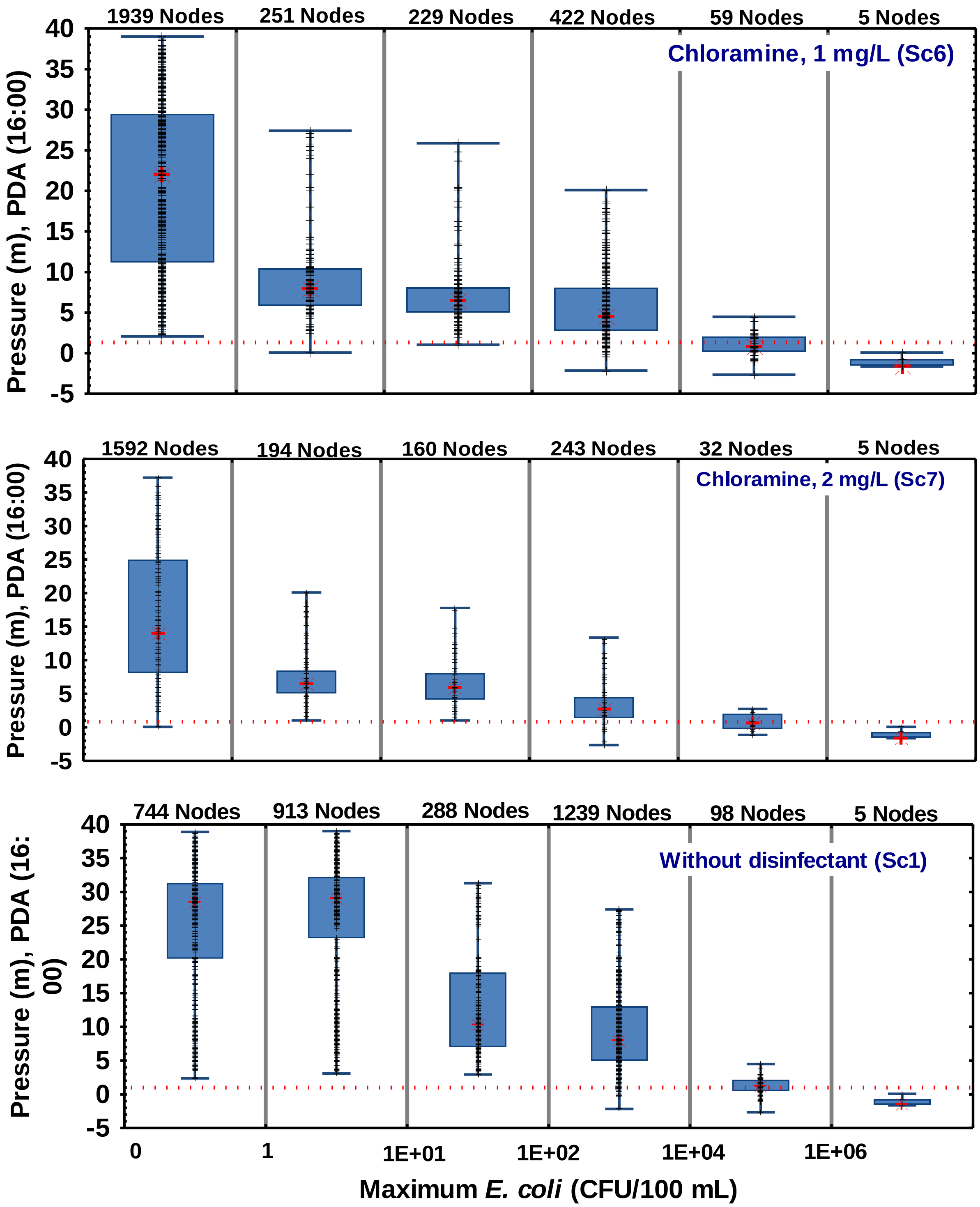


Figure 5.7. Effect of different chloramine concentrations (1 and 2 mg/L) at the WTPs on maximum *E. coli* concentration estimated over the whole simulation duration, only considering nodes positive for *E. coli*; *: Median; Box: 25%-75%; Whisker: Min-Max; +: Raw data.

5.4.6 Source of uncertainties

Several sources of uncertainties should be considered when interpreting predictions of ingress resulting from sustained and short term PDCs. Factors to consider include the volume of ingress at each node, the quality of water outside the pipe, the impact of ingress water on chlorine demand, the ability to predict demand and the selection of the external head (Ebacher et al. 2012, Yang and Boccelli 2014). In this study, some of these uncertainties are addressed by proposing two improvements: a node specific estimate of contaminant mass rate following intrusion and an enhanced chlorine decay modeling that adjusts chlorine decay in the presence of ingress water. A common simplification hypothesis consists of applying a constant concentration of microorganisms regardless of the actual low/negative pressure values at the intrusion nodes (Betanzo et al. 2008, Islam et al. 2017); others consider a random distribution of intrusion volumes and negative pressure durations to calculate the dilution factor at the negative pressure nodes (LeChevallier et al. 2011, Teunis et al. 2010). When considering the mitigating impact of disinfectant residual, it is important to consider the impact of contaminated water on instant and long-term chlorine decay. In this study, the intrusion volumes were computed based on nodal pressures from PDA and node specific leakage constants. Chlorine decay for sewage intrusion at different percentages of wastewater dilution was described by a first-order model and applied to the whole DS (Betanzo et al. 2008, LeChevallier et al. 2011). The application of the intrusion decay constant ($K_{intrusion}$) to the whole network after intrusion may underestimate chlorine residuals across the system, depending on network topology, duration and location of intrusions. To reduce the possible chlorine underestimation, we limited the nodes to which $K_{intrusion}$ is applied to those where intrusion water is transported as identified by the transport of a conservative species, while K_{normal} was applied to the remaining nodes. However, we recognized that considering same $K_{intrusion}$, representing a 0.1% wastewater intrusion, regardless of variations of dilution ratios in time and space, leaves some overestimation of chlorine losses in affected nodes.

5.4.7 Implications for management strategies

The novel approach combining PDA and multi-species water quality modeling provides more realistic results to estimate the prevalence and fate of *E. coli* across a DS after intrusion resulting from extended PDCs. These findings have several operational and regulatory implications. The case studies presented provide a basis for redefining optimal sampling approaches for: (1) the detection of contamination in response to a pressure loss in a DS, which is known as *confirmation sampling*; and (2) the confirmation of the elimination of any residual contamination after a confirmed event, which can be considered as *clearance sampling*. Furthermore, this study also brings valuable insights in the possibility of delineating areas that are at risk in order to better define areas for which advisories should be issued.

5.4.7.1 Implications for confirmation and clearance sampling

Responding to low-pressure conditions involves emergency response sampling to determine whether a contaminant has entered the system and how far it has spread. It is distinct from statutory sampling. Network sampling can be conducted to: (1) confirm the presence of contaminants as soon as possible after the event (2) determine the extent of the plume, and (3) confirm the system is clear of contaminants (Hart et al. 2019). Unlike intentional contamination events, the locations at risk of intrusion resulting from sustained low-pressure events are mostly known. Indeed, events causing sustained pressure losses (power outages, large breaks, plant shutdowns, etc.) are documented and the resulting low pressures on the network are monitored, as most networks have online pressure probes at critical pressure points. Unlike chemical contaminants, the detection of *E. coli* positive samples is constrained by the detection limits of statutory monitoring methods that mandate the absence of *E. coli* in a prescribed volume of 100 mL (EPA Office of Environmental Enforcement 2009). The specificities of these methods determine the probability of utilities detecting *E. coli*, which is a discrete particle present in low concentrations.

Figure 5.8 shows the distribution of the mean probability of detecting positive *E. coli* nodes, within 5 hours, in the chloraminated system. The mean probability of positive detection is estimated during the 5-hour intervals from the start of intrusion up to 20 hours using sampling volumes of 100 mL and 1 L (Figure 5.8 (a) to (d) for 100 mL and (e) to (h) for 1 L). Obviously, sampling at the nodes that remain positive longer increase the likelihood of detecting positive *E. coli*. The impact of the sampling volume of 100 mL (versus 1 L) is shown by the number of nodes positive with a mean detection probability > 0.1. Only 5 nodes have mean probability > 0.1 within all the four intervals of 5 hours as compared to 68 (74) nodes within the first 3 intervals. Quick response sampling offers even more sites with 166 (167) nodes having mean probability > 0.1 in both the first and second 5-hour intervals, while delayed deployment restricts it to 71 (185) nodes. Increasing the sampling volume improves sensitivity, especially for areas with lower *E. coli* concentrations. Extreme low probabilities at most affected nodes would render confirmation sampling unreliable unless sampling is targeted to areas with expected higher concentration at the right time.

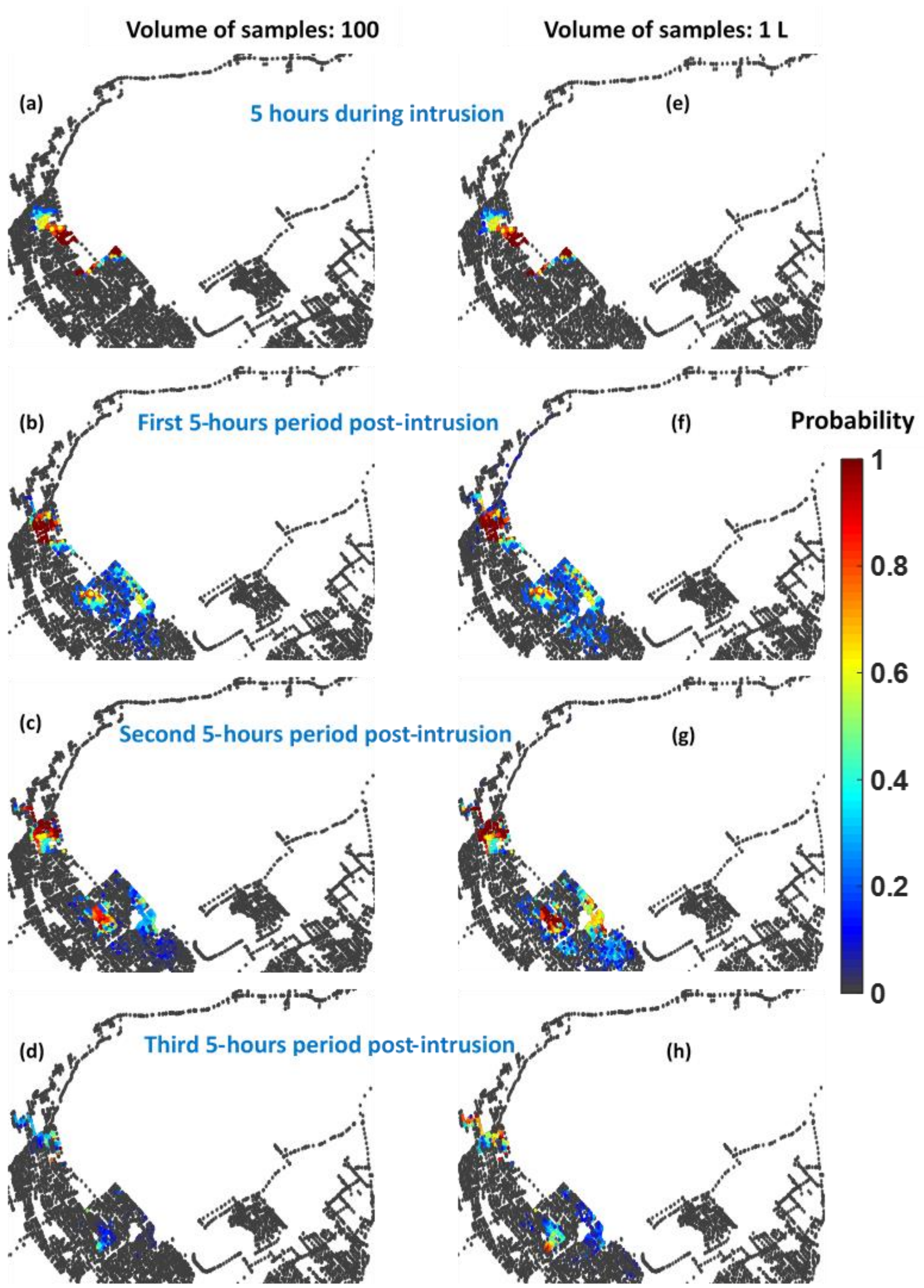


Figure 5.8. Mean probability of detecting *E. coli* for sampling volumes of 100 mL (a) to (d) and 1 L (e) to (h) for different periods.

Figure 5.9 shows the distribution of nodal mean probabilities over different time periods for the 2905 nodes that become positive for *E. coli* during at least one time step of the simulation in the chloraminated system (spatial distribution of nodes in Figure 5.4). Figure 5.9 illustrates that, for a 5-hour intrusion, it is very important to quickly sample in the vicinity of intrusion areas; otherwise, false negatives may occur. During the intrusion period as the contamination is not yet widely disseminated through the network the median and 75th percentile is around zero. For all post-intrusion intervals, the median probability is very low and the 25% of nodes with higher detection probabilities decreases with time after intrusion, less so when a 1 L volume is collected. The post-intrusion periods (5-20 hours) corresponds to the clearance-sampling window. To avoid false negatives, larger volumes should be collected at sampling locations with higher probabilities as determined by predicted contaminant concentrations in the first 10 hours after the event (Figure 5.8).

E. coli monitoring at predefined statutory sampling sites is not suited to confirm contamination or verify clearance in a timely manner. van Lieverloo et al. (2007) estimated the combined detection probability of 47 fixed statutory sampling locations to evaluate the sensitivity of monitoring programs for 12 contamination events. The probability calculations were based on the duration of *E. coli* present at more than 1 CFU/mL and sampling intervals. The probability of detection of positive *E. coli* after intrusion of up 160 L of sewage was quite low over 50 days unless the contamination occurred at the treatment plant or trunk main, even without disinfectant. In our studies, the probability of detecting positive *E. coli* is calculated based on the predicted nodal concentrations at each hour using a Poisson distribution that provides a better estimate of the probability of detection. More importantly, our results provide predictions directed to reevaluate sampling protocols and provide timely actionable information to water utilities.

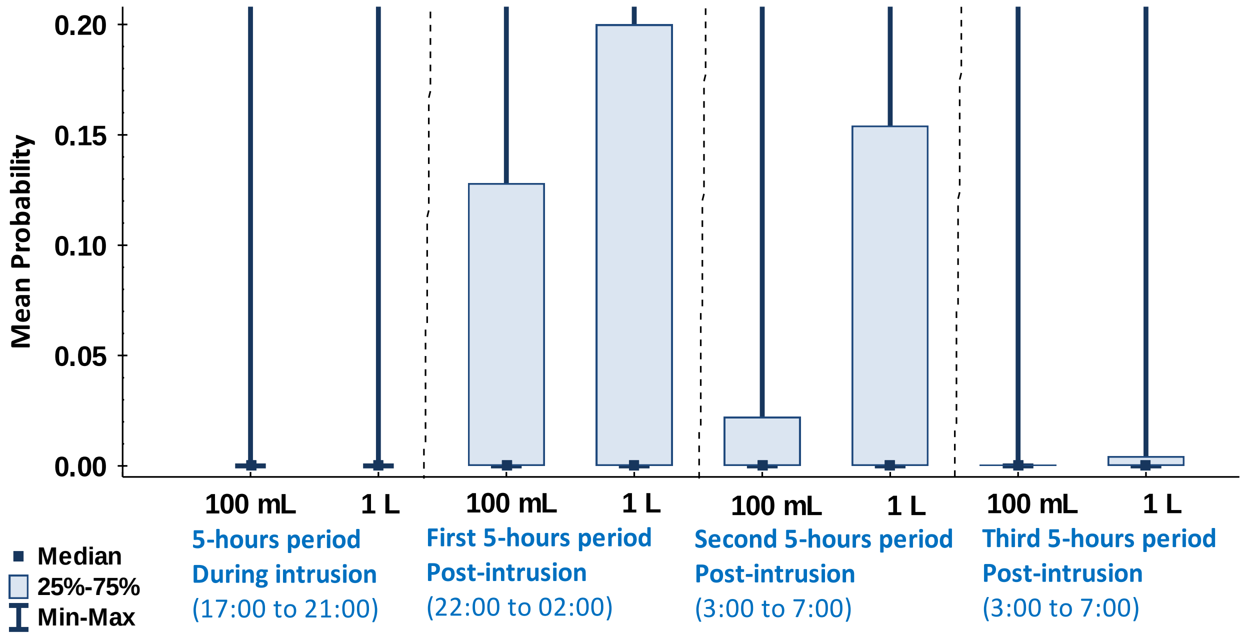


Figure 5.9. Box-plot of mean probability of detecting positive *E. coli* during 5 hours for 4 time periods for Sc6 (chloramine, 1 mg/L); each group consists of 2905 nodes, which are the nodes that experience *E. coli* at any time over the whole simulation duration; the y-axis is cut off at 0.2 while the maximum value is 1 for all the box.

In the presence of chlorine, if sampling is conducted once the intrusion is over, detecting *E. coli* is almost impossible even with a large total volume of sewage intrusion of 1,909 L (Figure 5.5). To assess if any contamination occurred, sampling should only be conducted during the event at sites close to the intrusion zones (119 nodes >10^{-6} *E. coli*/L). Deploying sampling personnel and identifying proper sampling sites may not be feasible at such short notice.

Implementing large volume sampling appears promising to improve sensitivity but raises issues of higher operational costs and practicality. Because it is likely to result in higher positive detection, it could meet some resistance from utilities fearful of more frequent or extended advisories. Increased sensitivity is desirable as *E. coli* is inactivated much more easily than most pathogens, and the absence of *E. coli* at a node does not ensure the absence of more resistant pathogens such as *Giardia* or *Cryptosporidium* (Payment 1999, Smeets et al. 2009).

In light of these results, using a combination of PDA hydraulic and water quality models to optimize *E. coli* sampling is proposed. This way, utilities could be informed of the likelihood of intrusion and adapt their sampling plan accordingly. If contamination is confirmed, the combined models would direct when and where to conduct the clearance sampling. Unless sampling is intensified in affected areas, the likelihood of detecting an *E. coli* positive will be so low that sampling resources will be wasted while contaminated areas remain undetected. To improve the confirmation of contamination, we propose a post-event intensive sampling approach conducted as early as possible after the event is known with sampling at intrusion nodes or nodes hydraulically close to the intrusion sites. The identification of these high-risk nodes should be done using PDA, not DDA, and considering readings from online pressure monitors and water quality probes, if available. For clearance sampling, timing and location of sample collection should also be identified using the hydraulic and water quality models, but more importantly, large volume samples should be considered.

Sampling for confirmation and clearance of fecal indicators in distribution systems has been developed to respond to a positive sample for *E. coli* and Total Coliforms. For example, the 1989 Total Coliform Rule prescribes that repeat samples be taken at locations within five connections up flow and down flow of the positive location. An alternative approach is also allowed in the 2013 Revised TCR to repeat locations that best verify and determine the extent of potential contamination in the distribution system (Environmental Protection Agency (EPA) 2013). Our results show that utilities could use the numerical tools proposed to best verify contamination.

5.4.7.2 Implications for the definition of areas subject to an advisory

There are several factors to consider when defining areas subjected to a preventive boil-water advisory (BWA). A geographical distribution of potentially affected areas can be determined based on a minimum pressure criterion during sustained PDCs. However, as proposed by Hatam et al. (2018a), intrusion circumstances should be incorporated as well. In Figure 5.10, positive *E. coli* nodes (blue circles) during the whole simulation period are overlaid on pressure mapping under PDCs. These observations are of value for water utility managers when in need of defining areas under a BWA. This figure shows some important points that may affect the preventive/corrective decisions. The BWA must be defined not only based on low-pressure areas, but also based on areas to which contamination will travel under pressure-deficient and normal-pressure conditions. Although the vulnerable low-pressure areas should be considered, Figure 5.10 shows that there are some areas in low-pressure zones where no contamination is transported. Depending on the water path during PDCs and NOCs, the contamination will reach areas other than the low-pressure nodes.

The definition of areas subjected to preventive/corrective actions should take into account pressure distribution under PDCs, intrusion locations and volumes, fate and transport of contaminants as well as the type of contaminant and its interaction with the disinfectant.

As the definition of a BWA can be quite complex in a large hydraulically connected DS, another option to avoid system-wide BWA would be to implement district metered areas (DMA). Sectorization of areas prone to intrusion under major PDC events such as plant failures could confine contamination to a smaller area allowing for the issuance of sectorial advisories.

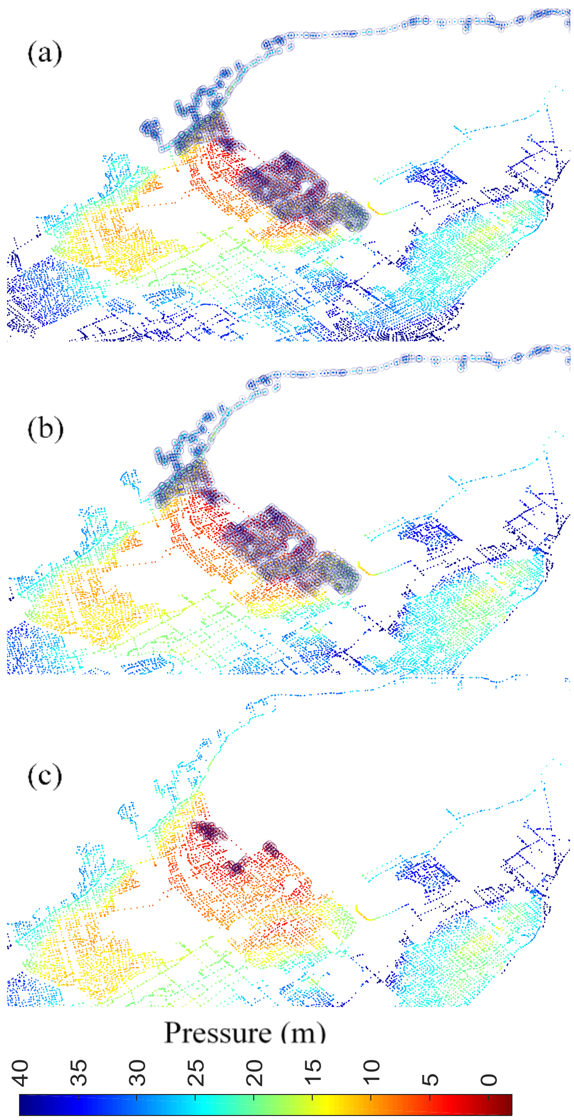


Figure 5.10. Superposition of pressure map under PDCs (16:00) using PDA on nodes with positive *E. coli* at any time during the simulation (blue circles) (a) in the absence of disinfectant, (b) with chloramine, and (c) with chlorine.

5.5 Conclusion

In this paper, the fate and transport of contaminated water as a result of accidental intrusion through leakage points caused by a sustained depressurization was investigated throughout a large full-scale water network. Then, the spatial and temporal water quality was simulated based on the realistic simulation of hydraulic conditions under pressure-deficient conditions using PDA. The interactions between *E. coli* and disinfectant residuals were considered, using a multi-species water quality analysis. This was possible using a novel methodology extended and applied to simulate accidental intrusion events due to sustained PDCs lasting a few hours (5 hours). The mass of *E. coli* entering at each intrusion node was estimated based on the pipe internal pressure under PDCs, and nodal leakage flow rates in the DS model under NOCs. Major findings are:

- Consideration of contaminants fate and transport based on the hydraulic behavior of the network is essential for adequate utility response to sustained depressurization events and to justify preventive/corrective actions.
- In the simulated scenarios, *E. coli* was transported to higher-pressure zones (up to ~40 m) in the absence of disinfectant residuals. Chloramine residuals decreased *E. coli* concentrations at higher-pressure nodes. Even more so, a chlorine residual of 0.5 mg/L limited the contaminated zone and restricted *E. coli* propagation to lower pressure areas ($P < 11$ m). Increasing the chlorine concentration to 2 mg/l prevented widespread transport of *E. coli* across the DS and confined contamination to lower pressure areas ($P < 5$ m).
- In the presence of chlorine, the probability of detecting *E. coli* by sampling is unlikely unless sampling is conducted rapidly and close to the intrusion zones. Improved sampling strategies (location and timing) are required. The location and timing of sampling should be determined considering the duration, location and intensity of PDCs, the severity of the contamination event in terms of ingress volumes and contaminant type and concentration, and the disinfectant efficacy on the pathogen of concern.
- Targeted spatial-temporal sample collection in combination with high volume sampling will increase the value of negative *E. coli* results.
- Modeling of the temporal variations of *E. coli* concentrations across the DS following an intrusion event should be used to guide confirmation sampling and establish a base for lifting an advisory by clearance sampling.

- The combined MSWQA-PDA method allows for the investigation of the propagation of the reactive contaminant by taking into account the effects of both PDCs and intrusion-associated demand on disinfectant decay. Appropriate numerical tools can assist utilities, increasing their ability of detecting accidental intrusion under low/negative pressure events, and consequently, applying appropriate preventive/corrective actions to protect public health.
- Timely response to sustained PDCs is now possible in smart DSs equipped with multiple online pressure sensors and emerging low-cost autonomous water quality sensors. Online chlorine sensors positioned in areas prone to intrusion could detect atypical loss of residual indicating the need for subsequent actions.

ACKNOWLEDGEMENTS:

The authors would like to thank the participating utility for providing data and DS modeling information. The NSERC Industrial Chair on Drinking Water at Polytechnique Montreal funded this research. The authors also wish to acknowledge Bentley Systems for technical support and providing academic access to their unlimited pipes WaterGEMS software model.

CHAPTER 6 ARTICLE 3 –USING NODAL INFECTION RISKS TO GUIDE INTERVENTIONS FOLLOWING ACCIDENTAL INTRUSION DUE TO SUSTAINED LOW PRESSURE EVENTS IN A DRINKING WATER DISTRIBUTION SYSTEM

In this chapter, the infection risk of accidental intrusion resulting from sustained PDCs, with different durations, is quantified using water quality calculations based on realistic PDA. This is done by integrating the impact of demand availability on the consumption during pressure drops in QMRA analysis and adjusting intrusion volume for nodal pressure and pipe state. During shorter pressure losses, utilities can avoid system wide advisories to limit the impact of depressurization events on their customers. The spatial/temporal distribution of nodal risks throughout the network, as proposed in this chapter, can help to determine the boundaries of sectorial boil water advisory or other preventive/corrective actions. This paper was published in *Journal of Water*. Supplementary information is presented in Appendix C.

USING NODAL INFECTION RISKS TO GUIDE INTERVENTIONS FOLLOWING ACCIDENTAL INTRUSION DUE TO SUSTAINED LOW PRESSURE EVENTS IN A DRINKING WATER DISTRIBUTION SYSTEM

Fatemeh Hatam[a], Mirjam Blokker[b], Marie-Claude Besner[c], Gabrielle Ebacher[d], Michèle Prévost[a]*

[a]NSERC Industrial Chair in Drinking Water, Department of Civil, Geological and Mining Engineering, Polytechnique Montréal, CP 6079, Succ. Centre-ville, Montréal (Québec), H3C 3A7, Canada
[b]KWR Watercycle Research Institute, Groningenhaven 7, 3433 PE Nieuwegein, the Netherlands
[c]R&D Engineer, Water Service, City of Montreal, Montréal, QC, Canada H3C 6W2
[d]Technical Engineer, Environment Service, Drinking Water Division,
City of Laval, QC, Canada, H7V 3Z4
*Corresponding author, E-mail address: fatemeh.hatam@polymtl.ca, Tel.: 514 340-4711 ext. 2983

Abstract

Improving the risk models to include the possible infection risk linked to pathogen intrusion into distribution systems during pressure-deficient conditions (PDCs) is essential. The objective of the present study was to assess the public health impact of accidental intrusion through leakage points in a full-scale water distribution system by coupling a quantitative microbial risk assessment (QMRA) model with water quality calculations based on pressure-driven hydraulic analysis. The impacts on the infection risk of different concentrations of *Cryptosporidium* in raw sewage (minimum, geometric mean, mean, and maximum) and various durations of intrusion/PDCs (24 h, 10 h, and 1 h) were investigated. For each scenario, 200 runs of Monte Carlo simulations were carried out to assess the uncertainty associated with the consumers' behavioral variability. By increasing the concentrations of *Cryptosporidium* in raw sewage from 1 to 560 oocysts/L for a 24-h intrusion, or by increasing the duration of intrusion from 1 to 24 h, with a constant concentration (560 oocysts/L), the simulated number of infected people was increased by 235-fold and 17-fold, respectively. On the first day of the 1-h PDCs/intrusion scenario, a 65% decrease in the number of infected people was observed when supposing no drinking water withdrawals during low-pressure conditions at nodes with low demand available (<5%) compared to no demand. Besides assessing the event risk for an intrusion scenario, defined as four days of observation, the daily number of infected people and nodal risk were also modeled on different days, including during and after intrusion days. The results indicate that, for the case of a 1-h intrusion, delaying the start of the necessary preventive/corrective actions for 5 h after the beginning of the intrusion may result in the infection of up to 71 people.

KEYWORDS: QMRA; Sustained pressure drops; Accidental intrusion; Infection risk from Cryptosporidium; Pressure-driven hydraulic analysis

6.1 Introduction

Distribution system (DS) deficiencies may play a role in the occurrence of waterborne disease outbreaks (Kirmeyer et al. 2001a). Ageing of pipeline infrastructure is going to become more problematic over time by increasing the probability of experiencing sustained low/negative pressure conditions in the network (pipe breaks), leading to possible intrusion from points of leakage. Assessment of public health risk associated with such type of events may be achieved through modeling. While reliable hydraulic and water quality models can be used to simulate ingress of contaminated water and its propagation into a network, the use of quantitative microbial risk assessment (QMRA) models is required to estimate the potential health risk. QMRA and management approaches can contribute in bringing safer water to consumers (World Health Organisation (WHO) 2016).

Modeling of water quality under pressure deficient conditions. Integration of pressure-driven hydraulic analysis into QMRA models is required for a more accurate risk analysis of water contamination resulting from accidental intrusion under sustained pressure-deficient conditions (PDCs). In such conditions, a reliable estimation of intrusion points, contamination mass rate entering the DS, and fate/transport of contamination through the network cannot be achieved using traditional demand driven-analysis (DDA) models such as EPANET 2 (Rossman 2000). Pressure-driven analysis (PDA) was coupled to single species water quality modeling to optimize management strategies (e.g., flushing and isolation actions) by minimizing the mass of consumed contaminant (Bashi-Azghadi et al. 2017a, Rasekh and Brumbelow 2014, Zafari et al. 2017). A more detailed literature review on hydraulic and water quality modeling under sustained PDCs can be found elsewhere (Hatam et al. 2018a).

Applications of QMRA to drinking water DSs. Despite evidence of drinking water DS deficiencies causing infectious waterborne diseases (Craun et al. 2010, Lindley and Buchberger 2002), the majority of QMRA work has been devoted to assessing risk of drinking water treatment failures (World Health Organisation (WHO) 2016). Viñas et al. (2019) and Hamouda et al. (2018) presented detailed literature reviews on QMRA models applied to microbial contaminants in drinking water DSs. Besner et al. (2011) developed a conceptual model to assess the public health risk associated with intrusion events. QMRA models have been applied to real DSs to evaluate the infection risk associated with the presence of viruses resulting from intrusion events caused from transient PDCs (LeChevallier et al. 2011, Teunis et al. 2010, Yang et al. 2011). Standard QMRA models consider the water is consumed randomly at any time or at fixed times during the day (Besner et al. 2010c, Davis and Janke 2009, Yang et al. 2011). The timing of water withdrawals for drinking purpose is an important factor when assessing the probability of infection as a result of intrusion events and may not be the same as the timing of the total consumption (Blokker et al. 2018, Davis and Janke 2009). An improved QMRA that integrates the consumer's behavior (probability density functions (PDFs) of the numbers of glasses and the volume consumed, and kitchen tap use) was developed and applied to assess the infection risk associated with contamination after main repairs (Blokker et al. 2014, Blokker et al. 2018). They investigated the impact of different parameters such as the location of contamination and the times of valve openings on the infection risk with various pathogens (*Campylobacter*, *Cryptosporidium*, *Giardia* and rotavirus), in the absence of any disinfectant residual. Schijven et al. (2016) also considered consumer behavior to estimate the infection risk from ingestion of contaminated water or inhalation of contaminated aerosol droplets in the case of intentional contamination of different durations and seeding concentrations in a DS.

Improving estimations of the infection risks due to sustained pressure deficient conditions requires numerical approaches that produce realistic estimations of nodal ingress volumes, predictions of propagation throughout the network, and integration of the consumer's behavior during and after pressure losses. Besner et al. (2010c) emphasized the necessity of performing PDA instead of DDA to simulate the infection risk associated with PDCs in future studies. Besides low pressure, the presence of external contamination and pathways are essential for intrusion to occur (Islam et al. 2017). Adjusting the presence of potential pathway for intrusion based on the state of decay of the piping has been proposed (Ebacher et al. 2012, Gibson et al. 2019).

The primary objective of this work was to estimate the infection risk associated with accidental intrusion through leakage points into a DS as a result of unplanned sustained low/negative pressure events (24 h, 10 h, and 1 h). To achieve this goal, several original improvements to the various models were made. First, the QMRA model developed by Blokker et al. (2018) was customized and linked with water quality calculations based on a pressure-driven hydraulic analysis. Then, the estimated contamination mass rate at each intrusion node was adjusted by the assigned leakage demand (proxy for pipe age and material) and the pressure values during PDCs, computed using PDA. Finally, to better simulate the consumers behavior during low-pressure conditions, the consumption of tap water was adjusted based on demand availability (no demand or <5%) on the infection risk. The secondary objective of this work was to propose a basis for the analysis of risk to guide the definition of areas subjected to a boil water advisory or corrective actions. To achieve this goal, we assessed the potential use of the temporal (daily versus event) and spatial distribution of nodal risks to determine the location and the duration of advisories. To the knowledge of the authors, no study so far has quantified the infection risk of accidental intrusion resulting from sustained PDCs, using realistic PDA to adjust intrusion volume for nodal pressure, perform water quality analysis and integrate the impact of demand availability on the consumption during pressure drops.

6.2 Methodology

The QMRA model developed by Blokker et al. (2018) was customized to be coupled with water quality calculations based on pressure-driven hydraulic analysis. The model was used to quantify the infection risk associated with accidental intrusion events as a result of sustained PDCs in a full-scale DS. The main steps for risk analysis are exposure analysis and calculation of infection risk. A simplified flow chart of the QMRA steps is illustrated in Figure 6.1. These steps include: (a) simulating the hydraulic behavior of the network under the intended PDCs to define the intrusion nodes, intrusion flow rates (based on size of opening leaks and pressure differential), and nodes with unsatisfied demand; (b) defining the outside pipe conditions to calculate the potential contaminant mass rate entering the system; (c) modeling fate/transport of ingress microorganisms through network; (d) specifying the microbial exposure (dose) considering consumers' drinking water behavior; and (e) estimating the risk of infection based on dose–response models.

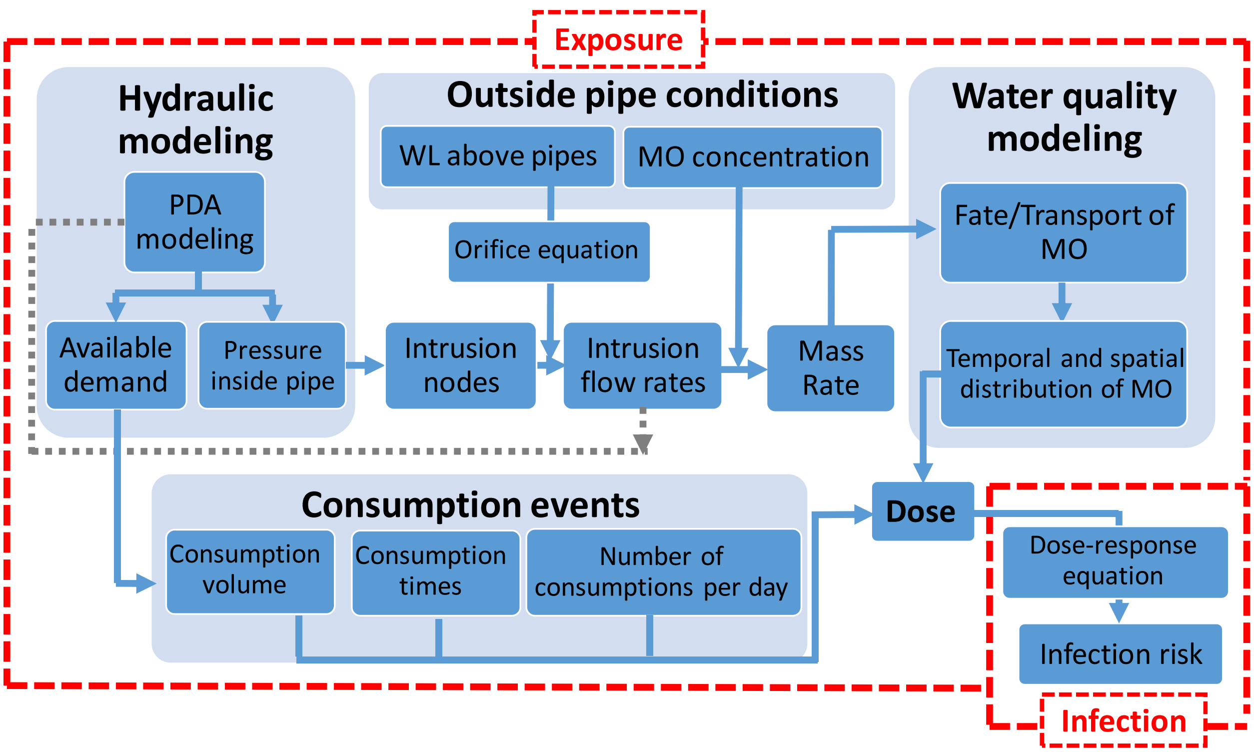


Figure 6.1. Flowchart for QMRA of accidental intrusion during sustained PDCs; WL, water level; MO, microorganism.

6.2.1 Exposure Analysis

6.2.1.1 Hydraulic and water quality analysis

To estimate the ingested dose, fate/transport of contaminants through the network should first be estimated using appropriate hydraulic and water quality models. Water quality modeling based on PDA was performed using WaterGEMS V8i (SELECTseries 5) (Bentley Systems 2014). Transport of *Cryptosporidium* oocysts through the network was simulated over time and, because *Cryptosporidium* is highly resistant to chlorine disinfection (World Health Organization (WHO) 2009), the chlorine decay was not included in the model. Sewage is defined as the source of contamination outside the pipes. Minimum, geometric mean, arithmetic mean, and maximum levels of *Cryptosporidium* in sewage were assumed to be 1, 6, 26, and 560 oocysts/L, respectively (Payment et al. 2001).

The DS model used in this study includes 30,077 nodes and 3 water treatment plants (WTPs), which serve nearly 400,000 residents. More details on the simulated full-scale network can be found in Hatam et al. (2018a). The unplanned shutdown of one WTP was simulated and a 5 m decrement in the outlet pressure of the two other WTPs was assumed as a result of the flow-rate increase. It should be noted that the two other WTPs might (partially) compensate the shutdown of the other WTP as the entire network is hydraulically interconnected. Following the shutdown duration (1, 10 or 24 h), the simulation was continued for 3 days to investigate the long-term public health impacts of the accidental intrusion events in this large DS. The impacts of intrusion duration on exposure and, consequently, risk of infection were studied. More details on accidental intrusion modeling can be found in the Supplementary Materials. Nodes with pressure head less than 1 m were considered as the potential intrusion sites (Figure C-4). In the hydraulic model, for the sake of simplicity, the demand is considered constant during the day and equal to the peak hour demand (i.e., 19:00) for the scenarios of 1, 10 and 24 h of PDCs/intrusion. Additional scenario with the daily water consumption pattern in the hydraulic model was studied for the intrusion event resulting from 1 h PDCs set to start at 18:30.

6.2.1.2 Consumption Events

The temporal concentrations of *Cryptosporidium* calculated from water quality analysis were then imported into MATLAB (MathWorks, Natick, MA, USA) where the QMRA was performed for exposure assessment and dose–response analysis. Consumption events or consumers' behavior in this study refer to: (1) the volume of consumption; (2) the number of times that one fills a glass; and (3) the times at which the glass is filled from the tap. In the present study, consumption times corresponded to the water use at the kitchen tap as proposed by Blokker et al. (2018). In the simulations, the average kitchen tap use was then modified for each node of the studied network based on the nodal residential demand and the availability of demand, calculated from PDA under PDCs. In this study, the average kitchen tap use for non-residential nodes (about 60% of the nodes) was set to zero. This differed from Blokker et al. (2018) who adjusted the average kitchen tap use at certain times to include zero demand periods identified by detailed residential demand. In this study, to account for demand satisfaction as computed by PDA at each node, the kitchen tap use was set to zero at times when there was no demand available under PDCs (Figure C-1). For PDCs with some demand satisfaction, it was assumed that consumers can adjust the filling duration based on the available flow at the tap. If the PDCs did not last for the whole day, the total daily volume of water consumed by each person at the nodes with no demand under PDCs would not be affected. The sensitivity of the results to the demand satisfaction ratio (DSR) was investigated in an additional scenario by fixing the kitchen tap use to zero at the time when there is low (<5%) demand available at the nodes. This approach is more realistic as the required time to fill a glass of water at a kitchen tap will increase by more than 20 times when the DSR is less than 5%.

The other important parameter for estimating the risk of exposure to microbial contamination is the volume of water that is ingested per person per day. The number of times each person would fill his/her glass or bottle during a day was estimated using a Poisson distribution. The ingested volume at each filling time was defined by a lognormal distribution. Due to the lack of information for the studied network, the data from Blokker et al. (2018) were used for the simulation and more details can be found in their paper.

In this study, the hydraulic and water quality conditions were assumed to be known for each scenario, and 200 runs of Monte Carlo simulations were performed to investigate consumers' behavior. In each Monte Carlo run, the number and times of consumption events as well as the ingested volume for each consumption event were randomly picked for each person every day of the simulation.

In the studied hydraulic model, the total nodal demands could be a combination of different types of demand defined as: residential, commercial, industrial, institutional, municipal or, leakage. In total, 11,194 of the nodes included residential demand. To determine the number of people supplied per node, the residential demand per node was considered and the daily per capita average demand was set to 220 L/person/day. Consequently, only the residential exposure from tap water as a result of the simulated accidental intrusion was investigated (e.g., exposure at school was not considered). More information on the estimation of the number of people at each node and the distribution of population is in the Supplementary Materials. Dose is equal to the number of consumed pathogens and was calculated by multiplying the intake volume by the concentration of pathogens at the time of withdrawal. This step was repeated for all the glasses that a person takes over the simulation duration, which is 1 day for daily risk and 4 days for the event risk. For each person, the total dose was calculated by summing the dose in each glass consumed.

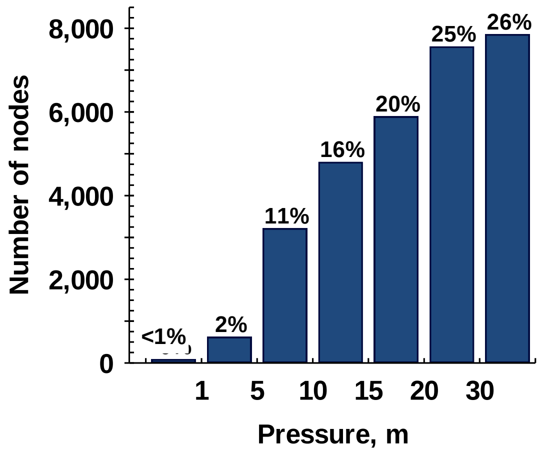
6.2.2 Calculation of Infection Risk

Dose–response analysis was performed to calculate the infection risk for each person resulting from accidental intrusion during sustained PDCs. The computed dose was implemented in the dose–response model employed by Blokker et al. (2014) for *Cryptosporidium* using the median (50th percentile) and maximum (100th percentile) dose–response relationships. The median infection risk is reported everywhere in this study unless otherwise stated.

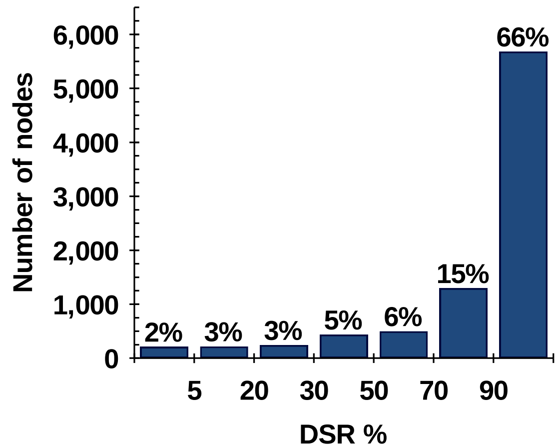
The calculated infection risks of all the people in the network were summed up and rounded to the nearest integer greater than or equal to the calculated value to estimate the equivalent number of infected people for the simulated event (Blokker et al. 2018). The number of infected people was calculated either for the whole observation period (4 days) or for each day separately. To calculate the nodal risk, the infection risks corresponding to all the people at the same node were summed up.

6.3 Results

Estimating ingress volumes. Histograms of nodal pressures and demand satisfaction ratios (DSRs: available nodal demand divided by the required demand) using PDA are illustrated in Figure 6.2. Fewer than 1% of the nodes (93 nodes) were prone to intrusion as they experienced pressures less than 1 m under PDCs, which corresponded to the set pressure head above pipes. For about 30% of the nodes, the pressure was less than or equal to the required pressure value assumed in this study for full demand satisfaction (15 m). The DSRs for these nodes are shown in Figure 6.2 (b), excluding nodes with no required demand. Figure 6.2 (b) shows that 1103 nodes have a DSR of less than 50% during depressurization.



(a)



(b)

Figure 6.2. Distribution of: (a) nodal pressures for the whole network (30,077 nodes); and (b) demand satisfaction ratios (DSRs) for nodes under pressure-deficient conditions (8578 nodes), excluding the nodes with zero demand.

The distribution of intrusion flow rates at the ingress nodes is illustrated in Figure 6.3. The maximum flow rate was 56 L/h and about half of the nodes had an intrusion flow rate less than 5 L/h. The contaminated water entered the network at a flow rate of 804 L/h through all the leakage orifices. For the scenarios of 10 and 24 h PDCs, the intrusion flow rate at each node remained constant during the event because of the use of a constant demand. As the 1 h event, with daily consumption pattern, was assumed to occur at the peak demand hour, the nodal intrusion flow rates also corresponded to those shown in Figure 6.3.

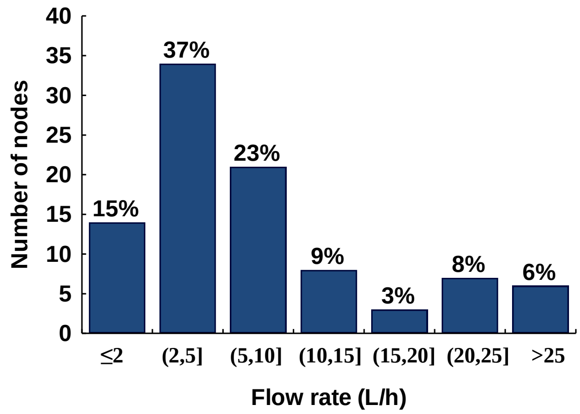


Figure 6.3. Distribution of nodal intrusion flow rates through 93 leak openings under the simulated pressure-deficient conditions.

Concentrations of pathogens in sewage. To cover different consumption behaviors, 200 Monte Carlo simulations were carried out for each scenario of *Cryptosporidium* concentration in sewage (1, 6, 26, and 560 oocysts/L). The resulting cumulative probability distributions of the number of infected people are plotted in Figure 6.4. In this figure, the solid lines correspond to the median infection risk, and the dotted lines are the maximum infection risk. For all concentrations, the number of infected people associated to the maximum infection risk was increased by about two folds compared to the median infection risk. For the concentration of 560 oocysts/L, 50% of the consumption events led to at least 1378 (2652) infected people considering the median (maximum) infection risk. As expected, the number of infected people increases when the *Cryptosporidium* concentration increased from 1 to 560 oocysts/L.

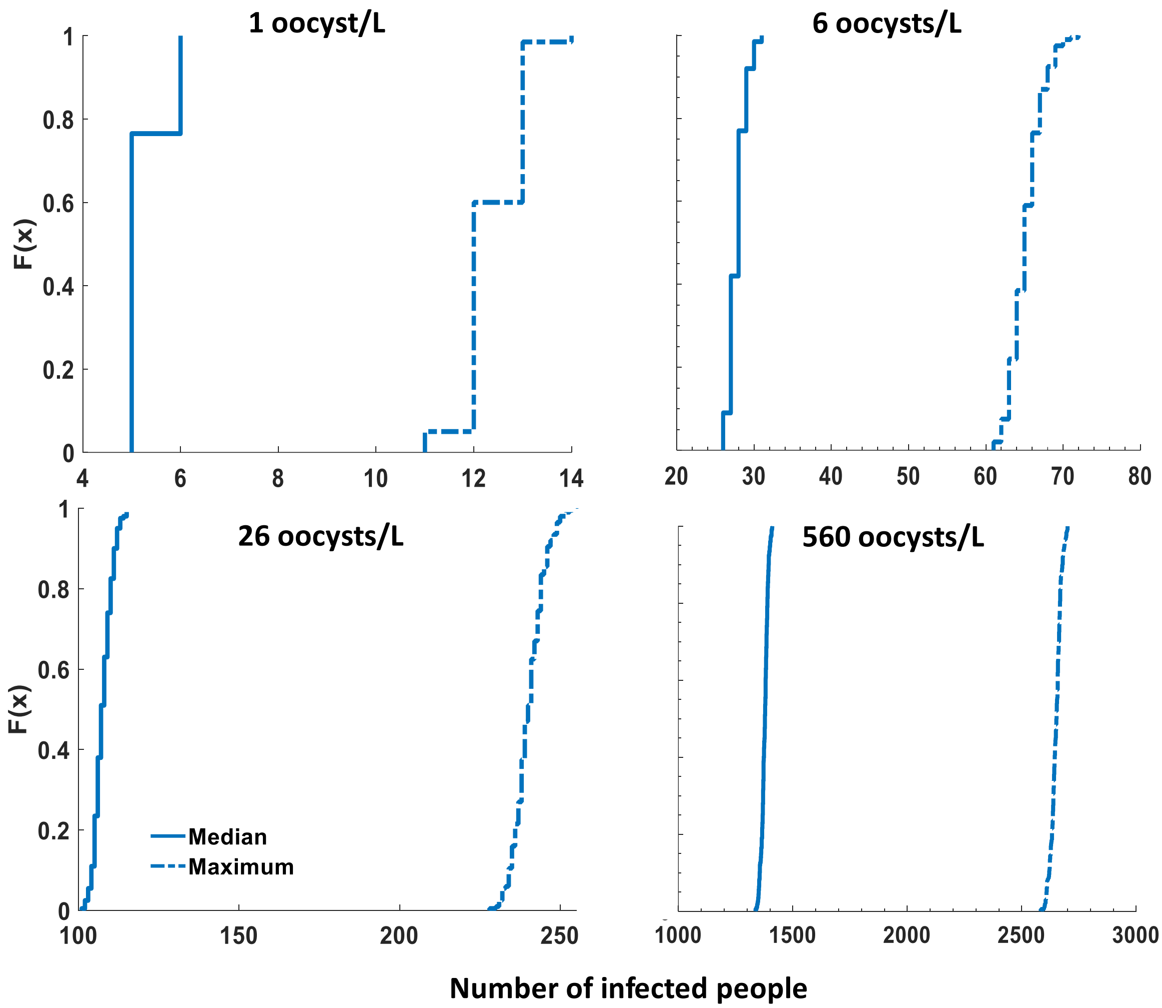


Figure 6.4. Number of infected people corresponding to median and maximum infection risks resulting from a 24-h depressurization; 200 Monte Carlo simulations (consumption events) for each *Cryptosporidium* concentration: 1, 6, 26, and 560 oocysts/L; number of infected people corresponds to the cumulative dose over four days of observation; F(x): probability that the median/maximum number of infected people will be less than or equal to x.

Consumption behavior. Figure 6.5 shows the sensitivity of the number of infected people over the four-day observation period to the volume of consumption (300 mL, 500 mL or 1 L per day per person) and number of glasses per day (1, 3, or 10). A total of nine scenarios were considered with a *Cryptosporidium* concentration of 560 oocysts/L and 24 h of PDCs. As expected, lower volumes of unboiled tap drinking water per person per day largely reduced the infection risk. By decreasing the volume by half (500 mL), the number of infected people decreased by 40%; decreasing the volume to 300 mL reduced the risk further by about 60%. By increasing the number of glasses per day from 1 to 3, 19 more people were likely to be infected for a 300 mL volume, and this value became 62 for a 1 L consumption volume per day per person (based on the values of F(x) = 1).

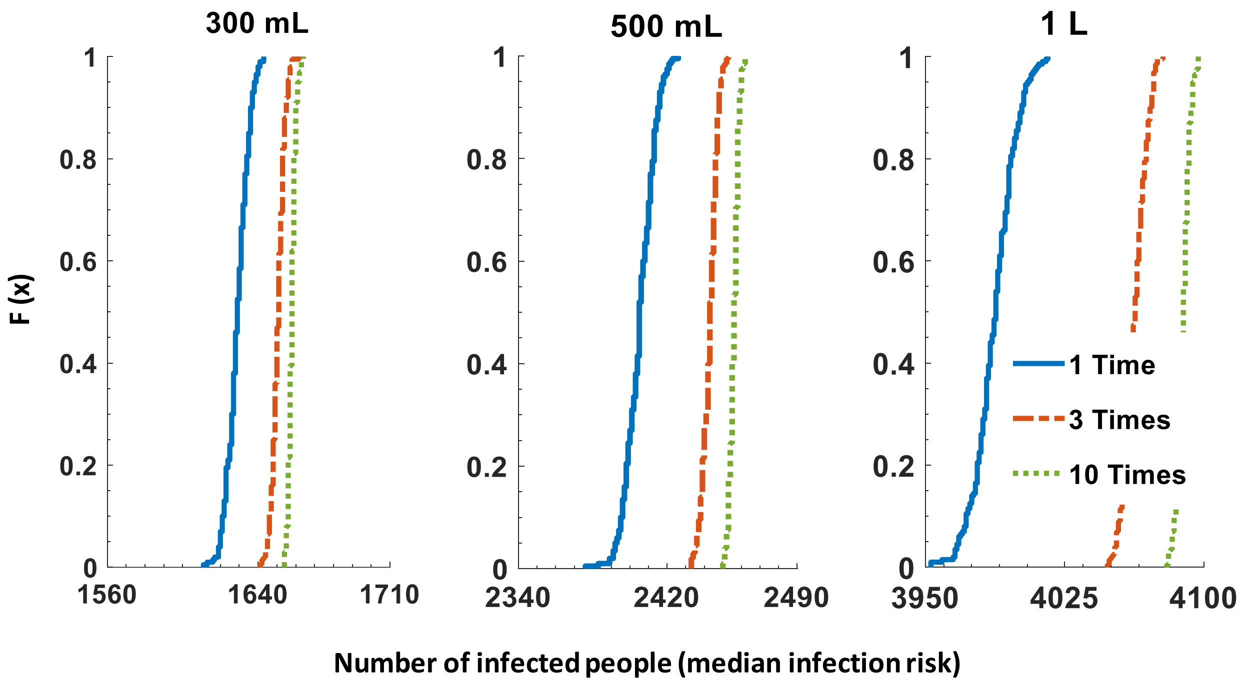


Figure 6.5. Impact of consumption volumes and number of glasses per day on the number of infected people corresponding to median infection risk over a four day-period; *Cryptosporidium* concentration = 560 oocysts/L; the x-axis scale is the same between the plots (150 people).

Duration. Shorter duration PDCs can take place in real networks because of WTP shutdowns, pipe breaks or fire flows. The cumulative probability distribution of the number of infected people for 200 random consumption behaviors is shown for different durations of PDCs: 1, 10, and 24 h (Figure 6.6). In all scenarios, the timing of the event is adjusted so that the network experienced low/negative pressures at the peak consumption time (i.e., 19:00) of the first day. A significant dependence of the infection risk with the intrusion duration was observed: a lower maximum number of infected people (84) was observed for a 1-h intrusion compared to 502 and 1410 for 10 and 24 h intrusion events, respectively.

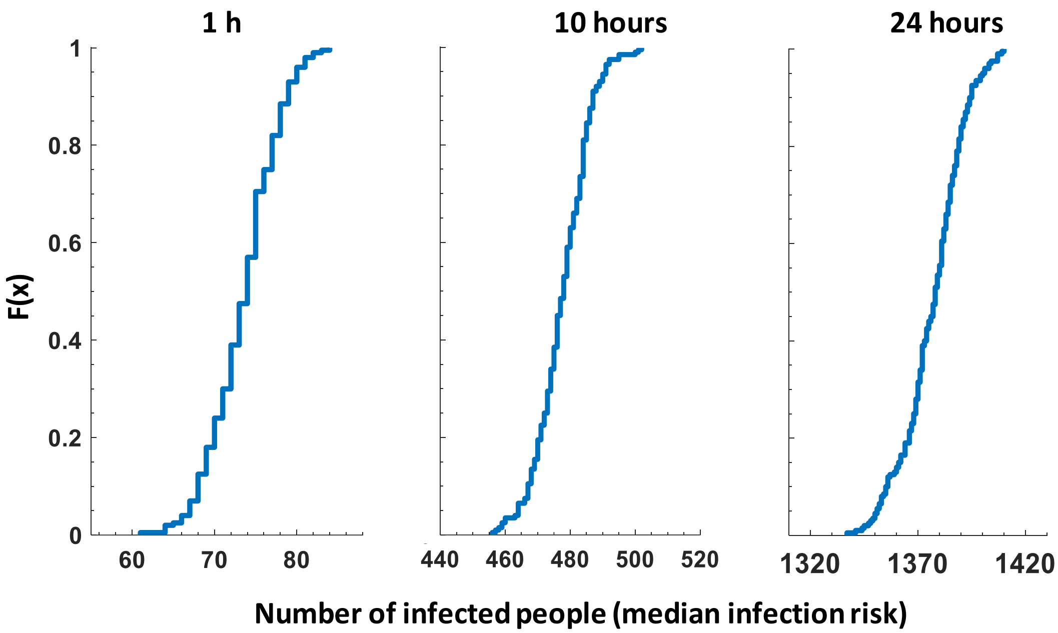


Figure 6.6. Comparing the probability distribution of the number of infected people over a four-day period for 200 Monte Carlo simulations for each duration of PDCs: 1, 10, and 24 h; *Cryptosporidium* concentration in sewage = 560 oocysts/L.

Spatial distribution of nodal infection risk. Besides the number of infected people under PDCs, the temporal and geographical distribution of infection risk is also essential in defining appropriate preventive/corrective actions. In this regard, the probability of infection of the individuals who were assigned to the same node were summed up to predict the nodal risk. Figure 6.7 shows the spatial distribution of risk for above-mentioned scenarios corresponding to the consumption events with the maximum number of infected people (F(x) = 1 in Figure 6.6). As shown, with increasing duration of intrusion event, not only the nodal risks were increased, but also larger areas were at risk.

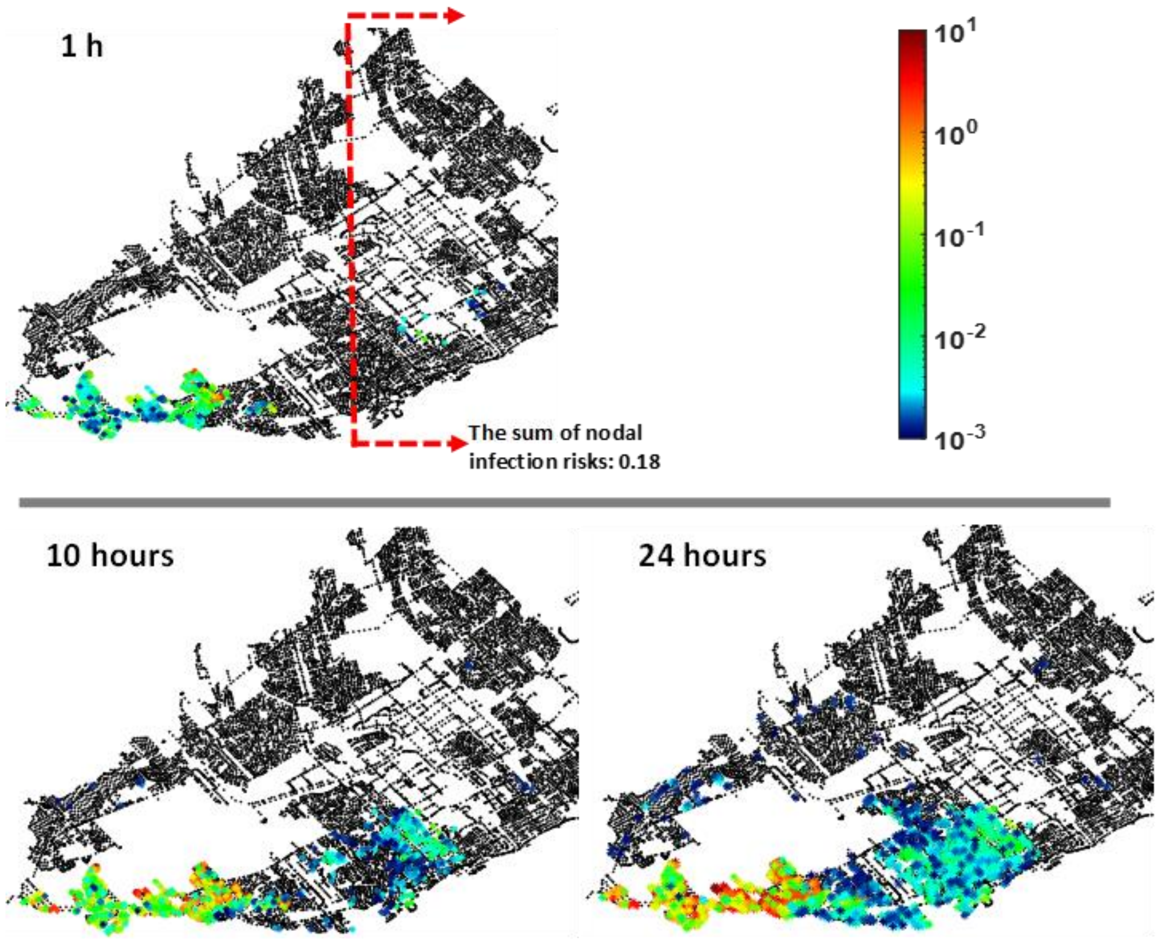


Figure 6.7. Spatial distribution of nodal risks for three durations of PDCs: 1, 10, and 24 h; *Cryptosporidium* concentration in sewage = 560 oocysts/L; nodes with an infection risk below 1 × 10^{-3} are drawn in black; infection risks corresponding to consumption events with F(x) = 1 (Figure 6.6) are illustrated.

Daily risk for the 1-h event with daily demand patterns. For the prior analyses, demand was considered constant during the day and equal to the peak hour demand (i.e., 19:00) in the hydraulic model. The reason is that adjusting different intrusion volumes and nodes at each hour of the duration of PDCs using PDA would be computationally intensive. However, we investigated a 1 h PDCs/intrusion using the daily water consumption pattern in the hydraulic model to assess its impact on the infection risk. Over four days of observation, the maximum number of infected people increased to 99 (Figure C-3) with demand patterns compared to 84 with a constant demand in the hydraulic model (Figure 6.6, 1 h).

Figure 6.8 illustrates the daily probability of the number of people infected by *Cryptosporidium* according to different consumption behaviors for the day that intrusion occurred (at 18:30) and the three days post-intrusion. The day after the event, the maximum number of infected people was reduced by 59% as compared to the event day. It indicates that, over time, the contaminated water left the network as large volumes of water were used for purposes other than drinking, such as toilet flushing and industrial usage. The maximum numbers of infected people for Days 1–4 were 71, 29, 3 and 1, respectively.

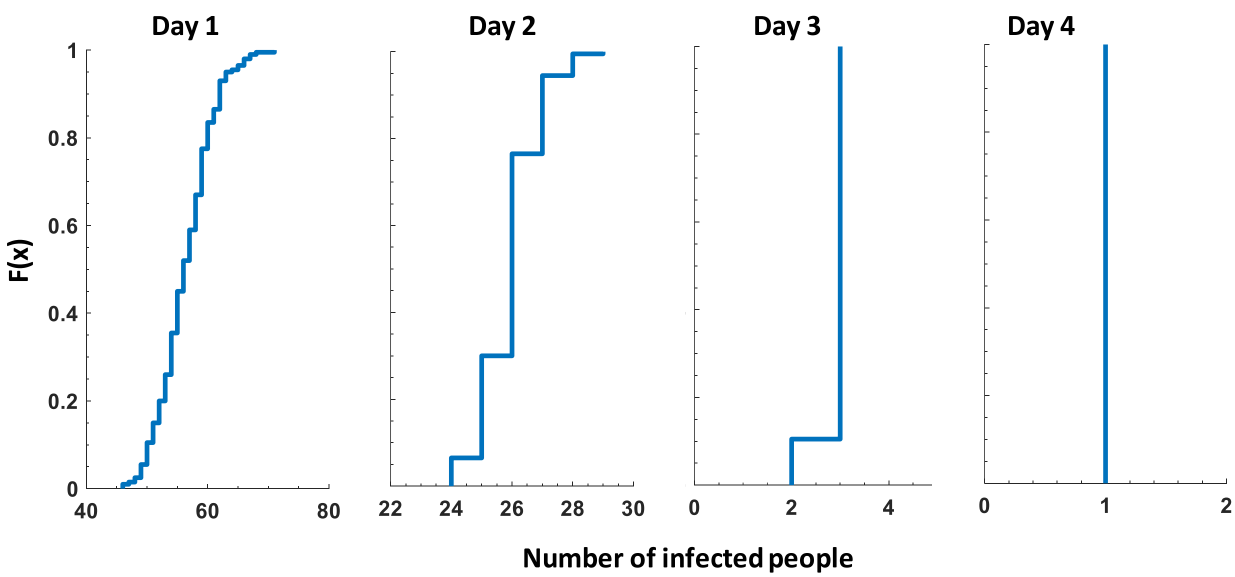


Figure 6.8. Number of infected people corresponding to median infection risk for Days 1 to 4 for the scenario of 1 h of PDCs with daily consumption patterns; C_{out} = 560 oocysts/L; 200 Monte Carlo simulations (consumption events) every day.

For Days 1–4, the total nodal risk corresponding to the consumption event with the maximum number of infected people (F(x) = 1 in Figure 6.8) was estimated, and the spatial distribution is plotted in Figure 6.9. The number of nodes at high risk decreased from Day 1 to Day 4 as well as the extent of the areas at risk. At the end of the first day, when the intrusion ended, the nodal infection risk was $\leq 1 \times 10^{-7}$ at 29,754 nodes and higher than 1×10^{-4} at 123 nodes. Only 16 of the nodes showed total nodal risks equivalent to more than one person. On Day 2, the total number of infected people through the whole network decreases to 29 compared to 71 for Day 1, but the number of nodes with an infection risk $\leq 1 \times 10^{-7}$ was lower compared to Day 1. The reason is that *Cryptosporidium* oocysts reached more nodes in the network on Day 2, but at lower concentrations as the ingress volume became diluted and flushed out. On Day 2, the nodal infection risk was more than one only at four nodes. On Days 3 and 4, the nodal infection risk was below one for all the nodes.

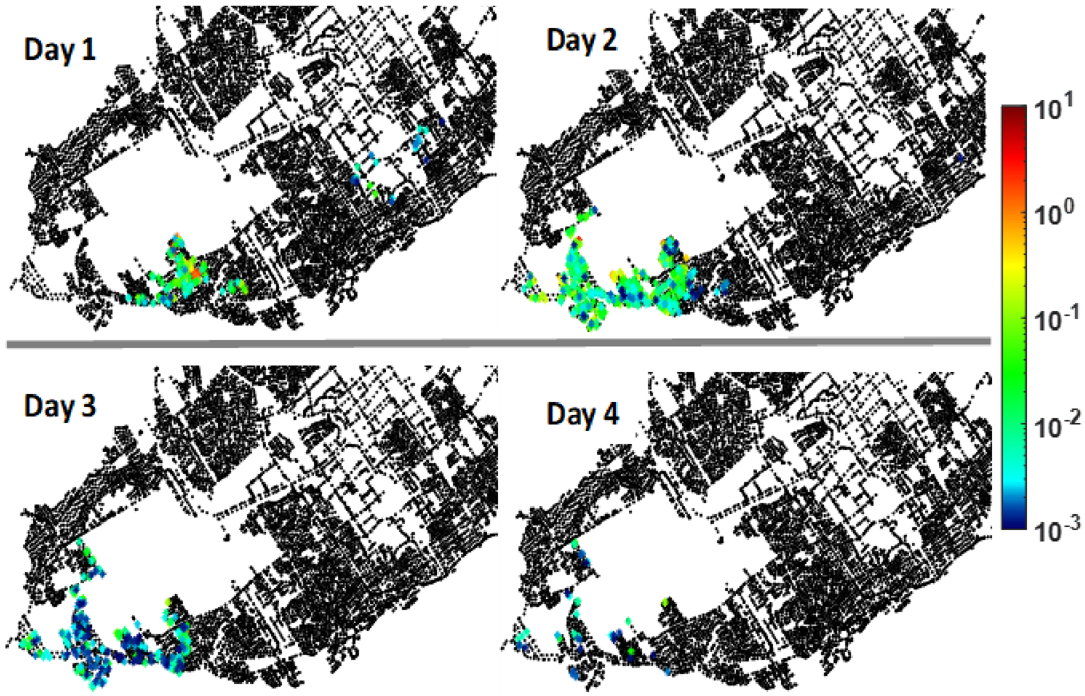


Figure 6.9. Spatial distribution of nodal risk; Days 1–4 for the scenario of 1 h of PDCs with daily consumption patterns; C_{out} = 560 oocysts/L; nodes with infection risk below 1×10^{-3} are drawn in black; infection risks corresponding to consumption events with F(x) = 1 (Figure 6.8) are illustrated.

Impact of demand satisfaction ratio on risk. In all simulations, when the DSR (pressure ≤ 0) became zero at a node, the kitchen tap use was set to zero. To study the influence of the DSR (shown in Figure 6.2 (b)) on the risk, the situation where no consumption happened at nodes with a DSR less than 5% was also modeled (Figure 6.10). For this investigation, the number of infected people following a 1-h PDCs/intrusion was computed on the day that intrusion occurred. As expected, the number of infected people decreased when the consumption only occurred at the nodes with a DSR $\geq$ 5% during low/negative pressure conditions (Figure 6.10).

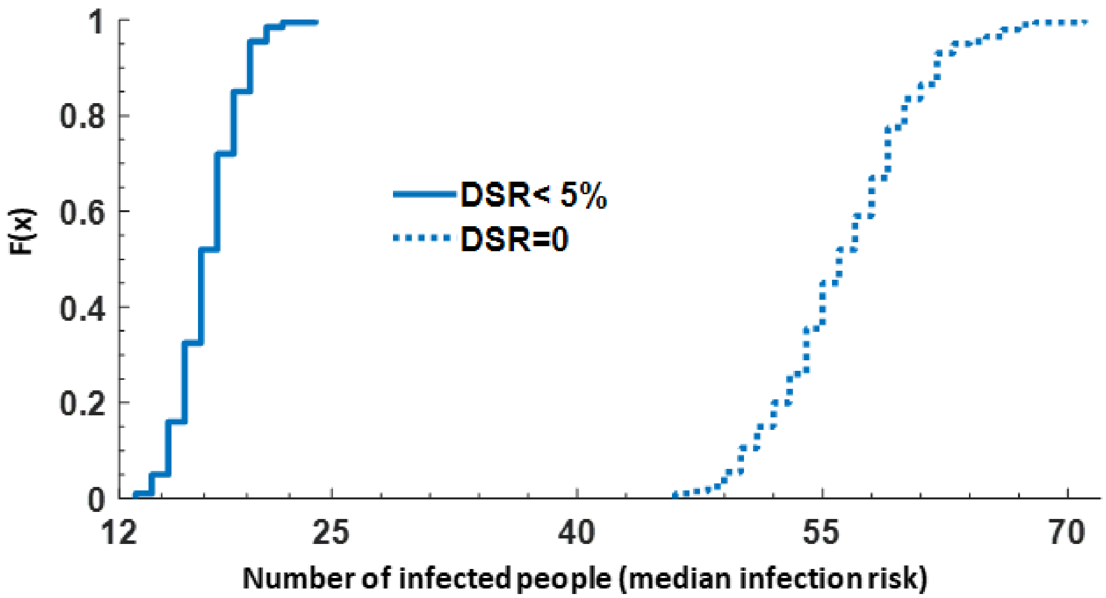


Figure 6.10. Probability distributions of the number of infected people during the first day of simulation when people with a DSR null and less than 5% do not drink water from tap; 200 Monte Carlo simulations for each scenario; C_{out} = 560 oocysts/L with 1 h of PDCs with daily consumption patterns.

6.4 Discussion

Impact of event duration on the spatial distribution of risk in the network. During an intrusion event, the intrusion risk was determined by several factors such as the intrusion volume, pathogen concentration, network hydraulics, fate and transport of the contaminants and consumers' behavior. The volume of contaminated water entering the network is a function of the duration of the event. For the events with 1, 10 and 24 h of sustained depressurization, the estimated intrusion volumes through all leak openings were 0.8, 8 and 19 m^3, respectively. Using the orifice equation, some studies have produced estimates of the intrusion volumes through leakage points for transient PDCs (Ebacher et al. 2012, Kirmeyer et al. 2001a, Teunis et al. 2010). The total intrusion volumes resulting from a momentary pump shutdown for different intrusion conditions through leakage orifices and submerged air vacuum valves (AVVs) ranged from 10 to 360 L in the same network (Ebacher et al. 2012). In contrast, these authors also showed that the maximum volume entering through a single submerged AVV during a transient could be about 95 times larger than the maximum volume entering through a single leakage orifice (227 L versus 2.4 L). In their study, the modeled intrusion volume was driven by the global leakage rate (5% versus 40%) and pressure differential. However, as these authors also stated, the orifice size at a given node should reflect the local leakage demand. Using Monte Carlo simulations, Gibson et al. (2019) investigated the impact of head differences, diameter of orifices, pipe age (number of holes), and low pressure duration on the intrusion volumes during transient negative pressure events. For a 25-year-old pipe, the probability of an intrusion volume greater than 10 L was low (1%), while it increased to 70% for a 150-year-old pipe.

In the current study, the orifice size at each node was considered proportional to the assigned nodal leakage demand in the calibrated model under normal operating conditions as described in detail by Hatam et al. (submitted). In the test DS, leakage demand reflects the state of pipes; older areas with aging cast iron being the dominant pipe material has higher leakage and thus offers more potential entry points for contaminated water. In this study, the effect of soil–leak interactions was ignored and the exponent in the orifice equation was considered equal to the theoretical value (0.5) that is valid for fixed leak openings. It was confirmed that the variation of the area of round hole with pressure is negligible and therefore the leakage exponent was close to 0.5 (van Zyl and Clayton 2007, van Zyl and Malde 2017). However, for longitudinal slits that have large head-area slope, a modified orifice equation should be used in which the leakage exponent can change within 0.5 to 1.5 (van Zyl et al. 2017).

In this study, long durations of PDCs were considered as opposed to relatively short durations of low and negative pressures. Sustained PDCs are reported in the literature due to transmission main repairs (Besner et al. 2007, Besner et al. 2011) and can happen during power outages. This type of event may be less frequent than transient pressure fluctuations, but of graver consequences, as shown by the potentially larger intrusion volumes. The duration of transient negative or low pressures is a key factor affecting the virus infection risks estimated by QMRA (LeChevallier et al. 2011, Teunis et al. 2010, Yang et al. 2011). As expected, for the simulated sustained PDCs, the number of infected people for the three different intrusion durations showed strong dependency on the intrusion duration (Figure 6.6), as it determines the total amount of *Cryptosporidium* oocysts introduced into the network. The maximum number of infected people was reduced to less than half when the intrusion duration decreased from 24 h (1410) to 10 h (502), and even more so if the event only lasted 1 h (84). Our results are in agreement with those of Schijven et al. (2016), who used QMRA to investigate the impact of intentional contamination. Exposed persons were increased by 2–3 folds when the duration of the injection of contaminants increased from 10 to 120 min.

More importantly, in this study, we showed that the duration determined the areas with high pathogen concentrations corresponding to a potentially significant infection risk. The geographical distribution of the nodal risk shown in Figure 6.7 emphasizes the importance of considering the duration of PDCs/intrusion when issuing sectorial boil water advisories (BWA) as well as other preventive/corrective actions. For 24 and 10 h intrusion events, the zones at risk were more or less the same with different risk levels. However, for a much shorter duration of intrusion (1 h), the zones at elevated risk were significantly reduced (Figure 8). The arbitrary cutoff line in Figure 6.8 can be used to compare the summation of the total risks at nodes in different zones affected by contaminated ingress water. On its right side, a very small cumulative risk of 0.2 infection for the 1 h intrusion was observed; this risk increased to 1.4 and 3.5 for the intrusion events of 10 and 24 h, respectively. These values include all low nodal risks ($\leq 1 \times 10^{-3}$) which are not plotted in Figure 6.7 for clarity.

Concentration of *Cryptosporidium* in ingress water. There are scarce data on the actual concentrations of pathogens in ingress water. Concentrations of pathogens in ingress water could range from those found in wastewater, representing a high-risk scenario of ingress directly from undiluted sewage (Payment et al. 2001), to the much lower concentrations measured in trench water, urban groundwater or runoff (Besner et al. 2010a, Ebacher et al. 2013). The number of infected people increased from 6 to 1410 when *Cryptosporidium* concentrations increased from 1 to 560 oocysts/L (Figure 6.4, median) for the worst-case consumption event (out of 200) (F(x) = 1). In agreement with our results, the contaminant concentration outside the pipe ranked among the top factors in previous QMRA studies (Blokker et al. 2018, LeChevallier et al. 2011, Teunis et al. 2010, Yang et al. 2015). When using the maximum dose–response relationship rather than the median relationship to account for uncertainties, the maximum number of infected people increased about two folds (Figure 6.4). The magnitude of differences between the median and maximum dose-response relationships is a critical factor to consider as recent evidence suggests that even higher dose–response values for *C. hominis* should be considered (World Health Organisation (WHO) 2016, World Health Organization (WHO) 2009). Therefore, both the concentrations and the selection of the dose–response will contribute to uncertainty (World Health Organisation (WHO) 2016).

Consumption behavior. Standard QMRA models usually consider only one consumption event per day (LeChevallier et al. 2011, Yang et al. 2011) or a constant volume of consumption per day for every person at fixed hours (Besner et al. 2010c, Islam et al. 2017). For the 24 h scenario, the amount of water consumed daily from the kitchen tap had a huge impact on the maximum number of infected people, with decreases of ~ 40% and 60% when consumption was reduced from a baseline of 1 L/day to 500 mL/day and 300 mL/day, respectively. The model was also sensitive, but to a lesser degree, to the number of glasses per day for a fixed volume (Figure 6.5). Increasing the number of glasses per day from 1 to 10 increased the overall infection risk (by up to 2%) for the 24-h scenario. This rise is more pronounced for larger consumption volumes (Figure 6.5). Impact of the number of glasses per day was most noticeable when switching from a single consumption event to 3 or 10 consumption events. Blokker et al. (2018) and Van Abel et al. (2014) also observed that three ingestion volumes per day result in higher numbers of infected people compared to only one withdrawal of the total volume per day.

Several studies have investigated and integrated probabilistic models to better represent the consumers' behavior into QMRA models, including PDFs of volume of unboiled tap water, number of glasses per day, volume per glass, timing of consumption, and household water usage (Blokker et al. 2018, Davis and Janke 2008, 2009, Schijven et al. 2016). Blokker et al. (2018) fully integrated consumers' behavior using a Poisson distribution for the number of glasses per person per day and a lognormal distribution for the ingested volume per glass and the kitchen tap use. This model was applied to investigate various scenarios of fecal contamination resulting from DS repairs and the potential for preventive actions to mitigate risks of infection. In this study, we used the Blokker model to investigate accidental intrusion due to sustained low/negative pressure event of various durations, adding 200 simulations to quantify the range of risks corresponding to different consumers' behavior. The differences between the numbers of infected people for minimum ($F(x) = 0$) and maximum ($F(x) = 1$) probabilities in Figure 6.8 reveal the potential impact of consumers' behavior for a specific event. The ranges were widest for the first day (from 71 to 46 people, 35% reduction) than for the following days. The variations observed were less important in the scenarios of 10 and 24 h (Figure 6.6). Understanding the uncertainty associated with a combination of plausible behaviors appears important.

Impact of daily demand. The diurnal consumption patterns result in variable intrusion volumes and numbers of intrusion nodes during different hours of the day because of the variations in nodal pressure values. In this study, the demand was set to peak hour demand, which could lead to overestimation of intrusion volumes if system pressure was not decreased for night flows. On the other hand, fixed peak water demand overestimated the flushing of contaminants from the network by leakage, commercial, industrial, institutional demands, etc. during periods of low human consumption, resulting in an underestimation of the risk. With the scenario of 1 h PDCs/intrusion which incorporates daily demand patterns in the hydraulic model, it was shown that the underestimation was about 15%, which we consider to be acceptable (Figure 6.6 compared to Figure C-3).

Integrating demand availability from PDCs. The novelty of this work lies in the coupling of the PDA and QMRA. Unlike DDA, PDA permits identification of areas with demand shortage, allowing for more realistic estimations of consumption based on water availability at the tap during pressure losses. For example, consuming at a DSR of 5% and less would mean that the filling time would increase by more than 20-fold. As shown on Figure 6.10, the number of infected people on Day 1 decreased sharply from 71 to 24 (65%) if only consumers at nodes with DSR >5% during low/negative pressures were considered. It should be noted that limitations to consumption only occur during the low-pressure conditions. Furthermore, the extent of these differences depends on the consumption time, and the duration and timing of the event. The results shows that restricting drinking water consumption during periods of low or intermittent flow would greatly reduce risks. Therefore, utilities and health authorities could consider educating people not to consume water during these periods of low flow. Further study is needed to define a minimal DSR criteria based on the amount of reduction in infection risk.

Implication for risk management. The nodal risks considered the contaminant transport in the network and the probability of coincidence of passage of contaminants at the tap and consumption. However, the spatial and temporal distribution of total nodal risks also reflected the distribution of the population between nodes (Figure 6.7 and Figure 6.9). The areas in which to issue a BWA, and those where corrective actions (e.g., flushing) would be effective, can be determined using nodal risk values in reference to an acceptable risk level.

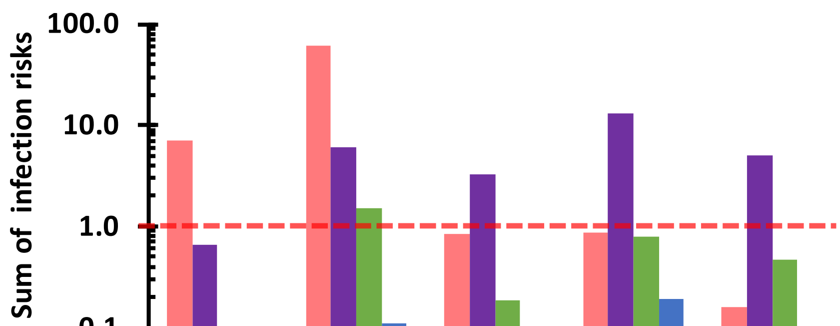
QMRA models have been used to evaluate the efficacy of different mitigation strategies such as BWAs, flushing, and disinfection for reducing the infection risk after main break repairs/transient pressures (Blokker et al. 2018, Yang et al. 2011, Yang et al. 2015). Yang et al. (2015) showed that flushing at >0.9 m/s reduced infection risks by 2–3 logs for norovirus, *E. coli* O157:H7 and *Cryptosporidium.* For viral and bacterial pathogens, disinfection with a CT of at least 100 mg·min/L using free chlorine was required after flushing to decrease the risk below the USEPA yearly microbial risk target value (1×10^{-4}) (National Research Council of the National Academies 2006). Issuing a system-wide BWA that decreased by 80% the average number of glasses of unboiled water consumed led to a four-fold reduction in the number of infected people (Blokker et al. 2018).

Estimating the daily risk, instead of the event risk, after an intrusion event can guide risk management decisions. The spatial distribution of risk as shown in Figure 6.9 is a key factor to define the boundaries and duration of sectorial BWAs. Figure 6.8 and Figure 6.9 show the contribution of each day to the total event risk over the four-day period. Notably, for the 1-h intrusion, delaying necessary preventive/corrective actions up to 5 h from the start of the intrusion may result in the infection of up to 71 people. After that 5-h mark, a BWA or other preventive/corrective actions would still offer protection for about 33 additional people (sum over the three following days). The reduced benefit of late interventions on the fourth day was evident with only one equivalent infection prevented. Timely response to sustained PDCs is therefore essential and can be achieved by improving sampling strategies using enhanced numerical model (Hatam et al. submitted) and equipping the DS with multiple online pressure sensors and water quality sensors. The duration of the BWA could be adjusted depending on the corrective actions implemented to meet the acceptable risk level for an event.

Figure 6.11 offers insights into whether pressure during PDCs can be used to determine areas to target for preventive/corrective actions. Pressure during the PDCs determine the extent of intrusion. However, whether contaminants will travel from low-pressure nodes to higher pressure nodes (based on pressure during PDCs) is determined by water paths during normal and PDCs. This was clearly illustrated by the fact that, for the 1-h PDCs, consumption of tap water at nodes other than negative pressure nodes resulted in 63, 28, 3, and 1 infected people on Days 1–4, respectively. This showed that the benefits of avoiding consumption at negative nodes (based on the pressure values under PDCs) after the PDCs was limited, as these values for the whole network, including negative nodes, were 71, 29, 3 and 1, respectively. Even with a pressure criterion of 15 m, the number of infected people on Day 2 would be significant (6) (Figure 6.11). These results are consistent with the study by Hatam et al. (submitted) who showed that *E. coli* can be transported to higher pressure zones (up to ~40 m) in the absence of disinfectant residuals during a 5-h PDCs/intrusion. Our results emphasize that issuing sectorial BWAs based only on pressure is not adequate to protect the population against infection, even for the scenario of 1-h PDCs/intrusion with a high *Cryptosporidium* concentration (560 oocyst/L). The simulation of the fate and transport of contaminants is necessary to define an effective sectorial BWA.

In future work, reporting the hourly risk, instead of the daily risk, could be helpful to utilities to define preventive/corrective actions and timely response. In this study, the PDCs occurred at 18:30 on Day 1, therefore some of the daily demands were already satisfied before the intrusion event. The timing of the event impacts the infection risk, which needs to be investigated in future studies. Blokker et al. (2018) showed limited effect for timing of repairs.

Although the field validation of the transport of pathogens and indicators appears desirable, it is however not feasible to conduct in complex operating distribution systems. Such validation would require extensive monitoring during intentional extended loss of pressure events and monitoring of infections by an epidemiological investigation that utilities and health authorities will not allow. The conservative modelling presented in this study nevertheless demonstrates the value of numerical tools combined to QMRA to quantify risk and assist utilities and regulators.



	P<=0	(0,5]	(5, 10]	(10,15]	>15
Day1	7.0	61.1	0.8	0.9	0.2
Day2	0.7	6.0	3.3	13.2	5.1
Day3	0.0	1.5	0.2	0.8	0.5
Day4	0.0	0.1	0.0	0.2	0.1

Figure 6.11. Number of infected people for different pressure (P) ranges (based on the pressure values under PDCs) on Days 1–4; Infection risks corresponding to the consumption event with F(x) = 1 (Figure 6.8) are illustrated. The event starts at 18:30 on Day 1 for a duration of 1 h. Daily patterns in the hydraulic model.

6.5 Conclusion

- An approach is proposed to couple QMRA and water quality calculations based on pressure-driven hydraulic analysis to assess the infection risk under sustained low/negative pressure events, causing accidental intrusion of potentially contaminated water surrounding the pipes. The intrusion volume at potential intrusion nodes is adjusted for nodal pressure and pipe state (age and material) using leakage demand.
- By implementing PDA, the pattern of kitchen tap use was dynamically modified to include the impact of demand availability during PDCs in the analysis. During the PDCs, using a higher critical value of the DSR (5% instead of no demand) for drinking water withdrawals led to a significant reduction in the number of infected people (~65% on Day 1 of 1-h PDCs). This reduction in infection risk if contaminated water is not consumed should be considered to guide preventive notices. It shows that customers should be advised not to drink water when flow at the tap is low (i.e., it takes much longer time to fill a glass).
- In this work, depending on the pathogen concentration in sewage, the number of infected people changed by 235-fold, showing the importance of selecting a representative level of contamination in a system. Using raw sewage as the ingress water is a conservative scenario as water surrounding water mains is likely to be less contaminated than sewage.
- Results show that the number of glasses per day (1, 3, or 10) was less important than the consumption volume (300 mL, 500 mL, or 1 L) for the scenario of 24-h PDCs.
- The duration of PDCs/intrusion is a decisive factor in determining the infection risk, issuing sectorial boil water advisories and other preventive/corrective actions. Spatial and temporal distribution of nodal risks presented in this study can help to determine the boundaries and duration of sectorial BWAs.
- A fast response by the utility is key to reducing the infection risk by limiting the contamination area. For a 1-h intrusion, delaying 5 h the necessary preventive/corrective actions from the start of the intrusion may result in the infection of up to 71 people.

ACKNOWLEDGEMENTS:

The participating utility gratefully provided information of the distribution system model. The authors would like to thank Bentley Systems for providing academic access, with unlimited pipes version, to the utility model.

CHAPTER 7 ARTICLE 4 –INVESTIGATING THE IMPACT OF SUSTAINED LOW PRESSURE EVENTS ON WATER QUALITY IN WATER SUPPLY NETWORKS USING PRESSURE-DRIVEN ANALYSIS

The main objective of this chapter is to assess the impact of different pressure-demand relationships under continuous PDCs, while using PDA, on the intrusion flow rates, hydraulic conditions and multiple water quality parameters (chlorine residual, THMs, and *Cryptosporidium*). This paper was published in the proceedings of *first International Joint Conference in Water Distribution Systems Analysis & Computing and Control* held in Kingston, Ontario, Canada, on July 2018.

INVESTIGATING THE IMPACT OF SUSTAINED LOW PRESSURE EVENTS ON WATER QUALITY IN WATER SUPPLY NETWORKS USING PRESSURE-DRIVEN ANALYSIS

Fatemeh Hatam[1], Marie-Claude Besner[2], Gabrielle Ebacher[3], Michèle Prévost[1]*

[1]NSERC Industrial Chair in Drinking Water, Department of Civil, Geological and Mining Engineering, Polytechnique Montréal, CP 6079, Succ. Centre-ville, Montréal (Québec), H3C 3A7, Canada
[2]R&D Engineer, Water Service, City of Montreal, Montréal, QC, Canada H3C 6W2
[3]Technical Engineer, Environment Service, Drinking Water Division, City of Laval, QC, Canada, H7V 3Z4
[*]Corresponding author, E-mail address: fatemeh.hatam@polymtl.ca, Tel.: 514 340-4711 ext. 2983

ABSTRACT

With infrastructure aging, sustained low/negative pressure events in distribution systems (DSs) may become more common. Therefore, more accurate numerical tools to predict hydraulic and water quality (WQ) behavior of DS under low/negative pressure conditions are needed to better identify areas where corrective/preventive actions are justified. A technique which allows combining pressure-driven hydraulic analysis and multi-species WQ model (i.e EPANET-MSX) is applied to investigate the impact of sustained pressure losses on hydraulic and WQ of a full-scale network. In this regard, chlorine residual and THMs concentrations are simulated during a severe sustained low/negative pressure event considering continuous intrusion of contaminated water.

Cryptosporidium oocysts resulting from the ingress of sewage at low/negative pressure nodes was considered as conservative tracer. The impact of using different pressure demand relationships (PDRs) while performing pressure-driven analysis (PDA), is investigated on both the hydraulic and WQ behavior of the network during simulated sustained pressure deficient conditions (PDCs).

KEYWORDS: Multi-species water quality model, pressure-driven analysis, continuous intrusion from sustained low-negative pressure events

7.1 Introduction

To ensure public health protection during pressure losses, appropriate emergency responses are required by water utility managers. Hydraulic and water quality modelling can be applied to predict the behavior of pressure deficient networks. To accurately simulate PDCs, a pressure-driven hydraulic analysis should be performed rather than the traditional demand-driven analysis (DDA). Different methods have been proposed in the literature to perform PDA (Ozger 2003, Wu et al. 2009). Some studies are based on iterative use of DDA, while others solve simultaneously the mass and energy conservation equations and an equation which express the relation between pressure and demand (PDR). In this regard, different PDRs have been proposed to perform PDA (Fujiwara and Li 1998, Tanyimboh and Templeman 2010, Wagner et al. 1988). Some investigations on selecting a representative PDR have been performed (Ciaponi et al. 2014, Shirzad et al. 2013); however, finding an appropriate PDR is a challenging task in the absence of field data.

A multi-species water quality model is required to be able to account for the interactions between microorganisms, disinfectant residual and different types of matrices. In 2007, EPANET-MSX which is a multi-species extension of EPANET was released. Yang et al. used EPANET-MSX to simulate the interactions between disinfectant decay and virus inactivation due to intrusion events (Yang et al. 2011). Other researchers have applied this software to simulate contaminant intrusion for *E. coli* (Islam 2017). However, standard modeling tools are usually limited to either single species water quality analysis or the hydraulic analysis is only valid under normal operating conditions. Some researchers modeled water quality using pressure-driven hydraulic analysis for optimization models (Rasekh and Brumbelow 2014). Also, the coupling of PDA and single species water quality analysis has been proposed for water quality reliability assessment (Gupta et al. 2012, Liserra et al. 2014).

In this study, the impact of sustained low/negative pressure events on water quality variations by the help of a recently developed methodology is demonstrated. This modeling approach allows performing multi-species water quality modelling under sustained PDCs based on pressure driven hydraulic analysis results. The efficiency and applicability of this methodology are evaluated by simulating multiple water quality species in a single run under a significant sustained PDCs. As a proof of concept, and because modeling work is still ongoing, the water quality species included in this demonstration include chlorine, THMs and *Cryptosporidium* oocysts as a conservative tracer. Chlorine residual and THM spatial variations under sustained PDCs comparing to normal operating conditions are evaluated and the contamination transport throughout the DS due to continuous intrusion is investigated. The impact of using different PDRs, when performing PDA, on hydraulic and WQ parameters is also demonstrated. The extent of areas which may need corrective/preventive actions are compared based on different criteria using different methods.

7.2 Methodology

A full-scale distribution system with three WTPs is selected for the simulations and evaluating the performance of the proposed methodology. This network is comprised of 30,077 nodes which serves a population of about 400,000. There are no storage tanks or pump stations in the water network. As the entire network is hydraulically interconnected the supply zone of each WTP can be modified under PDCs based on the hydraulic conditions of the network.

7.2.1 Hydraulic analysis

To simulate sustained PDCs, pressure-driven hydraulic analysis is performed using the commercial software WaterGEMS®. Different PDRs can be defined in this software using pressure-demand piecewise linear curve. In this study, the impact of using two different PDRs when performing PDA, on hydraulic and water quality parameters are compared. Tanyimboh relationship can be defined as follows (Tanyimboh and Templeman 2010):

$$q_j^{avl} = q_j^{req} \frac{\exp(\alpha_j + \beta_j H_j)}{1 + \exp(\alpha_j + \beta_j H_j)} \qquad \text{Eq. 7-1}$$

where q_j^{avl} and q_j^{req} are available and required demand at node j, respectively, H_j is available head. αj and βj are parameters defined using field data while in the absence of field data, they can be estimated by $\beta_j = 11.502/(H_j{}^{des} - H_j{}^{min})$ and $\alpha_j = (-4.595H_j{}^{des} - 6.907H_j{}^{min})/(H_j{}^{des} - H_j{}^{min})$.

In these equations H_j^{min} and H_j^{des} are minimum and desired pressure head, respectively. Wagner Equation (Wagner et al. 1988) can be presented as follows when pressure head is between H_j^{min} and H_j^{des}:

$$q_j^{avl} = \left(\frac{H_j - H_j^{min}}{H_j^{des} - H_j^{min}}\right)^{1/2} q_j^{req} \qquad \text{Eq. 7-2}$$

In this study, H_j^{min} and H_j^{des} are considered to be 0 and 15 m, respectively, for all the nodes. Demand Satisfaction Ratios (DSRs) are calculated by dividing the available demand to the required demand at each node.

A continuous sustained low/negative pressure event (Scenario 1) is simulated by assuming that only one WTP out of three is online and the hydraulic and water quality behavior are compared with the normal conditions (Scenario 2) in which all 3 WTPs are working. A constant demand corresponding to peak hour consumption in the studied distribution system is considered throughout the simulations for simplicity.

7.2.2 Water quality analysis

To enable performing multi-species water quality analysis during sustained low/negative pressure conditions a methodology is proposed which modify the EPANET input file based on the PDA results. This modified input file will then be used by EPANET-MSX for multi-species water quality analysis. More details on the developed technique (MSWQA-PDA) can be found in (Hatam et al. 2018a).

To demonstrate the advantage of the proposed technique, chlorine residual, THMs and *Cryptosporidium* oocysts (simulated as a conservative tracer as chlorine has no effect on this microorganism) are predicted during sustained PDCs. The overall chlorine decay considers reactions in the bulk flow (k_b) and at the pipe wall (k_w) using a first-order reaction model ($\frac{dC}{dt} = -(k_b + k_w)C$). THMs are calculated using the following equation:

$$THM = K_{tc}(C_0 - C) + THM_0 \qquad \text{Eq. 7-3}$$

in which C_0 is the initial chlorine concentration at t=0, C is the chlorine concentration (mg/L), and K_{tc} is the proportion of the chlorine bulk demand that leads to THM formation which is considered to be 41 $\mu g/L$ per mg/L free Cl_2 (Courtis et al. 2009).

At this step, for simplicity, a conservative scenario is simulated by assuming continuous contaminant intrusion at all the nodes with pressure less than 1 m, within the range of water table levels in this system (Ebacher et al. 2013), due to a sustained pressure drop event in the DS. The concentration of *Cryptosporidium* oocysts in sewage is assumed to be equal to 26 oocysts/L (mean concentration) (Payment et al. 2001). The contaminant is considered to be transported as a conservative tracer and no inactivation or interaction with other species is assumed. The intrusion flow rate (Q_i) at each node is calculated using the orifice equation ($Q_i = C_d \pi (D^2/4)\sqrt{2g(H_{ext} - H_{int})}$). The orifice diameter (D) is considered to be constant at all the nodes (1 mm) and the pressure head (H_{ext}) outside the pipe is considered to be equal to 1 m. The available demands for consumers are assumed to be zero at the intrusion nodes. The internal pressure head (H_{int}) at each node is calculated from the model. Intrusion volume may affect the hydraulic conditions of DSs and an iterative procedure can be applied for calculating Q_i through orifice equation if large intrusion volumes are coming into the DS. In this paper, the impact of intrusion flow rates on pressure variations was considered by adding the intrusion flow rates into the model. However, the intrusion volumes were not then corrected using the adjusted pressure values as the differences were considered negligible in terms of both pressure and intrusion volume.

For water quality analysis an extended period simulation of 20 days was carried out to reach the equilibrium conditions of water quality parameters and the results were then reported for the last hour.

7.3 Results and discussions

The distribution of nodal demand satisfaction ratios is demonstrated in Figure 7.1 (a), using Tanyimboh equation. The results are grouped by the pressure values to facilitate the comparison, as required demands are completely satisfied at nodes with pressure more than 15 m. The median DSR for nodes under PDCs (P ≤ 15) is 72% using Tanyimboh equation. For Wagner equation (results are not shown here) this value is 67% and, the mean is about 60% for both relationships. However, as it is shown in Figure 7.1 (b), using different PDRs can lead to different DSRs at some nodes in the network. For this scenario, the median, 75 percentile and maximum percentage of difference between the Tanyimboh and Wagner DSRs are 0.3%, 5% and 30%, respectively. Discrepancies in the available demand can impact WQ by affecting the path through which the water passes to reach a node.

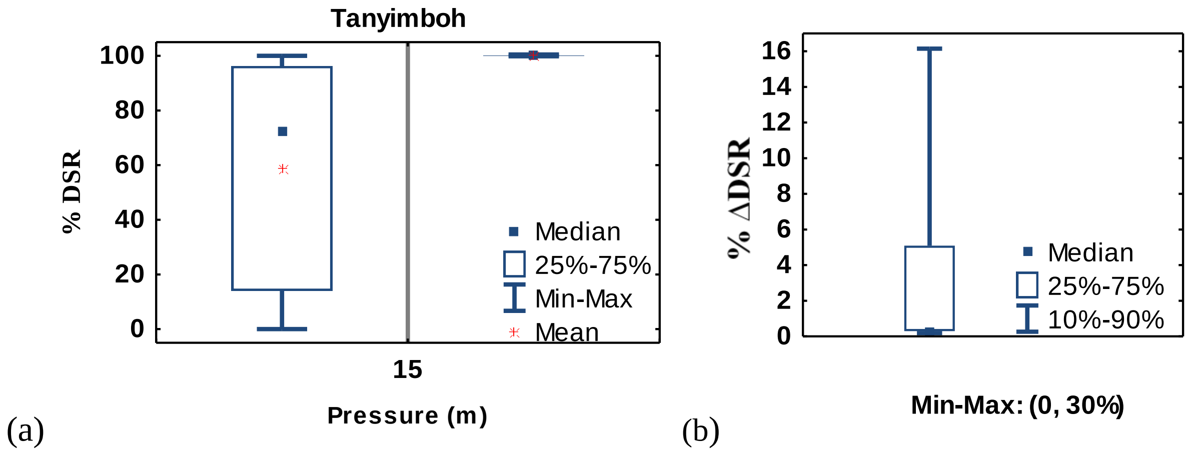


Figure 7.1. Distribution of (a) percentage of DSRs under pressure-deficient scenario when using Tanyimboh for two groups of nodes and (b) nodal DSRs absolute differences between different PDRs (% $\Delta DSR = |DSR_{Tanyimboh} - DSR_{Wagner}|$) while performing PDA, for all the nodes. These results exclude nodes with no required demand.

Pressure values under normal operating conditions and pressure deficient conditions using traditional DDA and PDA (Wagner and Tanyimboh) are compared in Figure 7.2. Again the pressure values under PDCs calculated by Tanyimboh equation are used to discriminate nodes with pressure less than or equal to 15 m and nodes with pressure more than 15 m.

During normal conditions, pressure values are between 21 to 63 m while under PDCs the minimum pressure in the network is decreased to –7 m using PDA (either Wagner or Tanyimboh equation) (Figure 7.2). However, the results show that DDA incorrectly estimates the pressure values under PDCs especially for nodes experiencing PDCs ($P \leq 15$m) (pressures are between 2 to -27 m).

Even though small pressure differences are observed between the use of the two PDRs (less than 1 m at all the nodes), they can affect the number of nodes prone to intrusion and volume of contaminated water which can enter into the DS. Therefore, water quality data will also be compared in the followings for these two PDRs to observe the importance of these discrepancies in the hydraulic parameters in water quality.

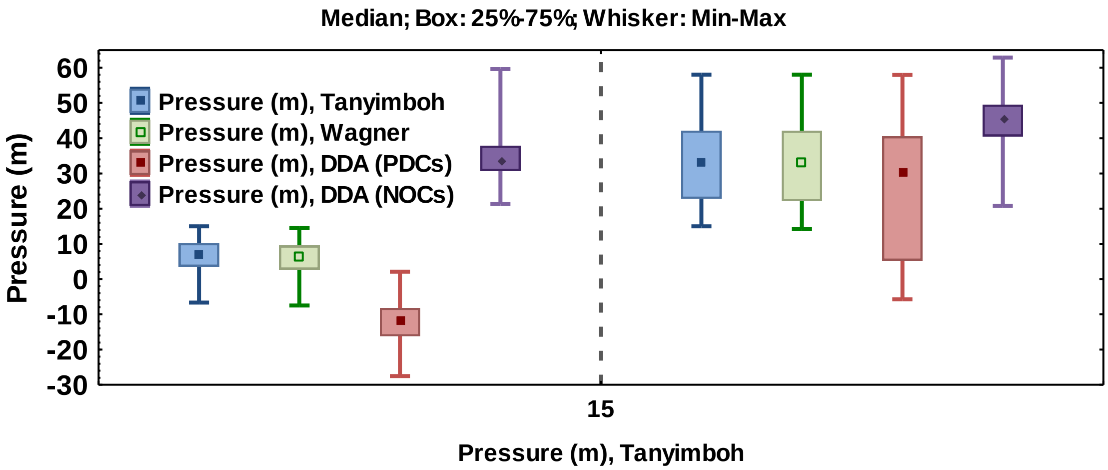


Figure 7.2. Comparison of pressure results calculated from PDA (Wagner and Tanyimboh) (modified EPANET input file) and DDA under pressure-deficient conditions and normal operating conditions (NOCs) (DDA).

The choice of a minimal pressure criteria is a critical factor when defining the nodes that may be susceptible to intrusion/backflow and areas which require corrective/preventive actions. Guidance to set these threshold pressure values remains poorly defined and do not consider the particular conditions of a specific network. Guideline reference values especially vary in their tolerance of low but positive pressures. Figure 7.3 shows the impact of different minimal pressure criteria choice (0, 5, 10 or 15 m) on the number of nodes at risk of intrusion/backflow for the simulated low/negative pressure event. It should be mentioned that the nodes which may need corrective/preventive actions also depend on the intrusion rate, the contamination level outside the pipe and fate and transport of microorganism throughout the network. The impact of using different PDRs on the number of nodes experiencing low pressure (based on different minimal pressure criteria) is shown in Figure 7.3. The differences are less than 1% for all the groups. However, as expected, DDA will overestimate the zones at risk of low pressure, potentially leading to unjustified boil water advisories. A more detailed discussion about the impact of different minimal pressure criteria on the number of nodes and geographical distribution of areas which may need corrective/preventive actions can be found in (Hatam et al. 2018a).

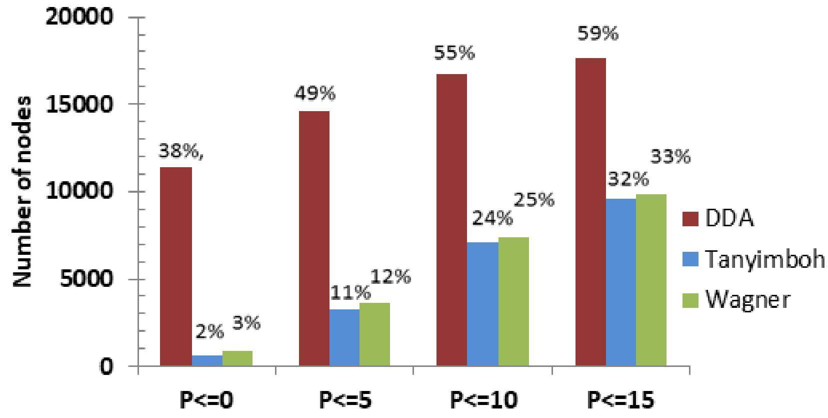


Figure 7.3. Number of nodes at risk of intrusion/backflow based on different minimal pressure criteria and different methods of estimation: traditional DDA and PDA (comparing Wagner and Tanyimboh).

The multi-species water quality analysis based on PDA was used to model a continuous intrusion of *Cryptosporidium* oocysts at nodes with pressures <1 m. The impact of the simulated sustained PDCs on chlorine and THM concentrations are shown by comparing the results of each pressure group to the corresponding values during normal operating conditions (Figure 7.4). As an example, for nodes with zero or negative pressure, the median chlorine residual decreased due to sustained pressure losses from 1.2 to 0.4 mg/L. For nodes with low but positive pressure the median chlorine residual drop from 1.1 to 0.9 mg/L while for nodes with P ≥ 15 m the median remains almost constant (~1 mg/L).

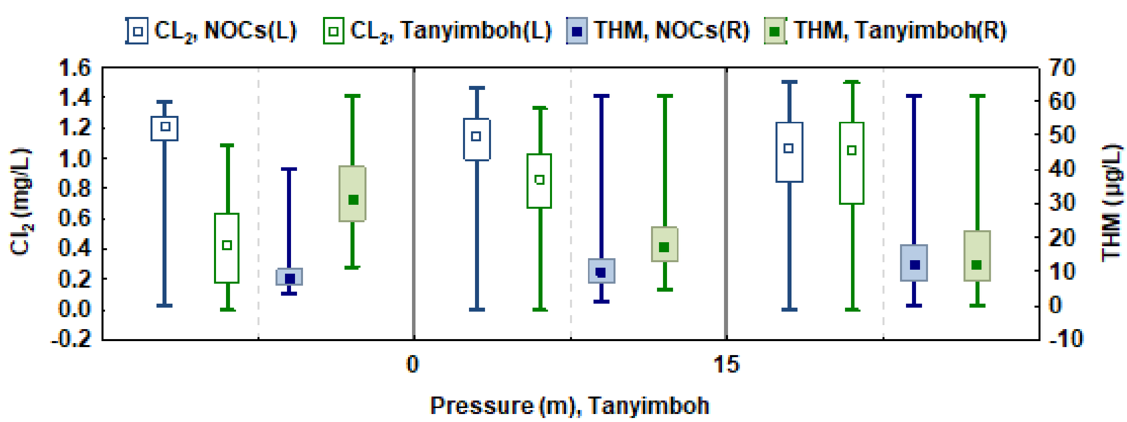


Figure 7.4. THM and chlorine concentration under normal and pressure deficient scenario, Tanyimboh equation used while performing PDA. Note: Median; Box: 25%-75%; Whisker: min-max.

Cryptosporidium oocysts in contaminated ingress water at low/negative pressure nodes are transported throughout the DS, reaching more than 8,000 nodes at different concentrations (Figure 7.5). The theoretical intrusion flow rate entering the DS is estimated to be 2.5 lps (968 nodes) for Tanyimboh, and 3.7 lps (1343 nodes) for Wagner equations.

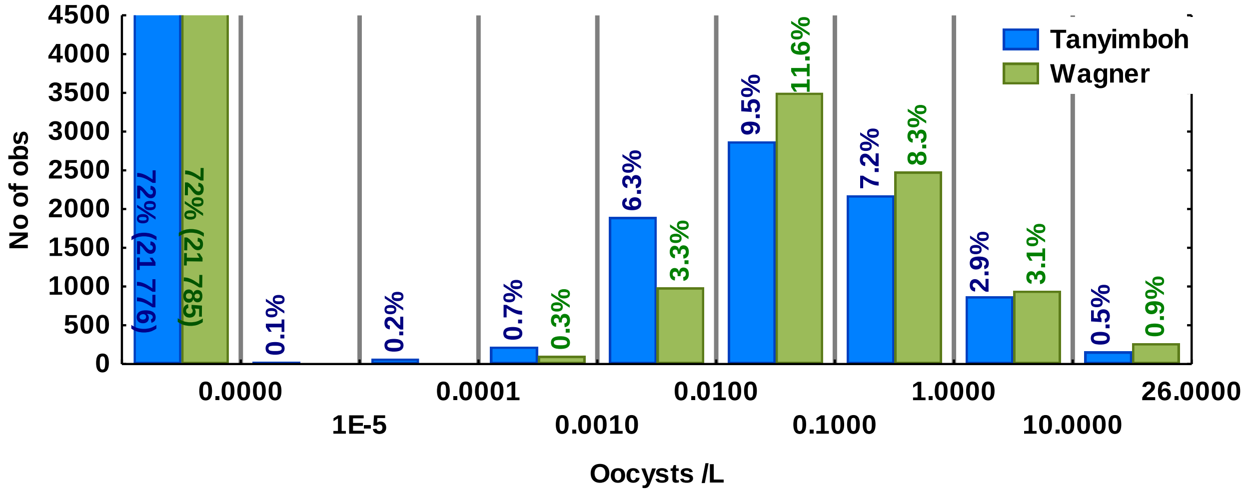
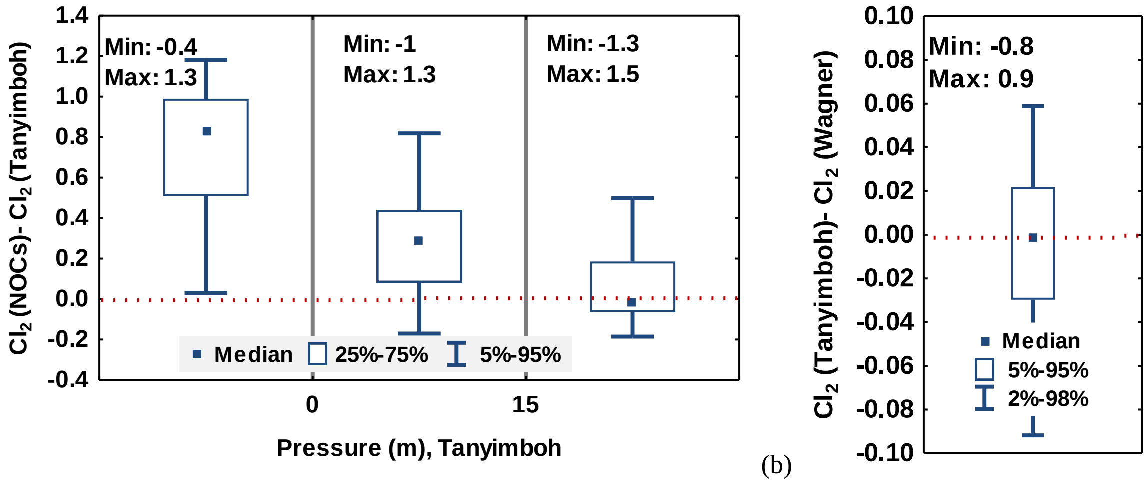


Figure 7.5. Number of nodes in the network for different ranges of *Cryptosporidium* concentration using Tanyimboh (blue) and Wagner (green) equations.

For better comparison, chlorine residual at each node under PDCs is also compared with the corresponding values under NOCs and the distribution of these differences is shown in Figure 7.6 (a). The results showed that generally the water quality gets poorer due to the simulated sustained pressure drop. These differences are generally more significant for the groups of nodes with lower pressure. The median of chlorine differences decreased from 0.8 mg/L, (for nodes with $P \leq 0$) to zero (for nodes with $P > 15$). It is important to note that these differences in chlorine residual are caused by changing hydraulic operating conditions (water age), during the simulated sustained PDCs. They do not take into account other possible causes of residual loss such as biofilm re-suspension and scouring of corrosion products caused by flow reversals. These other causes of residual loss can also become important and cause complete loss of residuals especially during unsteady flow conditions. It should be noted that in the current demonstration, the contamination intruded into the network during PDCs is considered to be non-reactive (conservative tracer). Therefore, its spatial and temporal distribution throughout the network is not affected by the nodal chlorine residuals, which is coherent with the high resistance of *Cryptosporidium* oocysts to chlorine.

Chlorine residual differences, under PDCs, based on the use of different PDRs (Wagner and Tanyimboh) at most of the nodes are small. As it is shown in Figure 7.6 (b), the median of differences is zero and about 90% of the nodes have chlorine differences less than 0.03 mg/L. This is while less than 4% of the nodes have chlorine differences higher than 0.1 mg/L while using different relationships.



(a) (b)

Figure 7.6.(a) distribution of nodal chlorine residual differences between normal (DDA) and pressure deficient conditions (PDA, Tanyimboh) (b) distribution of nodal chlorine residual differences under pressure deficient conditions between Wagner and Tanyimboh equations

7.4 Summary and conclusions

A recently developed methodology which enables multi-species water quality model based on a pressure-driven approach was applied to investigate the impact of sustained pressure losses on water quality in a distribution system. In this regard, chlorine residual and THMs were simulated during a severe sustained PDCs concurrently with modeling continuous intrusion of sewage contaminated water (*Cryptosporidium* oocysts) at nodes with low/negative pressures. However, this study is based on several conservative assumptions such as a continuous intrusion of contaminants with no reactions; future developments of this research will address extending the developed methodology to simulate less conservative scenarios. Ongoing work includes the consideration of scenarios with reactive contaminants and intrusion events in the range of hours.

DDA does not estimate correctly the pressure values and overestimates the number of nodes with low pressures during PDCs, potentially leading to unjustified boil water advisories. Therefore, realistic PDA should be linked with water quality models to predict water quality in the systems under pressure losses. Some differences, although negligible at most of the nodes, were observed in the predicted nodal pressures and values of available nodal demand when using different PDRs while performing PDA. These differences can impact on water quality modeling during PDCs. Under the scenario considered, the intrusion volume was significantly higher (48%) using the Wagner PDR. Although, PDA produces much more realistic results as compared to traditional DDA during PDCs, the selection of the PDRs which are more representative of the network model can improve the PDA results.

CHAPTER 8 GENERAL DISCUSSION

In this chapter, the main findings of the project are highlighted with respect to the initial research objectives and questions. The main goal of this project was to develop new tools to manage risks associated with accidental intrusion of contaminants into drinking water distribution systems as the result of sustained low/negative pressure conditions. This was achieved by proposing improved modeling approaches and assumptions. The first main step was to develop an approach that enables multi-species water quality analysis based on pressure-driven hydraulic analysis. The next was to apply this methodology in modeling intrusion due to sustained PDCs and fate and transport of contaminants across the network during and after intrusion events. Finally, a QMRA model was linked with water quality calculations based on PDA. The management implications of the results to reduce public health impacts and to improve sampling program are then discussed.

Different steps of the project are summarized in Figure 8.1. More details on the simulated scenarios can be found in Table 8.1. Corresponding chapters are also identified. The 8 hypotheses posed in Table 3.1 were all confirmed by our findings.

General objective:

To develop and integrate realistic hydraulic and water quality modeling concepts into a QMRA type model in order to improve the assessment of public health risks associated with the occurrence of sustained low/negative pressure events in drinking water distribution systems

Improved numerical tools (MSWQ-PDA):

- Create an interface that allows multi-species water quality analysis based on PDA
- Run the model as a proof of concept in a full-scale network (> 30,000 nodes) to verify the reliability of the proposed methodology
- Implement it to continuous PDCs/intrusion as well as sustained PDCs/intrusion lasting a few hours
- Model water age, disinfectant residual, THMs, and microbial intrusion
- Investigate the impact of different PDRs on hydraulic and water quality

Fate and transport of ingress water due to sustained PDCs:

- Estimate event-node-specific intrusion volume based on nodal pressure results using PDA
- Calculate the nodal intrusion volume by leakage constant representing the state of pipes
- Adjust the hydraulic for intrusion volume- regenerate the modified input file of EPANET
- Increase disinfectant decay constant only at areas affected by ingress water using a conservative fictitious species when using the nth-order model
- Model fate/transport of *E. coli* and *Cryptosporidium* under various scenarios of sustained PDCs and disinfectant residuals

Implications for management:

- Assess the propagation of maximum *E. coli* and *Cryptosporidium* concentrations at any time during the simulation time as a function of pressure
- Develop spatial and temporal maps of *E. coli*
- Integrate a Poisson distribution function of the likelihood of detecting *E. coli* with the fate and transport modeling
- Customize an advanced QMRA model to link with water quality calculations based on PDA to estimate the infection risk associated with sustained PDCs
- Calculate the daily nodal infection risks of *Cryptosporidium* that integrates affected population, local leakage demand, etc.
- Quantify the effect of contaminant concentration in ingress water and duration of events on the number of infected people
- Taking into account the consumers' behavioral variability using Monte-Carlo simulations

Figure 8.1. Summary of the research conducted.

Table 8.1. Overview of the simulated low/negative pressure events and modeled water quality parameters in different chapters.

Simulated sustained low/negative pressure events		**Water quality parameters**	**PDRs**	**Chapter**
Extent	**Duration**			
Normal operating conditions (No intrusion)	-	Age Chlorine THMs	-	Chapter 4 (Article 1)
Shutdown of 2 WTPs (WTP B and WTP C, Figure 3.2) *Different intensities: various water level at the remaining WTP* (No intrusion)	Continuous	Age Chlorine THMs	Tanyimboh	Chapter 4 (Article 1)
Shutdown of 1 WTP (WTP C, Figure 3.2) Fire-flow at 1 node (Intrusion)	5 hours	Age *E. coli*: *Fate and transport across the network* No disinfectant Chlorine & Chloramine: *With sewage impact*	Tanyimboh	Chapter 5 (Article 2)
Shutdown of 1 WTP (WTP A, Figure 3.2) *The one with the largest capacity* (Intrusion)	1 hour 10 hours 24 hours	*Cryptosporidium*	Tanyimboh	Chapter 6 (Article 3)
Shutdown of 2 WTPs (WTP B and WTP C, Figure 3.2) (Intrusion)	Continuous	Age Chlorine THMs *Cryptosporidium*	Wagner Tanyimboh	Chapter 7

This project can allow us to answer fundamental questions regarding water distribution systems behavior and health risk assessment due to accidental intrusion under sustained PDCs.

- What are the proper modeling tools/approaches to identify the nodes with unsatisfied demand, areas at risk of intrusion/backflow contamination under PDCs, and to estimate the node-event-specific contaminant mass rate/intrusion volume through leakage points?
- What are the appropriate modeling tools/approaches to more realistically simulate accidental intrusion resulting from sustained PDCs and propagation of contaminants throughout the network, considering the interactions between pathogens inactivation and disinfectant decay, and intrusion-associated demand of disinfectant decay?
- How sustained PDCs can affect the water quality variations regardless of any intrusion events?
- What are the key factors to determine the locations of poor water qualities in the case of intrusion events resulting from sustained PDCs? Are the low-pressure areas ($P < 15$ m) the sole zones at risk of poor water qualities?
- Can the intrusion events be detected by the standard *E. coli* sampling program?
- How does increasing the sampling volume affect the detection probability of *E. coli* throughout the network during confirmation and clearance sampling?
- What are the risks associated with the contaminant concentrations in different pressure zones throughout the network?
- What is the impact of the duration of sustained PDCs, the contaminants concentration surrounding the pipes and consumers' behavior on the probability of infection during an accidental intrusion through leakage points under sustained PDCs?

8.1 Can we approach to sectorial BWA issuance under PDCs? What are the proper modeling tools for a more realistic prediction of water quality under sustained pressure-deficient conditions?

The utility response to depressurizations should be based on the type of event, the magnitude, and the duration of pressure losses. Enhancement of modeling capabilities and accuracy can be a valuable tool for utility managers in decision-making under PDCs and have been a popular research topic (Cheung et al. 2005, Germanopoulos 1985, Giustolisi et al. 2008, Gorev and Kodzhespirova 2013, Gupta 2015, Gupta and Bhave 1996, Pathirana 2010, Seyoum and Tanyimboh 2017, Siew and Tanyimboh 2009, 2011, Siew and Tanyimboh 2012, Wu and Walski 2006, Wu et al. 2009).

8.1.1 Why investigate sustained low/negative pressure events?

Sustained pressure drops are reported in the literature (Besner et al. 2007, Besner et al. 2011, Douglas et al. 2018, Kirmeyer et al. 2014) and may become more frequent in ageing infrastructures. For the studied network, during 18 months monitoring, 17 negative pressure events were recorded. Among these events, the duration was > 3 hours for 3 events, and > 30 minutes but less than 1 hour for 4 events (Besner et al. 2010a). Previous studies had mostly focused on numerical analysis of water distribution systems under transient low/negative pressure events (Ebacher et al. 2012, Gullick et al. 2005, Teunis et al. 2010). Duration has been listed among the top-ranked factors in microbial risk estimates associated with low/negative pressure events (Teunis et al. 2010, Yang et al. 2011). The volume of contaminated water that can enter into the distribution systems through leakage points is a function of the duration of PDCs and can directly influence the public's health. Therefore, the present work concentrates on simulating extended duration low/negative pressure events from 1 to several hours.

Figure 8.2 illustrates three types of pathways and events, for intrusion to be occurring: (i) short duration event from transient negative pressures in both leakage orifices and submerged air valves, (ii) pipe breaks, and (iii) the work completed in this thesis, intrusion through leakage orifices during sustained PDCs. Results presented in Chapter 6 show that the total intrusion volumes through 93 nodes ($P < 1$ m) were 800 L and 19,000 L for 1 and 24 hours of PDCs, respectively. Even for 1 h pressure losses, the predicted intrusion volume was higher than the estimated volumes under transient low/negative pressure events described by Ebacher et al. (2012) for the same network, albeit the number of entry points was higher by a factor of 7-8 compared to our study. The volumes reached 15 L through 676 nodes (leakage rate 5%), and 109 L through 750 nodes (leakage rate 40%) with the external head of 1.5 m (Ebacher et al. 2012). For a single leakage point, the maximum intrusion volume was 56 L for 1 hour PDCs in our study. This value is 19-fold higher than the maximum intrusion volume reported by Ebacher et al. (2010) under transient PDCs in the same network with duration of < 3 minutes, leakage rate of 20% of inflow, and external head of 1 m.

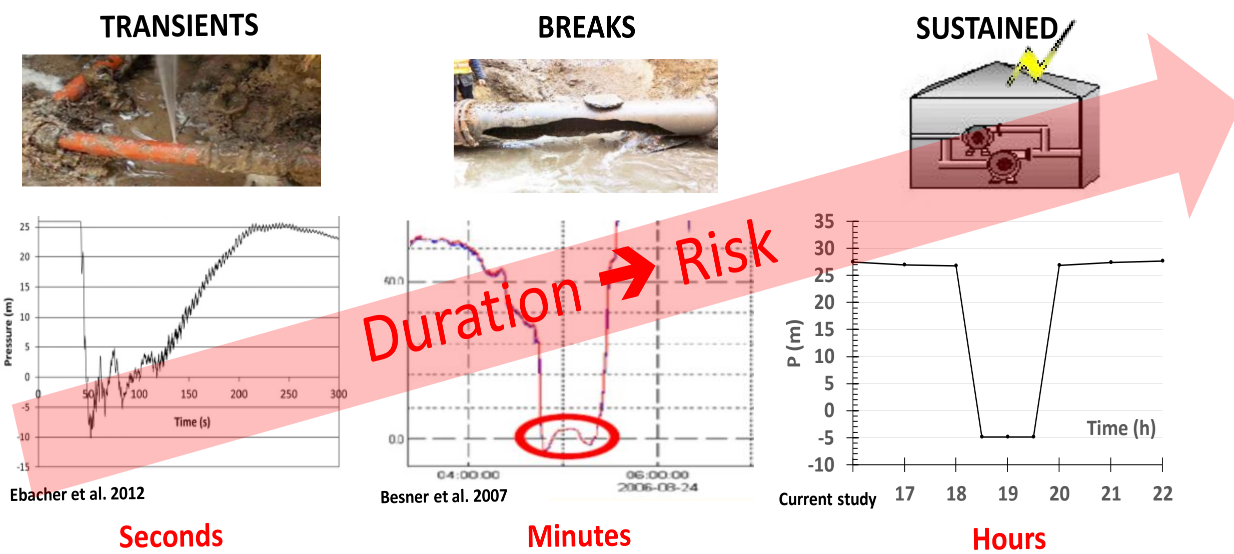


Figure 8.2. Different types of low/negative pressure events as a function of duration, potential intrusion and resulting risk.

8.1.2 Pressure-driven analysis versus demand-driven analysis

Many studies have demonstrated that DDA results are not realistic when modeling low/negative pressure conditions and that PDA should be used (Cheung et al. 2005, Lee et al. 2016, Siew and Tanyimboh 2012). However, water utilities rely on DDA to simulate water distribution systems even to respond to pressure losses. The most commonly open source tool is EPANET, which is based on demand-driven hydraulic analysis. DDA produces unrealistically low nodal pressures under low/negative pressure conditions. For the studied PDCs, PDA generated pressures were always higher than the lowest possible water gauge pressure (-10.1 m at 20°C, cavitation head), even under severe PDCs scenarios. Nodal pressure values decreased to less than -30 m at some nodes when using DDA, which is unrealistic. This was confirmed by field measurements during transient events in this distribution system (Ebacher et al. 2009). They reported that the measured pressure heads never reached the cavitation head at the monitoring points during a power failure at the water treatment plant causing transient negative pressures.

Our results in Chapter 4 indicate that the extent of the pressure differences between DDA and PDA was sensitive to pressure values under PDCs, and to the severities of the pressure losses. Although, these differences were more prominent in areas with lower demand satisfaction ratio, they were not limited only to nodes under PDCs ($P \leq 15$ m). Smaller differences were observed for nodes with higher pressures. However, within the studied pressure range (≤ 70 m), we could not define a minimum pressure for which the nodal pressures using PDA and DDA converge to the same value at all nodes.

Some PDA approaches may report the negative pressure values as zero, such as in the case of version of WaterGEMS (V8i SELECTseries 5) (Bentley Systems 2014) used in this study. This can be limiting when intrusion volumes need to be estimated at low/negative pressure nodes. To overcome this shortcoming, we used the modified INP file of EPANET, which was created by MATLAB, to calculate the nodal intrusion volumes. Reporting negative pressures as zero can also cause some misinterpretations, as in the study by Lee et al. (2015). These authors concluded that PDA can produce unacceptable results such as total head reverse occurrence (flow direction is from lower total head to higher total head). We believe these observations were caused by the fact that the negative pressures were reported as zero in their PDA tool. We proved our assumption by resolving the same network with the same pressure-deficient scenarios considering the negative pressure values using the proposed methodology in this study (Appendix D).

8.1.3 Multi-species water quality analysis combined with PDA results

Several studies have been published in recent years that combine PDA and water quality modeling. However, these studies are either a single-species water quality model (Afshar and Mariño 2014, Bashi-Azghadi et al. 2017a, Bashi-Azghadi et al. 2017b, Rasekh and Brumbelow 2014, Seyoum and Tanyimboh 2014, Seyoum et al. 2011, Zafari et al. 2017) or in the case of performing multi-species water quality analysis the hydraulic engine is based on DDA (Betanzo et al. 2008, Islam et al. 2017, Karamouz et al. 2017, Klosterman et al. 2009, Muray and Adachi 2011, Propato and Uber 2004, Teunis et al. 2010, Yang and Boccelli 2016). The main focus of the work described in this thesis is to predict the impact of sustained low/negative pressure events on water quality in the case of a contamination intrusion. No tool was available to simultaneously consider PDA and a multi-species water quality model. To this aim, a methodology that could incorporate the both advantages is proposed. Figure 3.1 and Figure 4.2 provide a good overview of the capabilities of this approach. Recently, Seyoum and Tanyimboh (2017) used a different approach that integrates PDA and MSX by modifying the source code of EPANET-MSX. This approach was then applied to a small network with 380 nodes to simulate water age, chlorine and THMs under PDCs. However, neither of these newly developed modeling methods has yet been applied to simulate contaminant intrusion due to pressure drops using PDA and multi-species water quality analysis.

In Chapter 5 and Chapter 7, we show that there are many challenging factors to consider when modeling intrusion events due to sustained PDCs and subsequent fate and transport of contaminants across the network. They include estimation of intrusion volume based on pipe state and nodal pressure, its impact on hydraulic behavior and vice versa and selectively increasing chlorine decay rates based on the existence of contaminants using conservative fictitious species.

8.1.4 How can the developed approach help the existing water distribution modeling community?

One of the advantages of the presented approach (MSWQA-PDA) is that it does not require modifying the algorithms within the EPANET source code, which is a difficult task. In addition, it can communicate with any PDA approach. This makes this approach available to a wide range of researchers. EPANET-MSX is an open source software that can be employed to model water quality behavior of distribution systems under sustained PDCs using this technique. However, it must be acknowledge that the application of the proposed methodology in its current format may not be straightforward for the typical end-user and more suited to research. In this project, the approach was tested successfully on a large full-scale network with > 30,000 nodes to simulate the water quality variations due to accidental intrusion events under sustained PDCs with duration of ≥ 1 hour.

Due to rapid evolution of commercial software market, the latest version of WaterGEMS now includes multispecies analysis based on the EPANET-MSX model and pressure dependent demand feature. However, there is a need for robust and user-friendly open source models that combine PDA analysis and multi-species water quality models, especially for academics. Recently, researchers have emphasized on the need of a modern approach to free and open source EPANET development by coordinating researches to jointly develop, improve, and maintain high quality software (Uber et al. 2018). Based on this work and the need for improved tools, some of the functionalities that could be included into future versions of EPANET are:

- A robust pressure-driven algorithm in the model.
- Integration multi-species water quality analysis and PDA.
- Addition of an arbitrary option to be able to account for the dispersion term by solving advection-dispersion-reaction equations in the software. Dispersion term can play an important role in the propagation of contaminants under low/negative pressure events at low flow rate areas.
- Enabling for using multi-core and parallel computing when running EPANET-MSX to speed up the simulations.
- Adding some options that can help verify if results from EPANET simulations are accurate. As an example, recently Davis et al. (2018) suggested that a capability to produce reports on the mass balance of water-quality constituents should be added to EPANET.

Finally, the commercially available software could be improve by adding a module to facilitate the simulations of intrusion events under low/negative pressure conditions. This can include the calculation of nodal intrusion volume and considering its impact on both hydraulic and water quality behavior.

8.1.5 Improved prediction of contaminant mass rate

In previous studies that simulated intrusion events due to PDCs, the contaminant mass rate was estimated either based on a random selection of the parameters such as intrusion volumes, negative pressure durations, pressure head values outside/inside the pipe or a constant mass flow rate of pathogens downstream of intrusion nodes was assumed (Besner et al. 2010c, Betanzo et al. 2008, Islam et al. 2017, LeChevallier et al. 2011, Propato and Uber 2004, Teunis et al. 2010). The amount of contaminant entering the system is a function of intrusion flow rate and the contaminant concentration outside the pipe. In this study, the nodal intrusion flow rates were calculated and used to be more event-specific and site-specific. Due to lack of data, the contaminant concentration and pressure head outside the pipe are considered to be constant at this step, while the presented approach has no limitation to use variable input data in case of availability.

The orifice equation was used to estimate the intrusion flow rates through leak opening in pipes. In previous study, the orifice diameter in this equation was either determined directly (Besner et al. 2010c, Hatam et al. 2018b, Kirmeyer et al. 2001a) or it was estimated using a global leakage rate (Ebacher et al. 2012, Ebacher et al. 2011b, LeChevallier et al. 2011). However, in both cases implementing a fixed orifice size to all nodes will lead to overestimation of potential intrusion flow in areas of low leakage and underestimating the infection risk in the zones of decaying infrastructure with multiple pathways. In Chapter 7, the intrusion volumes were estimated by orifice equation assuming a constant diameter (1 mm) and a discharge coefficient (0.62) at all the nodes. To improve the intrusion predictions, the intrusion volumes were adjusted at each node based on the nodal leakage demand in the calibrated model (Chapter 5 and Chapter 6). The leakage rates were attributed to the nodes as a function of pipe age and materials type in the tested network. This approach will be very beneficial to water utilities that have knowledge about sectorial leakage rates using leakage detection. Furthermore, the nodal interior pressure head obtained by PDA (the modified EPANET input file) was used to estimate the intrusion volume at each node to be more event-specific and node-specific.

In addition, to include the impact of intrusion volume on hydraulic behavior and vice versa, the intrusion volumes were implemented as negative demand in the PDA model. The modified EPANET input file was then regenerated based on the new hydraulic results. However, the above-mentioned studies used the estimated intrusion volume for calculating the contaminant concentration or mass rate and were not implemented in the EPANET model. Unlike EPANET and WaterGEMS, the transient analysis software such as InfoSurge automatically calculate the intrusion flow rates (Ebacher et al. 2012) and implement them in the model.

8.1.6 Improved prediction of disinfectant residuals

In the case of intrusion modeling, two-species second-order model can be used to model the reactions between chlorine, contaminant, and background organics (Klosterman et al. 2009, Muray and Adachi 2011, Yang and Boccelli 2016). However, the estimation of the decay rates between chlorine and background organics is a complicated task. The simple first-order decay model has been widely used to model chlorine decay thorough the network when modeling intrusion events (Betanzo et al. 2008, Islam et al. 2017, Propato and Uber 2004, Teunis et al. 2010). However, the first-order chlorine decay equation does not directly depend on the concentration of contaminants entering the system. Therefore, we believe that applying the first-order model with a fixed decay rate to the whole network regardless of the contamination propagation, which is a function of duration and location of intrusions, cannot simulate realistically the behavior of the system after intrusion. As an improvement, we proposed a simple and practical technique, applying increased decay constant ($K_{intrusion}$) only to areas at the time they experience contaminated water (Chapter 5). This can be done by defining another species in the model that is transported throughout the network as a tracer. For the remaining areas, K_{normal} should be applied. The areas with K_{normal} may change across time depending on the temporal and spatial distribution of the conservative species through the network. With this simple technique, one can significantly improve the prediction of chlorine residuals and contaminants through the network while using the simple first-order decay model in the case of contamination event.

For health risk modeling of intrusion during negative pressure transients, some researchers have proposed modeling a single intrusion node at a time, establishing system responses and integrating adjusted random virus concentrations in intrusion water in the hydraulic and water quality models (LeChevallier et al. 2011, Teunis et al. 2010). These assumptions may not hold for extended low-pressure conditions and is discussed in details in Appendix D (Figure E-1).

8.2 Water quality variations due to low/negative pressure events

Water quality variations due to PDCs in drinking water distribution systems can be resulted from (a) the variations in the hydraulic conditions which result in changes in traveling time and flow path (Chapter 4 and Chapter 5), (b) contaminant intrusion events (Chapter 5, Chapter 6, and

Chapter 7), (c) the impact of intrusion-associated demand on disinfectant decay (Chapter 5), and (d) flow reversal that may cause biofilm resuspension and scouring of corrosion products (which were not considered in this project).

8.2.1 Impact of low/negative pressure events on disinfectant residuals

Impact of variations in the hydraulic conditions: As a proof of concept, water age, chlorine, and THMs were simulated using MSWQA-PDA under continuous PDCs (Chapter 4). The results indicated that the water quality was generally poorer under the simulated PDCs, as compared to normal operating conditions, and was related to longer residence times under PDCs. These observations are in agreement with previous studies (Seyoum and Tanyimboh 2017, Seyoum et al. 2011, Seyoum et al. 2013). Furthermore, investigating water quality results as a function of pressure values, under PDCs, revealed that the differences were generally lower for the group of nodes with $P > 15$ m compared to the groups of nodes with $P \leq 0$ or $P \leq 15$ m. Differences in median chlorine concentrations, the were 0.7, 0.4 mg/L for the groups of nodes with $P \leq 0$ and $P \leq 15$ m, respectively, while this value was almost zero for nodes with $P > 15$ m (Figure 4.7). Yet, it should be recalled that these lower chlorine residuals under PDCs are only due to water age variations regardless of the intrusion associated demand. This loss of chlorine can be important, as the residual disinfectant is the final barrier against pathogen intrusion. The larger difference was observed for the group of nodes with lower pressure are especially of concerns as they are likely to occur where the risk of intrusion is highest under PDCs. It should be noted that these high differences were related to continuous PDCs compared to normal pressure condition scenario (Chapter 4). For shorted low/negative pressure events lasting a few hours (Chapter 5), lower chlorine loss was observed (median dropped 0.2 mg/L for nodes with $P \leq 1$, Figure B-3). This further emphasizes the role of duration of PDCs in the rate of chlorine loss as the result of changes in the hydraulic conditions (i.e. water age).

Impact of intrusion-associated demand: In order to provide a barrier against microbial contamination, maintaining a measurable disinfectant residual level (> 0.2 mg/L) at every point of the network has been recommended in North American practice (Propato and Uber 2004). From our simulation results in the case of sewage intrusion under 5 hours of PDCs (Chapter 5), we demonstrated that chlorine residuals decrease sharply following an intrusion event. The effect of immediate chlorine demand applied to the intrusion nodes during PDCs period, and the increased chlorine decay rate applied to affected nodes using a conservative fictitious species can explain this sudden and severe loss. For the nodes with positive *E. coli* at any time during and after the intrusion (166 nodes), the median chlorine concentrations decreased sharply from ~0.8 to less than 0.1 mg/L for about 2 hours (1 mg/L was the concentration at the outlet of WTPs). However, for the same nodes and a PDC scenario, but without any intrusion event, the median dropped to ~0.6 mg/L, which is about 0.5 mg/L higher compared to the intrusion scenario (Figure 5.3). Interestingly, the data showed that the loss of residuals persisted a while even after the intrusion event was over, as it took a while for chlorine residuals to be restored.

Chlorine versus chloramines: For a 5-hour PDCs scenario, the loss of chlorine was greater than the loss of chloramines under both scenarios of with and without intrusion associated demand. Without intrusion, chloramine concentrations remained above 0.4 mg/L (Figure B-3) at all intrusion nodes. Even with intrusion, the median chloramine residuals remained > 0.7 mg/L for the nodes with positive *E. coli* at any time during and after the intrusion (2,905 nodes) (Figure 5.3). This can be explained by the absence of immediate chloramine demand at the intrusion nodes as well as the lower intrusion decay constant as compared to chlorine. Our results indicate that even though the chloramine residuals remained higher in the distribution system as compared to the chlorine residuals, but the number of nodes receiving *E. coli* was higher in the chloraminated system (2,905 versus 166 in chlorinated system). This fact can be explained by the higher inactivation constant of *E. coli* in the presence of chlorine compared to chloramine by a factor of about 250 folds (246 versus 0.99 L/mg · h). Our findings are in agreement with previous studies showing that chlorine was more effective than chloramines in the case of contamination by *Giardia* or viruses (Propato and Uber 2004, Yang et al. 2011).

8.2.2 Does disinfectant type affect the contaminant fate and transport through the network?

EPANET-MSX has been used to model intrusion or intentional injection of *E. coli* and its fate and transport across the network in the presence of disinfectant residuals, showing the importance of chlorine residuals in limiting the widespread propagation of *E. coli* (Islam et al. 2017, Karamouz et al. 2017, Tinelli and Juran 2017). However, the hydraulic analysis was based on DDA in all of these studies. In the case of PDCs, intrusion nodes and volumes cannot be identified without PDA. The propagation of contaminants due to water path change during depressurization events will also drastically change. In Chapter 5, we took advantage of the presented MSWQA-PDA approach to simulate the ingress and fate/transport of contaminants (*E. coli)* by simultaneously accounting for (i) the interactions between contaminants and disinfectant residuals (chlorine or chloramine), and (ii) the effect of hydraulic conditions under sustained pressure losses (5 hours) applying a realistic hydraulic analysis (i.e. PDA). Our results showed that ~11% of the nodes experienced *E. coli* at any time over the whole simulation duration (4 days) without any disinfectant. The extent of areas positive for *E. coli* were reduced to ~7% in the chloraminated system, and much smaller (< 1%) in the chlorinated system (Figure 5.4). The maximum *E. coli* nodal concentration estimated over the whole simulation period was evaluated as a function of nodal pressure under PDCs. ***Findings show the significant role of disinfectant residual types and concentrations in confining the contaminants into low-pressure areas.*** It was observed that, for the studied PDCs, *E. coli* was transported to the areas with pressure up to 40 m in the case of no disinfectant residual in the system. A chloramine residual of 1 mg/L at the outlet of the WTPs did not prevent widespread propagation of *E. coli*. However, it decreased their concentrations to less than 1 CFU/100 mL at nodes with P > 20 m under PDCs. Interestingly, 1 mg/L chlorine residual at the outlet of the WTPs confined the contamination to a much smaller area with P < 8 m (Figure 5.6 and Figure 5.7).

8.3 What is the public health risk associated to accidental intrusion under sustained low/negative pressure conditions?

8.3.1 QMRA in drinking water distribution systems

Even though it is reported that deficiencies in the water distribution systems could lead to waterborne disease outbreaks (Craun et al. 2010, Guzman-Herrador et al. 2015, Lindley and Buchberger 2002, Payment et al. 1991, Payment et al. 1997), the potential risk from ingress into the network is generally not integrated into the risk assessment of drinking water systems. In the past decade, some studies have proposed using QMRA to evaluate the risk from intrusion events in DSs due to transient low pressure events, main repairs or intentional contamination (Blokker et al. 2014, Blokker et al. 2018, LeChevallier et al. 2011, Schijven et al. 2016, Teunis et al. 2010, Yang et al. 2011, Yang et al. 2015). However, there is no current QMRA analysis that models the infection risk associated with sustained low/negative pressure events based on water quality calculations using realistic hydraulic model under PDCs (i.e. PDA). Applying QMRA to drinking water distribution system can be challenging as many factors must be considered such as the location, concentration, and duration of contamination events as well as fate/transport of contaminants and the likelihood of intake of pathogens by consumers drinking tap water (Besner et al. 2011). To address these requirements, in Chapter 6, the improved QMRA framework proposed by Blokker et al. (2018) was customized and linked with water quality calculations based on PDA to assess the risk of accidental intrusion through leakage points due to sustained pressure losses in a full-scale network. The improved simulation techniques for intrusion modeling that were presented in Chapter 5 are incorporated into the QMRA framework (Figure 6.1).

8.3.2 Investigating the influence of different factors on the infection risk variation

In Chapter 6, specific probability distributions from Blokker et al. (2018) were used in the QMRA model to consider the consumers' behavior by accounting for the number of glasses per person per day, the ingested volume per glass, and the time of filling a glass. Then, for each specific hydraulic/quality condition, the consumers' behavioral variability was further investigated using 200 Monte Carlo simulations. ***Findings clearly show the importance of considering consumers' behavioral variability.*** The results showed large variations (up to 55% increase) for the 1 h PDCs/intrusion on the first day (560 oocyst/L). During the three following days the variability between maximum and minimum number of infected people was less. These results reveal the importance of taking into account the uncertainty associated with consumers' behavioral variability. Larger differences on the first day (1 h intrusion) can be explained by the fact that the nodal contaminant concentration varies rapidly with time. Therefore, the probability of drinking contaminated water is more sensitive to the number of glasses per day and can be augmented significantly when the number of glasses per day increases, in agreement with previous findings (Blokker et al. 2018, Davis and Janke 2008, Van Abel et al. 2014).

One of the advantages of coupling QMRA model with realistic PDA in this study was that we were able to take into account the consumers' behavior during PDCs. ***Demand availability was used to***

show the large impact of avoiding water consumption during low pressure events on infection risk. This was done by modifying the kitchen tap use based on the demand availability (DSR=0 or DSR < 5%) at each node for each person. Results showed a ~ 65% reduction in the number of infected people on the first day of 1-h intrusion, if assumed that people did not drink water from the kitchen tap at low-flow times (DSR < 5%) compared to not consuming only at no demand times. Timely response to depressurization events is a challenge. Delays in issuing advisories to all the system's consumers are common and excepted to occur with sectorial loss of pressure events that may go undetected. Therefore, our modeling results emphasize the need of public awareness to avoid drinking water from the tap if the flow is very low. Such a simple initiative would be effective in reducing the probability of infection risk due to PDCs in DSs and could be easily done by utilities.

Modeling results for different durations of PDCs/intrusion (1, 10, 24 hours), showed that the number of infected people was much lower for the shorter duration events (Chapter 6). ***A 1-hour PDCs/intrusion could lead to lower number of infected people by 17-fold than a 24-hour event.*** So that, over the 4-day period the maximum number of infected people (out of 200 Monte Carlo simulations) was decreased from 1410, for the 24-hour scenario, to 502 and 84 people under 10 hours and 1 hour PDCs/intrusion scenarios, respectively. The concentration of *Cryptosporidium* in sewage was the same for all scenarios (560 oocyst/L). This reflects the larger intrusion volume entering the network for the longer duration events (Figure 8.2).

For a fixed duration of intrusion (24 hours), ***the number of infected people increased by 235-fold when the concentrations of Cryptosporidium in raw sewage varied from 1 to 560 oocysts/L.*** This mainly points out the need of further improvement in estimating the concentration of contaminants outside the pipes in future studies. Also, it reveals the risk of ageing sewer mains located close to drinking water pipes. Previous QMRA studies associated with transient PDCs, showed virus concentration was the third-highest ranked factor after coincidence of water withdrawals from contaminated water, and the duration of negative pressure (LeChevallier et al. 2011, Teunis et al. 2010).

Applying the maximum dose-response relation increased the number of infected people by about two times as compared to the median dose-response relation for all the concentration scenarios

(1, 6, 26, and 560 oocysts/L). These differences in trends reflect the was observed in the study by Blokker et al. (2014). The reason can be explained by the fact that the differences between median and maximum relations at lower and higher doses. Therefore, the discrepancy between the median and maximum probability of infection could change based on the range of calculated doses (World Health Organization (WHO) 2009).

Consumption of daily volume was more important than the timing of consumption in defining infection risk. The sensitivity of the results to the consumption volume and number of glasses per day per person showed that, for 24 hours intrusion, the infection risk was more influenced by the consumption volume (from 300 mL to 1 L with fixed number of glasses), as compared to varying the number of glasses (1, 3 and 10 for a constant volume). These finding are in agreement with previous study by Davis and Janke (2008) showing that the quantity of ingested water is more important than the timing of ingestion for 24 hours intentional intrusion. In general, the variations were more noticeable when the number of glasses jumped from 1 to 3 than switching from 3 to 10 glasses. Previous studies also observed that 3 glasses per day can lead to higher infection risk compared to the scenario that assumed the total daily intake volume was collected once a day (Blokker et al. 2018, Van Abel et al. 2014).

8.4 What are the regulatory and management implications of the findings?

8.4.1 Can the intrusion events be detected by the standard *E. coli* sampling protocols?

The goal of regulatory sampling is to provide comprehensive understanding of water quality and ensure safe drinking water to consumers. *E. coli* is used in the regulations as a reference indicator organism of potential contamination in the distribution systems (Federation of Canadian Municipalities (FCM) and National Research Council (NRC-CNRC) 2004, United States Environmental Protection Agency (USEPA) 2010). In Chapter 5, the temporal and spatial distribution of *E. coli* using different types of disinfectants was evaluated and compared after 4, 9, and 14 hours from the start of intrusion. For both disinfectants, after 4 hours from the start of intrusion, while the contaminated water still was entering the network, high *E. coli* concentration > 1000 CFU/100 mL could be found at or downstream of intrusion zones. In the chlorinated system, the number of nodes with positive for *E. coli* was very low after the end of intrusion. ***The limited positive nodes in the presence of chlorine demonstrate the challenge of any confirmation of contamination, unless samples are collected during the intrusion event at or downstream of the intrusion locations***. However, determining these optimal sampling locations and deploying rapidly these areas for sampling at the right time may not be practical. The number of nodes was < 10 nodes after 4 and 9 hours after the end of intrusion (Figure 5.5).

In the chlorinated system, by the end of intrusion, *E. coli* was propagated to more nodes (826, after 9 hours) although at low concentrations (Figure 5.5). The probability of detecting positive *E. coli* was estimated using a Poisson distribution at each node and each hour from the beginning of the intrusion up to 20 hours. With this information, one can determine the best time and location for sampling. ***In chlorinated system, for sampling volume of 100 mL, the nodal mean detection probability of E. coli was more than 0.1 at 166 nodes in the first two 5-hour intervals (Figure 5.8).*** Our simulations offer a case study that can benefit the water utilities by allowing them to improve their sampling schedules using numerical predictions targeting areas with a high likelihood of detecting contaminants. With such an approach, negative results could be relied upon to provide a stronger basis to lift or avoid a BWA. Very few studies have investigated the effectiveness of existing statutory sampling protocols by using hydraulic modeling and simulations of contamination events (Blokker et al. 2018, van Lieverloo et al. 2007). Both studies indicate low detection probability of contamination using standard monitoring programs, even though they assumed that *E. coli* propagated throughout the network as conservative species with no inactivation. Our results are in agreement and show that the detection is even more challenging in the presence of chlorine.

Regulations mandate zero *E. coli* per 100 mL volume of the sample (EPA Office of Environmental Enforcement 2009). ***The selection of a reference volume influences the probability of detecting E. coli.*** Large volume sampling, rather than the conventional 100 mL, has been used in field study to increase the probability of detecting *E. coli* and total coliform in supply zones (Hambsch et al. 2007, Hargy et al. 2010). In the presence of chloramine, increasing the sampling volume by a factor of 10 (1 L) improved the detection probabilities, especially in the first 10 hours after the intrusion event is over (Figure 5.8 and Figure 5.9). During the second 5-hour period of post intrusion, the 75 percentile of the mean probability of detecting positive *E. coli* (for 2905 nodes that experience *E.*

coli ≥ 10-6 CFU/L at any time over the whole simulation) was increased from 2% to 15% by augmenting the sampling volume from 100 mL to 1 L. Our findings agree with those from Hanninen et al. (2003) who examined three waterborne outbreaks in Finland and observed that the detection probability of *E. coli* and coliform was increased for larger volumes (1 to 2 L) using membrane filtration.

8.4.2 Do we need a system wide BWA due to low/negative pressure events?

The main goal of a BWA is to protect consumers against potential microbiological risks (Health Canada 2015). One of the objectives of this project was to look at the possibility of issuing sectorial BWAs, instead of a system wide BWA, after events leading to sustained pressure losses.

DDA may lead to unjustified wide BWA. First, our results (Chapter 4) showed that DDA overestimated the number of nodes and the extent of areas at risk of low/negative pressures. Therefore, a more realistic approach under PDCs, i.e. PDA, should be used for predicting low/negative pressure values as well as spatial clustering of theses nodes, which can affect the boundaries of BWA zones.

BWA zones should not only be determined based on pressure values. Secondly, the spatial and temporal distribution of *E. coli* across the network during and after 5 hours of intrusion event was investigated in the absence and presence of different types and concentrations of disinfectant residuals (Chapter 5). The results showed that contamination can be transported to the areas other than the low-pressure nodes (> 10 m). On the other hand, contamination never reached some nodes in low-pressure zones (< 10 m) (Figure 5.10). Therefore, the BWA zones should not only be determined based on low/negative pressure nodes under PDCs, but also based on intrusion/backflow locations, volumes, contaminant concentrations, the efficacy of disinfectant residuals on the contaminant, and the fate and transport of contaminants that depend on the water path during both pressure-deficient and normal operating conditions.

Spatial/temporal distribution of nodal risks for issuing sectorial boil water advisory. In Chapter 6, the spatial distribution of nodal infection risk by *Cryptosporidium* resulting from different intrusion durations (1, 10 and 24 hours) showed that duration of the event is a key factor in defining the areas subjected to BWA. Short duration of PDCs/intrusion (1 h) may not necessarily lead to system wide BWA as the sum of nodal infection risk over a vast area of the network is < 0.2 as compared to 84 throughout the whole network (Figure 6.6). Furthermore, avoiding unjustified system wide BWA will limit the burden to the consumers. However, it should be noted that our finding only considers intrusion through leakage points. In the case of backflow from potential cross-connections or intrusion form AVVs, the areas at risk may be changed. The location of contaminants has a great impact on the extend of area receiving contaminates (Hart et al. 2019). The temporal distribution of nodal risks, daily versus event, is investigated in Chapter 6 to determine the duration of BWA and the impact of timely response on the public health risk. Data showed that for 1 h intrusion event (started from 6:30 to 7:30 PM), if the preventive/corrective action was delayed for 5 hours, it may lead to infection of up to 71 people. As compared to 99 for the 4-day observation. At the end, the infection risk for different pressure zones (identified based on nodal pressure during PDCs) at each day is calculated. Results showed that, on day 2 the number of infected people for nodes with P > 15 m was still significant (6 people) indicating that preventive/corrective actions cannot only be limited to the areas with low-pressure under PDCs. It is in agreement with results reported in Chapter 5 for *E. coli* propagation throughout the network in the absence of disinfectant or in the presence of chloramine.

The work presented here will benefit the water utilities by providing insight into when and where to issue a BWA during PDCs to minimize both the areas affected by BWA and the adverse effects of contaminant propagation in water distribution networks to ensure safe drinking water to consumers. More simulations are required to investigate other types of PDCs, with different durations and severities, to be able to provide more detailed guidance on the duration and extent of pressure drops that require corrective/preventive actions.

8.5 Project contributions

This project brought some original contributions to the field:

- First applications of multispecies water quality analysis based on pressure-driven hydraulic analysis using the developed approach in this study (MSWQ-PDA) to a full-scale distribution system (30,077 nodes).
- First estimation of intrusion volume under sustained PDCs by adjusting intrusion volumes, and consequently contamination mass rate, at each node based on internal pressure values using PDA and state of pipes (age/materials).
- Contribution to the improvement of available commercial tools.
- Development of several modeling techniques for more realistic simulation of intrusion events using the existing tool such as the variation of decay constant of nth-order model ($K_{intrusion}$ versus K_{normal}) in contaminated and non-contaminated zones.
- Demonstration that BWA cannot be determined only based on pressure criteria.
- First demonstration of modeling *E. coli* intrusion for confirmation and clearance sampling in the presence of disinfectant residuals.
- Probability of detecting *E. coli* calculated at each node at different times, during and after intrusion with different sampling volumes. The results can be used to reevaluate/improve the confirmation/clearance sampling strategies in terms of timing, location, and volume sample.
- Integration of the consumers' behavior during PDCs into the QMRA model by modifying the kitchen tap use based on demand availability during PDCs using PDA.
- Daily nodal infection risk maps for issuing timely boil water notices and identify areas to prioritize for corrective actions

8.6 Study limitations and sources of uncertainties

Validation our modeling results with field data in complex operating water distribution systems is not feasible as creating intentional sustained PDCs in the network and extensive monitoring would be required. In this study, it is attempted to reduce the uncertainties and improve assumptions in modeling accidental intrusion and propagation of contaminants under sustained PDCs lasting few hours.

There are however several limitations and sources of uncertainties in this work, which can be categorized into three groups:

A) Hydraulic sources of uncertainty

- Improved calibration of water quality model, taking into account nodal demand and residual disinfectant data would be needed to validate simulations.
- Field validation of PDA pressure estimates and more investigations on the pressure-demand relationships and the parameters in these equations to more accurately model the system behavior under substandard pressure conditions.
- Considering the difference between the elevation of the node in the model and the taps at different floors as the pressure may become zero at the elevated taps before the pipe internal pressure becomes zero.
- Investigating the impact of the level of skeletonization of the water distribution system model on hydraulic and water quality results.
- The impact of different factors such as the shape of leakage orifice, soil hydraulics and the spatial distribution of leaks on the estimation of intrusion volume are not considered.
- Evaluation if the discharge coefficient in the case of exit conditions (leakage) can be represented by entry conditions (intrusion).

B) Water quality sources of uncertainty

- The methodology used to attribute demand to specific nodes brings uncertainty in linking water quality to a specific node.
- Accounting for the variations of intrusion decay in time and space. Assuming the same intrusion decay for the contaminated zones regardless of dilutions may underestimate the chlorine residuals.
- More investigation on the selection of the disinfectant and microbial kinetic model and the decay constants on both bulk and biofilm.
- Investigating the impact of complete mixing and plug flow on the water quality throughout the network.
- The concentration of disinfectant consuming compounds and microorganisms outside the pipe are not known and could vary throughout the year.

C) QMRA sources of uncertainty

- Investigating more accurately the impact of a BWA on the infection risk. The demand at the nodes under advisory should be set to zero in the hydraulic model. The demand variations can influence the risk by affecting the hydraulic and water quality results.
- Investigating the impact of not considering the dispersion effect on the infection risk associated to intrusion events under sustained pressure losses.
- More investigation is needed on the selection of the dose-response equation and its contribution to the uncertainty.
- There is a lack of data on the consumption patterns, volume consumed and number of consumption events per day
- The timing of the intrusion events had a significant impact on the infection risk and should be investigated further.

In this study, due to lack of data, some conservative assumptions are made during simulation such as considering raw sewage as the contaminated water surrounding the pipes and not considering the impact of soil characteristics outside of pipelines when estimating intrusion flow rates. But, the presented approach can be used with variable input data when available. Nevertheless, the conservative modelling assumptions in this study demonstrate the value of numerical tools combined with quantitative microbial risk assessment models to quantify risk and assist regulators and utility managers. Further analysis of uncertainty can be useful to determine the impact of different assumptions on the modeling results.

CHAPTER 9 CONCLUSION AND RECOMMENDATIONS

This research project sought to assess the infection risk associated with intrusion of contaminants into drinking water distribution systems and predict changes in water quality as the result of sustained low/negative pressure conditions by proposing improved modeling tools/approaches. It was intended to provide insights to decision-makers for an appropriate and timely response to sustained PDCs.

Modeling the studied full-scale distribution system (> 30,000 nodes) under various severities of sustained pressure deficient conditions, showed that DDA:

- Cannot realistically identify the areas at risk of low/negative pressures, which can lead to system wide BWA that may not be justified.
- Can overestimate the risk of intrusion and the contaminated water ingress volume,
- Cannot define the nodes with low or no-demand during a system failure, which becomes more important for fire-flow analysis and infection risk analysis.

Therefore, a methodology was proposed that allows for the coupling of EPANET-MSX with PDA results (MSWQA-PDA) to enable simultaneous simulation of multiple water quality parameters and hydraulic conditions under sustained pressure losses. Due to simulated sustained PDCs, and without any intrusion event taking place, we found that:

- Water quality was generally poorer (i.e. lower chlorine residuals and higher water age and THM) under simulated sustained PDCs compared to normal conditions.
- The differences between water quality parameters during pressure-deficient and normal operating conditions were more pronounced for groups of nodes with low/negative pressure (< 0 or 15 m) compared to the higher-pressure zones (> 15 m) under PDCs.
- The duration of sustained low-pressure events can have a considerable impact on the water quality variations compared to normal conditions (continuous versus 5 hours).

MSWQA-PDA was used to model fate and transport of contaminants by taking into considerations the effects of both hydraulic variations during PDCs and intrusion demand on the estimated disinfectant concentrations. In the simulations, the intrusion volumes, and therefore contaminant mass rates, were adjusted for the state of pipes using the nodal leakage demands of the calibrated model, by help of a proposed approach, as well as the internal nodal pressures under PDCs using PDA.

- The presented methodology allowed us to model, for the first time, the fate and transport of *E. coli* following intrusion events resulting from sustained PDCs by considering the interactions between *E. coli* and disinfectant residuals based on realistic PDA.
- For 5 hours PDCs/intrusion scenario, chlorine residuals limited the contaminated zones and *E. coli* propagation is limited to lower pressure areas based on the pressure values under PDCs. While, without disinfectant, *E. coli* transported to higher-pressure zones ($P > 15$ m).
- For 5 hours PDCs scenario, and in the absence of any ingress of contaminated water, some chlorine is decayed during PDCs because of increase of water age. However, a typical decay was observed with intrusion-associated demand at specific areas. This indicates that online chlorine sensors, if installed at optimal locations, might help in detecting intrusion events and contributed to a timely response to a sustained depressurization event. However, monitoring the residuals cannot be used as an option to detect intrusion events in the chloraminated system.
- During 5 hours intrusion/PDCs, loss of residuals persisted for some time after the pressure was back to normal and required some time for chlorine residuals to be stabilized again.
- For continuous PDCs/intrusion scenario, *Cryptosporidium* was transported to higher-pressure areas based on the pressure values under PDCs ($P > 15$ m).
- Pressure differences were < 1 m using different pressure-demand relationships (Wagner and Tanyimboh); however, it led to significantly higher intrusion flow rate with Wagner equation (48%). In this comparison, the orifice diameter was considered as a fixed parameter (1 mm) at all the nodes, regardless of the state of pipes.

Concerning the question as if regulatory compliance *E. coli* sampling protocols can be used to detect the intrusion events, we estimated the temporal and spatial probability of detecting *E. coli* and found that:

- In the chloraminated systems, targeted spatial-temporal sampling with high volume will increase the probability of detecting *E. coli* and will assist in avoiding false negatives.

- The probability of detecting *E. coli* by sampling in the chlorinated system is extremely low unless sampling is immediately directed to the targeted sites. For simulated scenarios, the spatial and temporal maps of *E. coli* suggest that a timely deployment for effective sampling is unlikely in the presence of chlorine.

- Following pressure losses in the network, using standard monitoring programs to confirm contamination or verify clearance may lead to false negatives as sampling is likely to be conducted at the wrong sites and too late

- Appropriate numerical tools can provide valuable insight into the regulation to revise sampling programs in terms of timing, location and sample volume for more reliable confirmation and clearance sampling. This can be done by taking into account the duration, intensity and locations of intrusion events caused by the pressure drop as well as the efficacy of disinfectant residuals in the network on the related contaminant.

The quantification of the infection risk associated with the occurrence of sustained low/negative pressure events in drinking water distribution systems using the improved tools is an important contribution of this thesis. To this aim, the advanced QMRA model developed by Blokker et al. (2018) was customized and coupled with the water quality calculations based on PDA by taking into account the consumers’ behavior under PDCs. In summary, we conclude:

- Varying the sewage concentration surrounding buried water mains in the model (1 to 560 oocysts/L) led to increase in the number of infected people by 235-fold, for 24 hour intrusion. Therefore, selectively choosing site-specific outside contamination concentration can highly improve the infection risk estimations. Event of 1 h led to lower numbers of infected people by 17-fold as compared with a long duration 24-hour event. The nodal risk maps confirm that duration is a key factor to identify the boundaries of BWA or corrective actions.

- Temporal infection risk distribution for the 1 h system wide event showed that delaying response for 5 hours could lead to infection of up to 71 people. Such a delay is highly probable.

- Considering the consumption event for consumers at nodes with DSR > 5% (instead of DSR > 0) during low/negative pressures led to a sharp decrease of 65% in the number of infected people at the day that intrusion occurred (1 h). Informing consumers not to drink water when pressure is low (low flow at the tap) is a simple and effective measure to lower risk.

This project can offer insight into the development/improvement of regulations or practical recommendations for managing drinking water distribution systems under sustained pressure losses and minimize the adverse public health effects. This project also highlighted new questions/ideas for future research:

- Apply an efficient optimization approach for sensor placement to detect the contamination due to different types of low/negative pressure events in drinking water distribution systems using improved hydraulic and water quality models.
- Use the improved modeling techniques in this study to assess the risk associated with backflow of contaminated water from cross connections during sustained pressure losses using the QMRA model. In addition, to estimate the critical duration of pressure events and related pressure ranges required to contaminate the distribution system from backflows through cross-connections. It is worthy to consider, at the same time, the cost of necessary infrastructures and their maintenance for preventing huge and dangerous backflows.
- Evaluate the public health risk for system contamination by other types of microorganisms (e.g. *Giardia*, and virus) and the efficacy of disinfectant residuals on reducing the infection risks associated to accidental intrusion due to sustained PDCs.
- Use improved numerical tools to find the proper locations of chlorine booster stations and related chlorine concentrations to minimize the health risk after any intrusion event due to sustained pressure losses.
- Review guidelines for issuing boil water advisories in terms of duration and intensity of pressure losses by running more cases using the improved numerical tool.
- Investigate the implementation of district metered areas for the studied network, based on the modeling results, to limit the extent of the BWA areas and avoid system wide BWA.

- Even though PDA provides a more realistic simulation of the pressure losses compared to DDA, but the selection of an appropriate PDRs and the parameters in these equations using field data can improve the PDA predictions, especially in the case of intrusion modeling.

BIBLIOGRAPHY

Ackley, J. R. L., Tanyimboh, T. T., Tahar, B., & Templeman, A. B. (2001, Sep). *Head-driven analysis of water distribution systems.* Paper presented at the Water Software Systems: Theory and Applications- International Conference on Computing and Control for the Water Industry CCWI, Leicester (Vol. 1, pp. 183-192).

Afshar, A., & Mariño, M. A. (2014). Multiobjective consequent management of a contaminated network under pressure-deficient conditions. *Journal - American Water Works Association, 106*(10), E470-E480. doi:10.5942/jawwa.2014.106.0125

Ang, W. K., & Jowitt, P. W. (2006). Solution for water distribution systems under pressure-deficient conditions. *Journal of Water Resources Planning and Management, 132*(3), 175-185. doi:10.1061//asce/0733-9496/2006/132:3/175

Baranowski, T. M., & LeBoeuf, E. J. (2006). Consequence management optimization for contaminant detection and isolation. *Journal of Water Resources Planning and Management-Asce, 132*(4), 274-282. doi:10.1061/(ASCE)0733-9496(2006)132:4(274)

Bashi-Azghadi, S. N., Afshar, A., & Afshar, M. H. (2017a). Multi-period response management to contaminated water distribution networks: Dynamic programming versus genetic algorithms. *Engineering Optimization, 50*(3), 415-429. doi:10.1080/0305215x.2017.1318871

Bashi-Azghadi, S. N., Afshar, M. H., & Afshar, A. (2017b). Multi-objective optimization response modeling to contaminated water distribution networks: Pressure driven versus demand driven analysis. *KSCE Journal of Civil Engineering, 21*(6), 2085-2096. doi:10.1007/s12205-017-0447-7

Bentley Systems, Incorporated. (2014). WaterGEMS V8i users manual. Watertown, CT, USA.

Besner, M.-C., Broséus, R., Lavoie, J., Di Giovanni, G., Payment, P., & Prévost, M. (2010). Pressure monitoring and characterization of external sources of contamination at the site of the Payment drinking water epidemiological studies. *Environmental Science and Technology, 44*(1), 269-277. doi:10.1021/es901988y

Besner, M.-C., Ebacher, G., Jung, B. S., Karney, B., Lavoie, J., Payment, P., & Prévost, M. (2010). Negative pressures in full-scale distribution system: Field investigation, modelling, estimation of intrusion volumes and risk for public health. *Drinking Water Engineering and Science, 3*(2), 101-106. doi:10.5194/dwes-3-101-2010

Besner, M.-C., Ebacher, G., Lavoie, J., & Prévost, M. (2007, May 15-19). *Low and negative pressures in distribution systems: Do they actually result in intrusion?* Paper presented at the 9th Annual Water Distribution System Analysis Symposium, ASCE-EWRI World Environmental and Water Resources Congress, Tampa, FL, USA (pp. 10).

Besner, M.-C., Messner, M., & Regli, S. (2010, Sep 12-15). *Pathogen intrusion in distribution systems: model to assess the potential health risks.* Paper presented at the 12th Annual Conference on Water Distribution Systems Analysis (WDSA), Tucson, AZ, USA (pp. 484-493).doi:10.1061/41203(425)46

Besner, M.-C., Prévost, M., & Regli, S. (2011). Assessing the public health risk of microbial intrusion events in distribution systems: conceptual model, available data, and challenges. *Water Research, 45*(3), 961-979. doi:10.1016/j.watres.2010.10.035

Betancourt, W. Q., & Rose, J. B. (2004). Drinking water treatment processes for removal of Cryptosporidium and Giardia. *Veterinary Parasitology, 126*(1-2), 219-234.

Betanzo, E. W., Hofmann, R., Hu, Z. F., Baribeau, H., & Alam, Z. (2008). Modeling the impact of microbial intrusion on secondary disinfection in a drinking water distribution system. *Journal of Environmental Engineering, 134*(4), 231-237.

Bhave, P. R. (1981). Node flow analysis of water distribution systems. *Transportation Engineering Journal, 107* 457-467.

Blokker, E. J. M., Vreeburg, J. H. G., Buchberger, S. G., & van Dijk, J. C. (2008). Importance of demand modeling in network water quality models: a review. *Drinking Water Engineering and Science Discussions, 1* 1-20.

Blokker, M., Smeets, P., & Medema, G. (2014). QMRA in the Drinking Water Distribution System. *16th Water Distribution System Analysis Conference (Wdsa2014): Urban Water Hydroinformatics and Strategic Planning, 89* 151-159. doi:10.1016/j.proeng.2014.11.171

Blokker, M., Smeets, P., & Medema, G. (2018). Quantitative microbial risk assessment of repairs of the drinking water distribution system. *Microbial Risk Analysis, 8* 22-31. doi:10.1016/j.mran.2017.12.002

Boccelli, D. L., Tryby, M. E., Uber, J. G., Rossman, L. A., Zierolf, M. L., & Polycarpou, M. M. (1998). Optimal scheduling of booster disinfection in water distribution systems. *Journal of Water Resources Planning and Management, 124*(2), 99-110.

Boccelli, D. L., Tryby, M. E., Uber, J. G., & Summers, R. S. (2003). A reactive species model for chlorine decay and THM formation under rechlorination conditions. *Water Research, 37*(11), 2654-2666. doi:10.1016/s0043-1354(03)00067-8

Boulos, P. F., Karney, B. W., Wood, D. J., & Lingireddy, S. (2005). Hydraulic transient guidelines for protecting water distribution systems. *Journal American Water Works Association, 97*(5), 111-124.

Brown, D. (2009). *The management of trihalomethanes in water supply systems.* (Ph.D., The University of Birmingham, Birmingham, UK). Retrieved from http://etheses.bham.ac.uk/364/

Brown, D., Bridgeman, J., & West, J. R. (2011). Predicting chlorine decay and THM formation in water supply systems. *Reviews in Environmental Science and Bio/Technology, 10*(1), 79-99. doi:10.1007/s11157-011-9229-8

Canadian Council of Ministers of the Environment (CCME). (2004). *From source to tap: guidance on the multi-barrier approach to safe drinking water* (Report No. PN 1334). Winnipeg, Manitoba, Canada: Retrieved from http://www.ccme.ca/assets/pdf/mba_guidance_doc_e.pdf

Centers for Disease Control and Prevention (CDC). (2013). *Drinking water advisory communication toolbox*. Retrieved from http://www.cdc.gov/healthywater/emergency/dwa-comm-toolbox/index.html

Chase, D. V. (2000). Operation of water distribution systems. In *Water Distribution Systems Handbook* (pp. 15.11-15.16).

Cheung, P. B., Van Zyl, J. E., & Reis, L. F. R. (2005, Sep 5-7). *Extension of epanet for pressure driven demand modeling in water distribution system.* Paper presented at the Eighth International Conference on Computing and Control for the Water Industry CCWI2005 - Water Management for the 21st Century, Exeter, UK (pp. 215-226).

Ciaponi, C., & Creaco, E. (2018). Comparison of pressure-driven formulations for WDN simulation. *Water, 10*(4). doi:10.3390/w10040523

Ciaponi, C., Franchioli, L., Murari, E., & Papiri, S. (2014). Procedure for defining a pressure-outflow relationship regarding indoor demands in pressure-driven analysis of water distribution networks. *Water Resources Management, 29*(3), 817-832. doi:10.1007/s11269-014-0845-2

Clayton, C. R. I., & van Zyl, J. E. (2007, June 1,). *The effect of pressure on leakage in water distribution systems.* Paper presented at the Proceedings of the ICE - Water Management (Vol. 160, pp. 109-114).doi:10.1680/wama.2007.160.2.109

Collins, R., Besner, M.-C., Beck, S., Karney, B., & Boxall, J. (2010, September 13, 2010). *Intrusion modelling and the effect of ground water conditions.* Paper presented at the 12th Annual WDSA Conference, The University of Arizona, Tucson, Arizona, USA.

Courtis, B. J., West, J. R., & Bridgeman, J. (2009). Chlorine demand-based predictive modeling of THM formation in water distribution networks. *Urban Water Journal, 6*(6), 407-415. doi:10.1080/15730620903038461

Craun, G. F., Brunkard, J. M., Yoder, J. S., Roberts, V. A., Carpenter, J., Wade, T., . . . Roy, S. L. (2010). Causes of outbreaks associated with drinking water in the United States from 1971 to 2006. *Clinical Microbiology Reviews, 23*(3), 507-528. doi:10.1128/cmr.00077-09

Craun, G. F., & Calderon, R. L. (2001). Waterborne disease outbreaks caused by distribution system deficiencies. *Journal American Water Works Association, 93*(9), 64-75.

Craun, G. F., Nwachuku, N., Calderon, R. L., & Craun, M. F. (2002). Outbreaks in drinking-water systems, 1991-1998. *Journal of Environmental Health, 65*(1), 16-23.

Davis, M. J., & Janke, R. (2008). Importance of exposure model in estimating impacts when a water distribution system is contaminated. *Journal of Water Resources Planning and Management, 134*(5), 449-456.

Davis, M. J., & Janke, R. (2009). Development of a probabilistic timing model for the ingestion of tap water. *Journal of Water Resources Planning and Management, 135*(5), 397-405.

Davis, M. J., Janke, R., & Taxon, T. N. (2018). Mass imbalances in EPANET water-quality simulations. *Drinking Water Engineering and Science, 11*(1), 25-47. doi:10.5194/dwes-11-25-2018

Digiano, F. A., & Zhang, W. (2005). Pipe section reactor to evaluate chlorine-wall reaction. *Journal American Water Works Association, 97*(1), 74-85.

Douglas, I., Elliott, J., & Besner, M.-C. (2018, Nov 11-14). *Evaluating risks to water quality from sustained loss of pressure events in the distribution system.* Paper presented at the American Water Works Association-Water Quality Technology Conference (WQTC), Toronto, ON, Canada (pp. 26).

Ebacher, G., Besner, M.-C., Clément, B., & Prévost, M. (2012). Sensitivity analysis of some critical factors affecting simulated intrusion volumes during a low pressure transient event in a full-scale water distribution system. *Water Research, 46*(13), 4017–4030. doi:10.1016/j.watres.2012.05.006

Ebacher, G., Besner, M.-C., Lavoie, J., Jung, B. S., Karney, B. W., & Prévost, M. (2009, May 17-22). *Comparison of pressures simulated using transient analysis with field data from a full-scale distribution system.* Paper presented at the 11th Water Distribution Systems Analysis Symposium, Kansas City, MO, USA (pp. 9).

Ebacher, G., Besner, M.-C., Lavoie, J., Jung, B. S., Karney, B. W., & Prévost, M. (2011). Transient modeling of a full-scale distribution system: Comparison with field data. *Journal of Water Resources Planning and Management, 137*(2), 173-182. doi:10.1061/(ASCE)WR.1943-5452.0000109

Ebacher, G., Besner, M.-C., & Prevost, M. (2013). Submerged appurtenances and pipelines: An assessment of water levels and contaminant occurrence. *Journal American Water Works Association, 105*(12), E684-E698. doi:10.5942/jawwa.2013.105.0156

Ebacher, G., Besner, M.-C., & Prévost, M. (2011, May 22-26). *Quantification of the relative importance of factors contributing to intrusion in a distribution system using a full factorial design.* Paper presented at the World Environmental and Water Resources Congress 2011: Bearing Knowledge for sustainability Palm Springs, CA, USA (pp. 291-303).doi:10.1061/41173(414)32

Ebacher, G., Besner, M.-C., Prévost, M., & Allard, D. (2010, Sep 12-15). *Negative pressure events in water distribution systems: Public health risk assessment based on transient analysis outputs.* Paper presented at the 12th Annual Conference on Water Distribution Systems Analysis (WDSA), Tucson, AZ, USA (pp. 471-483).doi:10.1061/41203(425)45

Environmental Protection Agency (EPA). (2013). *Federal register Part II -National primary drinking water regulations: revisions to the total Coliform rule*. Federal register. Retrieved from http://www.gpo.gov/fdsys/pkg/FR-2013-02-13/pdf/2012-31205.pdf

EPA Office of Environmental Enforcement. (2009). *EPA drinking water advice note. Advice note no. 3: E. coli in drinking water. Version 1*. Retrieved from https://www.epa.ie/pubs/advice/drinkingwater/Advice%20Note%20No3.pdf

Erickson, J., Roberson, J. A., Friedman, M., & Smith, C. (2015). Low-pressure events: Variation in state regulations and utility practices. *Journal American Water Works Association, 107*(3), E120-E129. doi:10.5942/jawwa.2015.107.0024

Federation of Canadian Municipalities (FCM), & National Research Council (NRC-CNRC). (2004). *Monitoring water quality in the distribution system. A best pratice by the national guide to sustainable municipal infrastructure* (Report No. Version N0. 1.0). Federation of Canadian Municipalities and National Research Council.

Fisher, I., Kastl, G., & Sathasivan, A. (2011). Evaluation of suitable chlorine bulk-decay models for water distribution systems. *Water Research, 45*(16), 4896-4908.

Fujiwara, O., & Li, J. (1998). Reliability analysis of water distribution networks in consideration of equity, redistribution, and pressure-dependent demand. *Water Resources Research, 34*(7), 1843-1850. doi:10.1029/98wr00908

Germanopoulos, G. (1985). A technical note on the inclusion of pressure dependent demand and leakage terms in water supply network models. *Civil Engineering Systems, 2*(3), 171-179. doi:10.1080/02630258508970401

Gibson, J., Karney, B., & Guo, Y. (2019). Predicting health risks from intrusion into drinking water pipes over time. *Journal of Water Resources Planning and Management, 145*(3), 04019001. doi:10.1061/(ASCE)WR.1943-5452.0001039

Giustolisi, O., & Laucelli, D. (2011). Water distribution network pressure-driven analysis using the enhanced global gradient algorithm (EGGA). *Journal of Water Resources Planning and Management-Asce, 137*(6), 498-510. doi:10.1061/(Asce)Wr.1943-5452.0000140

Giustolisi, O., Savic, D., & Kapelan, Z. (2008). Pressure driven demand and leakage simulation for water distribution networks. *Journal of Hydraulic Engineering, 134*(5), 626-635. doi:10.1061/(ASCE)0733-9429(2008)134:5(626)

Giustolisi, O., & Walski, T. M. (2012). Demand Components in Water Distribution Network Analysis. *Journal of Water Resources Planning and Management, 138*(4), 356-367. doi:10.1061/(asce)wr.1943-5452.0000187

Gorev, N. B., & Kodzhespirova, I. F. (2013). Noniterative implementation of pressure-dependent demands using the hydraulic analysis engine of EPANET 2. *Water Resources Management, 27*(10), 3623-3630. doi:10.1007/s11269-013-0369-1

Government of Ontario. (2003). *Procedure for disinfection of drinking water in Ontario*. Ontario, Canada: Retrieved from http://www.ene.gov.on.ca/envision/gp/4448e.pdf

Great Lakes Upper Mississippi River Board of State Public Health and Environmental Managers. (2007). *Recommended standards for water works*. Albany, New York, USA: Health Research Inc., Health Education Services Division. Retrieved from http://www.leafocean.com/test/10statepreface.html

Gullick, R. W., LeChevallier, M. W., Case, J., Wood, D. J., Funk, J. E., & Friedman, M. J. (2005). Application of pressure monitoring and modelling to detect and minimize low pressure events in distribution systems. *Water Supply: Research and Technology-Aqua, 54*(2), 65-81.

Gullick, R. W., Lechevallier, M. W., Svindland, R. C., & Friedman, M. J. (2004). Occurrence of transient: Low and negative pressures in distribution systems. *Journal American Water Works Association, 96*(11), 52-66.

Gupta, R. (2015, May 17-21). *History of pressure-dependent analysis of water distribution networks and its applications.* Paper presented at the World Environmental and Water Resources Congress 2015, Austin, TX, USA (pp. 755-765).doi:10.1061/9780784479162.070

Gupta, R., & Bhave, P. R. (1996). Comparison of methods for predicting deficient-network performance. *Journal of Water Resources Planning and Management, 122*(3), 4. doi:10.1061/(ASCE)0733-9496(1996)122:3(214)

Gupta, R., Dhapade, S., Ganguly, S., & Bhave, P. R. (2012). Water quality based reliability analysis for water distribution networks. *ISH Journal of Hydraulic Engineering, 18*(2), 80-89. doi:10.1080/09715010.2012.662430

Guzman-Herrador, B., Carlander, A., Ethelberg, S., Freiesleben de Blasio, B., Kuusi, M., Lund, V., . . . Nygard, K. (2015). Waterborne outbreaks in the Nordic countries, 1998 to 2012. *Eurosurveillance, 20*(24), 1-10.

Haas, C. N., & Karra, S. B. (1984a). Kinetics of microbial inactivation by chlorine. I. Review of results of demand-free systems. *Water Research, 18*(11), 1443-1449.

Haas, C. N., & Karra, S. B. (1984b). Kinetics of wastewater chlorine demand exertion. *Journal of the Water Pollution Control Federation, 56*(2), 170-173.

Hambsch, B., Bockle, K., & van Lieverloo, J. H. M. (2007). Incidence of faecal contaminations in chlorinated and non-chlorinated distribution systems of neighbouring european countries. *Journal of Water and Health, 5*(Suppl. 1), 119-130.

Hamouda, M. A., Jin, X., Xu, H., & Chen, F. (2018). Quantitative microbial risk assessment and its applications in small water systems: A review. *Science of The Total Environment, 645* 993-1002. doi:10.1016/j.scitotenv.2018.07.228

Hanninen, M. L., Haajanen, H., Pummi, T., Wermundsen, K., Katila, M. L., Sarkkinen, H., . . . Rautelin, H. (2003). Detection and Typing of *Campylobacter jejuni* and *Campylobacter coli* and analysis of indicator organisms in three waterborne outbreaks in Finland. *Applied and Environmental Microbiology, 69*(3), 1391-1396. doi:10.1128/aem.69.3.1391-1396.2003

Hargy, T. M., Rosen, J., LeChevallier, M., Friedman, M., & Clancy, J. L. (2010). A high-volume sampling method for total coliform and *E. coli*. *Journal American Water Works Association, 102*(3), 79-+.

Hart, D., Rodriguez, J. S., Burkhardt, J., Borchers, B., Laird, C., Murray, R., . . . Haxton, T. (2019). Quantifying hydraulic and water quality uncertainty to inform sampling of drinking water distribution systems. *Journal of Water Resources Planning and Management, 145*(1), 04018084. doi:10.1061/(ASCE)WR.1943-5452.0001005

Hatam, F., Besner, M.-C., Ebacher, G., & Prévost, M. (2018a). Combining a multispecies water quality and pressure-driven hydraulic analysis to determine areas at risk during sustained pressure-deficient conditions in a distribution system. *Journal of Water Resources Planning and Management, 144*(9), 04018057. doi:10.1061/(ASCE)WR.1943-5452.0000976

Hatam, F., Besner, M.-C., Ebacher, G., & Prévost, M. (2018b, Jul 23-25). *Investigating the impact of sustained low pressure events on water quality in water supply networks using pressure-driven analysis* Paper presented at the 1st International WDSA/CCWI 2018 Joint Conference, Kingston, ON, Canada.

Hatam, F., Besner, M.-C., Ebacher, G., & Prévost, M. (submitted). Improvement of Accidental Intrusion Prediction Due to Sustained Low-Pressure Conditions: Implications for Chlorine and E. coli Monitoring in Distribution Systems. *Journal of Water Resources Planning and Management*.

He, G., Zhang, T., Zheng, F., & Zhang, Q. (2018). An efficient multi-objective optimization method for water quality sensor placement within water distribution systems considering contamination probability variations. *Water Research, 143* 165-175. doi:10.1016/j.watres.2018.06.041

Health Canada. (2015). *Guidance for issuing and rescinding boil water advisories in canadian drinking water supplies*. Ottawa, ON, CANADA: Minister of Health. Retrieved from http://publications.gc.ca/collections/collection_2013/sc-hc/H128-1-09-578-eng.pdf

Helbling, D. E., & Vanbriesen, J. M. (2009). Modeling residual chlorine response to a microbial contamination event in drinking water distribution systems. *Journal of Environmental Engineering, 135* 918-927.

Hlavinek, P., Popovska, C., Marsalek, J., & Kukharchyk, T. (2008). *Risk management of water supply and sanitation systems.* Paper presented at the Proceedings of the NATO Advanced Research Workshop, Ohrid, Macedonia.

Hua, F. (2000). *The effects of water treatment works on chlorine decay and THM formation.* (Ph.D., University of Birmingham, UK).

Hua, F., West, J. R., Barker, R. A., & Forster, C. F. (1999). Modelling of chlorine decay in municipal water supplies. *Water Research, 33*(12), 2735-2746.

Hundsdorfer, W. H., & Verwer, J. G. (2003). *Numerical solution of time-dependent advection-diffusion-reaction equations*. Berlin; New York: Springer.

Hunter, P. R., Chalmers, R. M., Hughes, S., & Syed, Q. (2005). Self-reported diarrhea in a control group: a strong association with reporting of low-pressure events in tap water. *Clinical Infectious Diseases, 40*(4), e32-e34.

Islam, N., Farahat, A., Al-Zahrani, M. A. M., Rodriguez, M. J., & Sadiq, R. (2015). Contaminant intrusion in water distribution networks: Review and proposal of an integrated model for decision making. *Environmental Reviews, 23*(3), 337-352. doi:10.1139/er-2014-0069

Islam, N., Rodriguez, M. J., Farahat, A., & Sadiq, R. (2017). Minimizing the impacts of contaminant intrusion in small water distribution networks through booster chlorination optimization. *Stochastic Environmental Research and Risk Assessment, 31*(7), 1759-1775. doi:10.1007/s00477-017-1440-x

Islam, N., Rodriguez, M.J., Farahat, A. and Sadiq, R. (2017). Minimizing the impacts of contaminant intrusion in small water distribution networks through booster chlorination optimization. *Stochastic Environmental Research and Risk Assessment, 31(7)* 1759-1775.

Jadas-Hécart, A., El Morer, A., Stitou, M., Bouillot, P., & Legube, B. (1992). The chlorine demand of a treated water. *Water Research, 26*(8), 1073-1084.

Jinesh Babu, K. S., & Mohan, S. (2012). Extended period simulation for pressure-deficient water distribution network. *Journal of Computing in Civil Engineering, 26*(4), 498-505. doi:10.1061/(asce)cp.1943-5487.0000160

Jun, L., & Guoping, Y. (2013). Iterative Methodology of Pressure-Dependent Demand Based on EPANET for Pressure-Deficient Water Distribution Analysis. *Journal of Water Resources Planning and Management, 139*(1), 34-44. doi:10.1061/(asce)wr.1943-5452.0000227

Kabaasha, A. M., Piller, O., & van Zyl, J. E. (2018). Incorporating the modified orifice equation into pipe network solvers for more realistic leakage modeling. *Journal of Hydraulic Engineering, 144*(2). doi:10.1061/(asce)hy.1943-7900.0001410

Karamouz, M., Zanjani, S., & Zahmatkesh, Z. (2017). Vulnerability assessment of drinking water distribution networks to chemical and biological contaminations: Case study. *Journal of Water Resources Planning and Management, 143*(6). doi:10.1061/(asce)wr.1943-5452.0000764

Khorshidi, M. S., Nikoo, M. R., & Sadegh, M. (2018). Optimal and objective placement of sensors in water distribution systems using information theory. *Water Research, 143* 218-228. doi:10.1016/j.watres.2018.06.050

Kirmeyer, G. J., Friedman, M., Martel, K., Howie, D., LeChevallier, M., Abbaszadegan, M., . . . Harbour, J. (2001). *Pathogen intrusion into the distribution system* (Report No. 90835). Denver, Colorado, USA: American Water Works Association Research Foundation, American Water Works Association and United States Environmental Protection Agency. Retrieved from Il y a une copie PDF dans le répertoire Directions//Publications_Électroniques France

Kirmeyer, G. J., Friedman, M., Martel, K. D., Noran, P. F., & Smith, D. (2001). Practical guidelines for maintaining distribution system water quality. *Journal American Water Works Association, 93*(7), 62-73.

Kirmeyer, G. J., Thomure, T. M., Rahman, R., Marie, J. L., LeChevallier, M. W., Yang, J., . . . Schneider, O. (2014). *Effective microbial control strategies for main breaks and depressurization* (Report No. 4307). Denver, CO, USA: Water Research Foundation. Retrieved from http://www.waterrf.org/Pages/Projects.aspx?PID=4307

Klosterman, S., Hatchett, S., Murray, R., Uber, J., & Bocelli, D. (2009). *Comparing single- and multi-species water quality modeling approaches for assessing contamination exposure in drinking water distribution systems.* Paper presented at the World Environmental and Water Resources Congress: Great Rivers Kansas City, Missouri, USA (pp. 1-14).

Kohpaei, A. J., Sathasivan, A., & Aboutalebi, H. (2011). Effectiveness of parallel second order model over second and first order models. *Desalination and Water Treatment, 32*(1-3), 107-114. doi:10.5004/dwt.2011.2685

LeChevallier, M. W. (1999). The case for maintaining a disinfectant residual. *Journal American Water Works Association, 91*(1), 86-94.

LeChevallier, M. W., Xu, M., Yang, J., Teunis, P., & Fleming, K. K. (2011). *Managing distribution system low transient pressures for water*. Water Research Foundation and American Water Works Service Company, Inc. Retrieved from PDF dans le répertoire Étudiants/AAAAEtudiant_EndNote2011/PUBLICATIONS_Electroniques France

Lee, H., Yoo, D., Kim, J., & Kang, D. (2015). Hydraulic simulation techniques for water distribution networks to treat pressure deficient conditions. *Journal of Water Resources Planning and Management* 06015003. doi:10.1061/(ASCE)WR.1943-5452.0000624

Lee, M. H., Yoo, D. G., Kang, D., Jun, H., & Kim, J. H. (2016). Uncertainty quantification of pressure-driven analysis for water distribution network modeling. *Water Science and Technology, 16*(3), 599-610. doi:10.2166/ws.2015.168

Lee, Y., & Buchberger, S. G. (2000). *Is Dispersion Important in Water Distribution Systems?* Paper presented at the In Proceedings of ASCE 2000 Joint Conference on Water Resources Engineering and Water Resources Planning and Management, Minneapolis, MN, USA.

Lindley, T. R., & Buchberger, S. G. (2002). Assessing intrusion susceptibility in distribution systems. *Journal American Water Works Association, 94*(6), 66-79.

Liserra, T., Maglionico, M., Ciriello, V., & Di Federico, V. (2014). Evaluation of reliability indicators for wdns with demand-driven and pressure-driven models. *Water Resources Management, 28*(5), 1201-1217. doi:10.1007/s11269-014-0522-5

Liu, J., Yu, G., & Savic, D. (2011). *Deficient-network simulation considering pressure-dependent demand.* Paper presented at the ICPTT 2011: Sustainable Solutions For Water, Sewer, Gas, And Oil Pipelines (pp. 886-900).doi:10.1061/41202(423)94

Mahmoud, H. A., Savić, D., & Kapelan, Z. (2017). New pressure-driven approach for modeling water distribution networks. *Journal of Water Resources Planning and Management, 143*(8). doi:10.1061/(ASCE)WR.1943-5452.0000781

Mamizadeh, J., & Sharoonizadeh, S. (2016). Application of modified complementary reservoir approach in analysis of water distribution networks under pressure-deficient conditions. *Urban Water Journal, 14*(4), 386-393. doi:10.1080/1573062x.2016.1171884

Mays, L. W. (2000). *Water distribution systems handbook*: McGraw-Hill.

Mays, L. W. (2004). *Water supply systems security*. New York: McGraw-Hill.

McInnis, D. (2004). A relative-risk framework for evaluating transient pathogen intrusion in distribution systems. *Urban Water Journal, 1*(2), 113-127.

Ministère de l'environnement du Québec. (2002). *Directive 001 - Captage et distribution de l'eau*. Québec, Canada: Retrieved from http://www.mddep.gouv.qc.ca/eau/potable/installation/documents/Directive001.pdf

Ministère du Développement Durable de l'Environnement et des Parcs du Québec (MDDEP). (2005). *Règlement sur la qualité de l'eau potable*. Canada: Gouvernement du Québec. Retrieved from http://www2.publicationsduquebec.gouv.qc.ca/dynamicSearch/telecharge.php?type=2&file=//Q_2/Q2R18_1_1.htm

Muray, R., & Adachi, J. (2011). *Predicting inactivation of Bacillus spores and E. coli when introduced into a water distribution system with growth medium.* Paper presented at the American Water Works Association AWWA-WQTC Conference Proceedings, Phoenix, Arizona, USA (pp. 3).doi:10.1061//asce/0733-9496/2002/128:5/334

National Research Council of the National Academies. (2006). *Drinking water distribution systems: assessing and reducing risks*. Washington, DC, USA: The National Academies Press.

Nyende-Byakika, S., Ngirane-Katashaya, G., & Ndambuki, J. M. (2012). Comparative analysis of approaches to modelling water distribution networks. *Civil Engineering and Environmental Systems, 29*(1), 79-89. doi:10.1080/10286608.2012.663358

Nygard, K., Wahl, E., Krogh, T., Tveit, O. A., Bohleng, E., Tverdal, A., & Aavitsland, P. (2007). Breaks and maintenance work in the water distribution systems and gastrointestinal illness: a cohort study. *International of Journal Epidemiology, 36*(4), 873-880.

Ohar, Z., Lahav, O., & Ostfeld, A. (2015). Optimal sensor placement for detecting organophosphate intrusions into water distribution systems. *Water Res, 73* 193-203. doi:10.1016/j.watres.2015.01.024

Ozger, S. S. (2003). *A semi-pressure-driven approach to reliability assessment of water distribution.* (Ph. D., Arizona State University). (UMI Number: 3109593)

Pacchin, E., Alvisi, S., & Franchini, M. (2017). A new non-iterative method for pressure-driven snapshot simulations with *EPANET*. *Procedia Engineering, 186* 135-142. doi:10.1016/j.proeng.2017.03.219

Paez, D., Suribabu, C. R., & Filion, Y. (2018). Method for extended period simulation of water distribution networks with pressure driven demands. *Water Resources Management, 32*(8), 2837-2846. doi:10.1007/s11269-018-1961-1

Pathirana, A. (2010, Sep 12-15). *Epanet2 desktop application for pressure driven demand modeling.* Paper presented at the Water Distribution System Analysis 2010 – WDSA2010,, Tucson, AZ, USA (pp. 10).

Payment, P. (1999). Poor efficacy of residual chlorine disinfectant in drinking water to inactivate waterborne pathogens in distribution systems. *Canadian Journal of Microbiology, 45*(8), 709-715.

Payment, P. (2003). *Enlèvement des microorganismes pathogènes et des bactéries indicatrices par les stations de traitement des eaux usées municipales situées sur la rivière des Mille îles* (Report No. 3336.11.00.01). Ministère de l'Environnement du Québec. Programme d'aide à la recherche et au développement en environnement (PARDE). Retrieved from http://sdis.inrs.uquebec.ca/documents/2003_PARDE_Mille_Iles.pdf

Payment, P., Plante, R., & Cejka, P. (2001). Removal of indicator bacteria, human enteric viruses, Giardia cysts, and Cryptosporidium oocysts at a large wastewater primary treatment facility. *Canadian Journal of Microbiology, 47*(3), 188-193.

Payment, P., Richardson, L., Siemiatycki, J., Dewar, R., Edwardes, M., & Franco, E. (1991). A randomized trial to evaluate the risk of gastrointestinal disease due to consumption of drinking water meeting current microbiological standards. *American Journal of Public Health, 81*(6), 703-708.

Payment, P., Siemiatycki, J., Richardson, L., Renaud, G., Franco, E., & Prévost, M. (1997). A prospective epidemiological study of gastrointestinal health effects due to the consumption of drinking water. *International Journal of Environmental Health Research, 7*(1), 5-31.

Propato, M., & Uber, J. G. (2004). Vulnerability of water distribution systems to pathogen intrusion: How effective is a disinfectant residual? *Environmental Science & Technology, 38*(13), 3713-3722. doi:10.1021/es035271z

Rasekh, A., & Brumbelow, K. (2014). Drinking water distribution systems contamination management to reduce public health impacts and system service interruptions. *Environmental Modelling & Software, 51* 12-25. doi:10.1016/j.envsoft.2013.09.019

Rasekh, A., & Brumbelow, K. (2015). A dynamic simulation–optimization model for adaptive management of urban water distribution system contamination threats. *Applied Soft Computing, 32* 59-71. doi:10.1016/j.asoc.2015.03.021

Reddy, L. S., & Elango, K. (1989). Analysis of water distribution networks with head-dependent outlets. *Civil Engineering Systems, 6*(3), 102-110. doi:10.1080/02630258908970550

Renzetti, S., & Dupont, D. (2013). *Buried treasure: The economics of leak detection and water loss prevention in Ontario*.

Rossman, A. L. (2007). Discussion of "solution for water distribution systems under pressure-deficient conditions" by Wah Khim Ang and Paul W. Jowitt. *Journal of Water Resources Planning and Management, 133*(6), 568-568. doi:10.1061/(ASCE)0733-9496(2007)133:6(568)

Rossman, L. A. (2000). *EPANET 2. User's manual* (Report No. EPA 600-R-00-57). Cincinnati, Ohio, USA: National Risk Management Research Laboratory, Office of Research and Development, United States Environmental Protection Agency (USEPA). Retrieved from http://www.epa.gov/nrmrl/wswrd/dw/epanet/EN2manual.PDF

Sayyed, M. A. H. A., & Gupta, R. (2013). Predicting deficient condition performance of water distribution networks. *Civil Engineering Infrastructures Journal, 46*(2), 161-173.

Sayyed, M. A. H. A., Gupta, R., & Tanyimboh, T. T. (2014, Jul 14-17). *Modelling pressure deficient water distribution networks in EPANET*. Paper presented at the Procedia Engineering-16th Water Distribution System Analysis Conference, WDSA2014 — Urban Water Hydroinformatics and Strategic Planning, Bari, Italy (Vol. 89, pp. 626-631).doi:10.1016/j.proeng.2014.11.487

Sayyed, M. A. H. A., Gupta, R., & Tanyimboh, T. T. (2015). Noniterative application of EPANET for pressure dependent modelling of water distribution systems. *Water Resources Management, 29*(9), 3227-3242. doi:10.1007/s11269-015-0992-0

Schijven, J., Forêt, J. M., Chardon, J., Teunis, P., Bouwknegt, M., & Tangena, B. (2016). Evaluation of exposure scenarios on intentional microbiological contamination in a drinking water distribution network. *Water research, 96* 148-154. doi:10.1016/j.watres.2016.03.057

Schijven, J. F., Teunis, P. F. M., Rutjes, S. A., Bouwknegt, M., & de Roda Husman, A. M. (2011). QMRAspot: a tool for quantitative microbial risk assessment from surface water to potable water. *Water Research, 45*(17), 5564-5576.

Schneider, O. D., Bukhari, Z., Hughes, D. M., Fleming, K., LeChevallier, M., Schwartz, P., . . . Lee, J. J. (2010). *Determining vulnerability and occurrence of residential backflow*. Denver, Colorado, USA: Water Research Foundation and United States Environmental Protection Agency. Retrieved from http://www.waterrf.org/ProjectsReports/PublicReportLibrary/3022.pdf

Seyoum, A. G., & Tanyimboh, T. T. (2014). Pressure-dependent network water quality modelling. *Proceedings of the Institution of Civil Engineers ICE - Water Management, 167*(6), 342-355. doi:10.1680/wama.12.00118

Seyoum, A. G., & Tanyimboh, T. T. (2017). Integration of hydraulic and water quality modelling in distribution networks: EPANET-PMX. *Water Resources Management, 31*(14), 4485-4503. doi:10.1007/s11269-017-1760-0

Seyoum, A. G., Tanyimboh, T. T., & Siew, C. (2011, Sep 5-7). *Comparison of demand driven and pressure dependent hydraulic approaches for modelling water quality indistribution networks.* Paper presented at the 11th International Conference on Computing and Control for the Water Industry CCWI 2011, Exeter, UK (pp. 619-624).

Seyoum, A. G., Tanyimboh, T. T., & Siew, C. (2013). Assessment of water quality modelling capabilities of EPANET multiple species and pressure-dependent extension models. *Water Science and Technology: Water Supply, 13*(4), 1161-1166. doi:10.2166/ws.2013.118

Shafiee, M. E., & Berglund, E. Z. (2017). Complex Adaptive Systems Framework to Simulate the Performance of Hydrant Flushing Rules and Broadcasts during a Water Distribution System Contamination Event. *Journal of Water Resources Planning and Management, 143*(4). doi:10.1061/(asce)wr.1943-5452.0000744

Shang, F., Uber, J. G., & Rossman, L. A. (2008). Modeling reaction and transport, of multiple species in water distribution systems. *Environmental Science and Technology, 42*(3), 808-814.

Shang, F., Uber, J. G., & Rossman, L. A. (2011). *EPANET multi-species extension user's manual* (Report No. EPA/600/S-07/021). Cincinnati, OH, USA: United States Environmental Protection Agency (USEPA).

Shirzad, A., Tabesh, M., Farmani, R., & Mohammadi, M. (2013). Pressure-discharge relations with application to head-driven simulation of water distribution networks. *Journal of Water Resources Planning and Management, 139*(6), 660-670. doi:10.1061/(asce)wr.1943-5452.0000305

Siew, C., & Tanyimboh, T. T. (2009, May 17-21). *Augmented gradient method for head dependent modelling of*

Water distribution networks. Paper presented at the World Environmental and Water Resources Congress 2009: Great Rivers, Kansas City, Missouri, United States (pp. 10).

Siew, C., & Tanyimboh, T. T. (2010a, Sep 1-3). *Assessment of the head dependent gradient method with reference to PRAAWDS.* Paper presented at the Integrating Water Systems – Boxall & Maksimovic (eds) (pp. 6).

Siew, C., & Tanyimboh, T. T. (2010b, September 12-15). *Pressure-dependent EPANET extension: Pressure-dependent demands.* Paper presented at the Water Distribution System Analysis 2010, Tucson, AZ, USA (pp. 10).

Siew, C., & Tanyimboh, T. T. (2011, May 22-26). *The Computational Efficiency of "EPANET-PDX".* Paper presented at the World Environmental and Water Resources Congress 2011: Bearing Knowledge for Sustainability, Palm Springs, California, United States (pp. 10).

Siew, C., & Tanyimboh, T. T. (2012). Pressure-Dependent EPANET Extension. *Water Resources Management, 26*(6), 1477-1498. doi:10.1007/s11269-011-9968-x

Smeets, P. W. M. H., Medema, G., & van Dijk, J. C. (2009). The Dutch secret: how to provide safe drinking water without chlorine in the Netherlands. *Drinking Water Engineering and Science, 2*(1), 1-14.

Smeets, P. W. M. H., Rietveld, L. C., van Dijk, J. C., & Medema, G. J. (2010). Practical applications of quantitative microbial risk assessment (QMRA) for water safety plans. *Water Science and Technology, 61*(6), 1561-1568.

Suribabu, C. R., & Neelakantan, T. R. (2011). Balancing reservoir based approach for solution to pressure deficient water distribution networks. *International Journal of Civil & Structural Engineering, 2* 9.

Suribabua, C. R., Neelakantana, T. R., & Sivakumarb, P. (2017). Improved complementary reservoir solution to evaluate nodal outflow under pressure-deficient conditions. *ISH Journal of Hydraulic Engineering* 1-7.

Tanyimboh, T. T. (2008, Aug 17-20). *Robust algorithm for head-dependent analysis of water distribution systems.* Paper presented at the Proceedings of the 10th Annual Water Distribution Systems Analysis Conference WDSA2008,, Kruger National Park, South Africa (pp. 11).

Tanyimboh, T. T., & Templeman, A. B. (2004). *A New nodal outflow function for water distribution networks.* Paper presented at the Proceeding of the 4th International Conference On Engineering Computational Technology (Vol. 80).doi:10.4203/ccp.80.64

Tanyimboh, T. T., & Templeman, A. B. (2010). Seamless pressure-deficient water distribution system model. *Proceedings of the ICE - Water Management, 163*(8), 389-396. doi:10.1680/wama.900013

Ten States Standards. (2012). *Recommended standards for water works*. Great Lakes Upper Mississippi River Board of State Public Health and Environmental Managers. Retrieved from http://10statesstandards.com/waterrev2012.pdf

Teunis, P., Davidson, A., & Deere, D. (2004). *Short term fluctuations in drinking water quality and their significance for public health*.

Teunis, P. F. M., Xu, M., Fleming, K. K., Yang, J., Moe, C. L., & LeChevallier, M. W. (2010). Enteric virus infection risk from intrusion of sewage into a drinking water distribution network. *Environmental Science and Technology, 44*(22), 8561-8566.

Tfaily, R., Papineau, I., Andrews, R. C., & Barbeau, B. (2015). Application of quantitative microbial risk assessment at 17 Canadian water treatment facilities. *Journal American Water Works Association, 107*(10), 75-75. doi:10.5942/jawwa.2015.107.0141

Tinelli, S., & Juran, I. (2017). *Numerical modeling of early bio-contamination in a water distribution system and comparison with laboratory experiments.* Paper presented at the International Conference on Sustainable Infrastructure 2017 (pp. 258-269).

Tinelli, S., Juran, I., & Cantos, W. P. (2018). Development of risk assessment tools for early detection of bio-contamination in water distribution systems. *Water Science and Technology: Water Supply, 18*(6), 1-11. doi:10.2166/ws.2018.036

Todini, E. (2006, Aug 27-30). *On the convergence properties of the different pipe network algorithms.* Paper presented at the 8th Annual Water Distribution Systems Analysis Symposium, Cincinnati, Ohio, USA (pp. 16).

Trifunovic, N., & Vairavamoorthy, K. (2012, Sep 24-27). *Simplified emitter based approach for pressure-driven demand calculations of networks with extreme topography.* Paper presented at the WDSA 2012: 14th Water Distribution Systems Analysis Conference, Adelaide, South Australia (pp. 1400-1417).

Tucciarelli, T., Criminisi, A., & Termini, D. (1999). Leak analysis in pipeline systems by means of optimal valve regulation. *Journal of Hydraulic Engineering-Asce, 125*(3), 277-285. doi:10.1061/(Asce)0733-9429(1999)125:3(277)

Tzatchkov, V., Aldama, A., & Arreguin, F. (2002). Advection-dispersion-reaction modeling in water distribution networks. *Journal of Water Resources Planning and Management, 128*(5), 334-342. doi:10.1061/(ASCE)0733-9496(2002)128:5(334)

Uber, J., Shang, F., & Rossman, L. (2004). *Extensions to EPANET for fate and transport of multiple interacting chemical or biological components.* Paper presented at the ASCE/EWRI World Water Congress, Critical transitions in Water and Environment Resources Management, Salt Lake City, Utah, USA (pp. 9).

Uber, J. G. (2010). *Multi-species network water quality modeling: Current examples, future potential, and research needs.* Paper presented at the Integrating Water Systems. Proceedings of the Tenth International Conference on Computing and Control for the Water Industry, CCWI 2009 - 'Integrating Water Systems', London, UK (pp. 13-19).

Uber, J. G., Boccelli, D. L., Hatchett, S., Kapelan, Z., Saldarriaga, J., Simpson, A. R., . . . van Zyl, J. E. (2018). Let’s get moving and write software: An open source project for *EPANET*. *Journal of Water Resources Planning and Management, 144*(4). doi:10.1061/(asce)wr.1943-5452.0000918

United States Environmental Protection Agency (USEPA). (2001). *Potential contamination due to cross-connections and backflow and the associated health risks*. Washington, DC, USA: Retrieved from http://www.epa.gov/safewater/disinfection/tcr/pdfs/issuepaper_tcr_crossconnection-backflow.pdf

United States Environmental Protection Agency (USEPA). (2006). *National primary drinking water regulations: stage 2 disinfectants and disinfection byproducts rule: final rule. Federal Register, Part II*. Washington, DC, USA: Office of Science and Technology, Office of Water. Retrieved from http://www.likuidnanotek.com/pdfamericana/1222164307.pdf

United States Environmental Protection Agency (USEPA). (2010). *National primary drinking water regulation: revisions to the total coliform rule* (Report No. 40 CFR Parts 141, and 142). Washington, DC, USA: Retrieved from https://www.epa.gov/dwreginfo/revised-total-coliform-rule-and-total-coliform-rule

United States Environmental Protection Agency USEPA. (2012). Microbial risk assessment guideline. Pathogenic microorganisms with focus on food and water. In Ed.) Ed.), (pp. 231).

Vairagade, S., Sayyed, M., & Gupta, R. (2015, May 17–21). *Node head flow relationships in skeletonized water distribution networks for predicting performance under deficient conditions.* Paper presented at the World Environmental and Water Resources Congress 2015:, Austin, TX, USA (pp. 810-819).doi:10.1061/9780784479162.075

Van Abel, N., Blokker, E. J., Smeets, P. W., Meschke, J. S., & Medema, G. J. (2014). Sensitivity of quantitative microbial risk assessments to assumptions about exposure to multiple consumption events per day. *Journal of Water and Health, 12*(4), 727-735. doi:10.2166/wh.2014.037

van Lieverloo, J. H., Mesman, G. A., Bakker, G. L., Baggelaar, P. K., Hamed, A., & Medema, G. (2007). Probability of detecting and quantifying faecal contaminations of drinking water by periodically sampling for E. coli: a simulation model study. *Water Research, 41*(19), 4299-4308. doi:10.1016/j.watres.2007.06.003

van Zyl, J. E., & Clayton, C. R. I. (2007). The effect of pressure on leakage in water distribution systems. *Institution of Civil Engineers-Water Management, 160*(2), 109-114.

van Zyl, J. E., Lambert, A. O., & Collins, R. (2017). Realistic modeling of leakage and intrusion flows through leak openings in pipes. *Journal of Hydraulic Engineering, 143*(9). doi:10.1061/(asce)hy.1943-7900.0001346

van Zyl, J. E., & Malde, R. (2017). Evaluating the pressure-leakage behaviour of leaks in water pipes. *Journal of Water Supply: Research and Technology - Aqua, 66*(5), 287-299. doi:10.2166/aqua.2017.136

Viñas, V., Malm, A., & Pettersson, T. J. R. (2019). Overview of microbial risks in water distribution networks and their health consequences: quantification, modelling, trends, and future implications. *Canadian Journal of Civil Engineering, 46*(3), 149-159. doi:10.1139/cjce-2018-0216

Wagner, J. M., Shamir, U., & Marks, D. H. (1988). Water distribution reliability: Simulation methods. *Journal of Water Ressources Planning and Management, 114*(3), 276-294.

Walski, T. (2017, May 21–25). *Pressure dependent demand accounting for customer properties.* Paper presented at the World Environmental and Water Resources Congress 2017, Sacramento, CA, USA (pp. 9).doi:10.1061/9780784480625.041

Walski, T., Havard, M., Yankelitis, B., Youells, J., & Whitman, B. (2019). Pressure-dependent demand under pressure-deficient conditions. *AWWA Water Science, 1*(2). doi:10.1002/aws2.1135

Walski, T. M., Chase, D. V., Savic, D. A., Grayman, W., Beckwigh, S., & Koelle, E. (2003). *Advanced water distribution modeling and management (First Edition)* (First Edition ed.). Waterbury, CT, USA: Haestad Methods Inc.

Walski, T. M., & Lutes, T. L. (1994). Hydraulic transients cause low-pressure problems. *Journal American Water Works Association*, *86*(12), 24-32.

Warton, B., Heitz, A., Joll, C., & Kagi, R. (2006). A new method for calculation of the chlorine demand of natural and treated waters. *Water Research*, *40*(15), 2877-2884.

World Health Organisation (WHO). (2006). *Protecting groundwater for health. Managing the quality of drinking-water sources*. London, UK: IWA publishing.

World Health Organisation (WHO). (2016). *Quantitative microbial risk assessment: Application for water safety management*. Geneva, Switzerland:

World Health Organization (WHO). (2009). *Risk assessment of Cryptosporidium in drinking water* (Report No. WHO/HSE/WSH/09.04). Geneva, Switzerland: Public Health and Environment, Water, Sanitation, Hygiene and Health. Retrieved from http://whqlibdoc.who.int/hq/2009/WHO_HSE_WSH_09.04_eng.pdf

Wu, Z. Y. (2007). Discussion of "Solution for Water Distribution Systems under Pressure-Deficient Conditions" by Wah Khim Ang and Paul W. Jowitt. *Journal of Water Resources Planning and Management, 133*(6), 568-569. doi:10.1061/(ASCE)0733-9496(2007)133:6(568)

Wu, Z. Y., & Walski, T. (2006, Sep 10-14). *Pressure dependent hydraulic modelling for water distribution systems under abnormal conditions.* Paper presented at the IWA World Water Congress and Exhibition, Beijing, China (pp. 11).

Wu, Z. Y., Wang, R. H., Walski, T. M., Yang, S. Y., Bowdler, D., & Baggett, C. C. (2006, Aug 27-30). *Efficient pressure dependent demand model for large water distribution system analysis.* Paper presented at the 8th Annual International Symposium on Water Distribution System Analysis,, Cincinnati, Ohio (pp. 15).

Wu, Z. Y., Wang, R. H., Walski, T. M., Yang, S. Y., Bowdler, D., & Baggett, C. C. (2009). Extended global-gradient algorithm for pressure-dependent water distribution analysis. *Journal of Water Resources Planning and Management-Asce, 135*(1), 13-22. doi:10.1061/(Asce)0733-9496(2009)135:1(13)

Yang, J., LeChevallier, M. W., Teunis, P. F. M., & Xu, M. (2011). Managing risks from virus intrusion into water distribution systems due to pressure transients. *Journal of Water and Health, 9*(2), 291-305. doi:10.2166/wh.2011.102

Yang, J., Schneider, O. D., Jjemba, P. K., & Lechevallier, M. W. (2015). Microbial risk modeling for main breaks. *Journal American Water Works Association, 107*(2), E97-E108. doi:10.5942/jawwa.2015.107.0010

Yang, X., & Boccelli, D. L. (2014). Simulation study to evaluate temporal aggregation and variability of stochastic water demands on distribution system hydraulics and transport. *Journal of Water Resources Planning and Management, 140*(8), 04014017.

Yang, X., & Boccelli, D. L. (2016). Dynamic Water-Quality Simulation for Contaminant Intrusion Events in Distribution Systems. *Journal of Water Resources Planning and Management, 142*(10). doi:10.1061/(asce)wr.1943-5452.0000674

Yoo, D. G., Suh, M. Y., Kim, J. H., Jun, H. D., & Chung, G. (2012). Subsystem-based pressure dependent demand analysis in water distribution systems using effective supply. *KSCE Journal of Civil Engineering, 16*(3), 457-464. doi:10.1007/s12205-012-1448-1

Yoo, T. J., Trifunovic, N., & Tairavamoorthy, K. (2005). *Reliability assessment of the Nonsan distribution network by the method of Ozger*. Paper presented at the 31st WEDC International Conference, Kampala, Uganda (pp. 325-332).

Yu, T., Jin, H., Zhang, T., Shao, Y., & Wu, X. (2016). Experimental observation on factors affecting intrusion volumes during low or negative pressure events. *Journal of Water Supply: Research and Technology-Aqua, 65*(5), 396-406. doi:10.2166/aqua.2016.112

Zafari, M., Tabesh, M., & Nazif, S. (2017). Minimizing the adverse effects of contaminant propagation in water distribution networks considering the pressure-driven analysis method. *Journal of Water Resources Planning and Management, 143*(12). doi:10.1061/(asce)wr.1943-5452.0000848

Zhao, Y., Schwartz, R., Salomons, E., Ostfeld, A., & Poor, H. V. (2016). New formulation and optimization methods for water sensor placement. *Environmental Modelling & Software, 76* 128-136. doi:10.1016/j.envsoft.2015.10.030

APPENDICES

APPENDIX A COMBINING A MULTI-SPECIES WATER QUALITY AND PRESSURE-DRIVEN HYDRAULIC ANALYSIS TO DETERMINE AREAS AT RISK DURING SUSTAINED PRESSURE-DEFICIENT CONDITIONS IN A DISTRIBUTION SYSTEM

Journal: Water Resources Planning and Management

Title: Combining a multi-species water quality and pressure-driven hydraulic analysis to determine areas at risk during sustained pressure-deficient conditions in a distribution system

Authors: Fatemeh Hatam, Marie-Claude Besner, Gabrielle Ebacher, Michèle Prévost

Pressure Demand Relationship and the selection of parameters

Tanyimboh equation can be presented as follows:

$$q_j^{avl} = q_j^{req} \frac{\exp(\alpha_j + \beta_j H_j)}{1 + \exp(\alpha_j + \beta_j H_j)} \qquad \text{Eq. A-1}$$

where q_j^{avl} and q_j^{req} are available and required demand at node j, respectively, H_j, is available head, and αj and βj are parameters defined using field data. In the absence of field data, they can be estimated as follows (Tanyimboh and Templeman 2004, 2010):

$$\beta_j = \frac{11.502}{H_j^{des} - H_j^{min}} \qquad \text{Eq. A-2}$$

$$\alpha_j = \frac{-4.595 H_j^{des} - 6.907 H_j^{min}}{H_j^{des} - H_j^{min}} \qquad \text{Eq. A-3}$$

in which H_j^{min} and H_j^{des} are minimum and desired pressure head, respectively. One advantage of the Tanyimboh equation and its derivative is that they do not have discontinuities between zero and partially supplied zones and between partially and fully supplied zones (Tanyimboh and Templeman 2004, 2010). In a PDR, the desired pressure head is the value below which the nodal demand cannot be fully supplied. Actually, this is a unique value for each node and network and its exact value should be determined from field measurements (Ozger 2003). As this task is not often practical, this critical value is usually approximated for the system using existing guidelines. For example, according to Ministère de l'environnement du Québec (2002) and other similar guidelines (Ten States Standards 2012), the pressure at any point in the distribution network should never fall below 14 m (20 psi) at ground level when the network is subjected to a maximum daily demand and fire flow.

Equations related to water quality modeling

The EPANET-MSX software uses a Lagrangian transport algorithm to solve the advection-reaction equation:

$$\frac{\partial c_i}{\partial t} + v_i \frac{\partial c_i}{\partial x} = f(c_i) \qquad \text{Eq. A-4}$$

where c_i is the concentration of a certain species in pipe i as a function of time $t \geq 0$ and distance x, v_i is the flow velocity in pipe i, and $f(c_i)$ accounts for reactions between various species. Axial dispersion is ignored and it is considered that the mixing of fluid at pipe junctions is complete and instantaneous. In the Lagrangian transport algorithm, the movement and reaction of constituents are tracked in segments which are transported through network pipes at the same velocity as the bulk fluid (Shang et al. 2008). EPANET-MSX can model multiple species as well as the interactions between them in both the bulk flow and at the pipe wall by solving a set of differential-algebraic equations (DAEs) that are supplied by the user. A complete description of multi-species water quality modelling and the numerical integration methods for solving the system of DAEs can be found elsewhere (Shang et al. 2008, Uber et al. 2004).

Modelling water age, chlorine decay and THM formation

The reaction equations used to simulate water quality are indicated in Table A-1. Water age is modeled by a zero-order reaction with the reaction rate coefficient equal to one. To simulate chlorine decay, a first-order decay model was selected due to its simplicity and wide use. The overall chlorine decay is considered to occur due to reactions in the bulk flow and at the pipe wall. A summary of bulk and overall chlorine decay constants for different test conditions can be found in Brown et al. (2011) and the values used in this study are indicated in Table A-1. A constant chlorine residual of 1.5 mg/L was considered at the outlet of each WTP. Hua (2000) investigated the THM formation and its variation with different water quality parameters. This author noticed that THM formation is mostly related to chlorine consumption due to reaction with organic matter in water and therefore proposed Eq. A-7. This equation is used to model THM formation in the present study. The constant K_{tc} represents the proportion of the chlorine bulk demand that leads to THM formation (Brown 2009). K_{tc} was set to 41 μg/L per mg/L free Cl_2, based on the literature (Boccelli et al. 2003, Courtis et al. 2009).

Table A-1 Reaction equations of simulated water quality parameters.

Parameter	Reaction		Constant values
Water age	$R = k_1$ (zero-order reaction)	Eq. A-5	$k_1=1$
Chlorine	$\frac{dC}{dt} = -kC$ (first-order reaction)	Eq. A-6	$k = k_b + k_w$, k_b=0.02 h-1 (0.48 day^{-1}), k_w=0.01 h^{-1} (0.24 day^{-1})
THM	$THM = K_{tc}(C_0 - C) + THM_0$	Eq. A-7	$C_0 = 1.5$ mg/L $K_{tc} = 41$ μg/L per mg /L free Cl_2

Note: R is the instantaneous rate of reaction, k_1 is the reaction rate coefficient, k_b is the bulk decay constant (h^{-1}), k_w is the wall decay constant (h^{-1}), k is the overall decay constant (h^{-1}), THM_0 is the initial THM concentration at t=0, C_0 is the initial chlorine concentration at t=0, C is the chlorine concentration (mg/L), and K_{tc} is an indicator of the THM productivity of the water, (μg/L of THM per mg/L of free chlorine).

Satisfaction of required demand for different pressure-deficient scenarios

For the nodes located in zone 1, median DSR showed large variations (from 22% to 99%) depending on the hydraulic grade at the only working WTP, while the 75th percentile remained constant (100%), and the 25th percentile changed from 1% to 64% (Figure A-1). For the consumers in zone 2, the differences in median DSR between various pressure-deficient scenarios were less than 1%, while the 25th percentile changed from 27% to 99%. Zone 3 generally showed less variation in DSR with the change of hydraulic grade at the sole supply point (WTP 3).

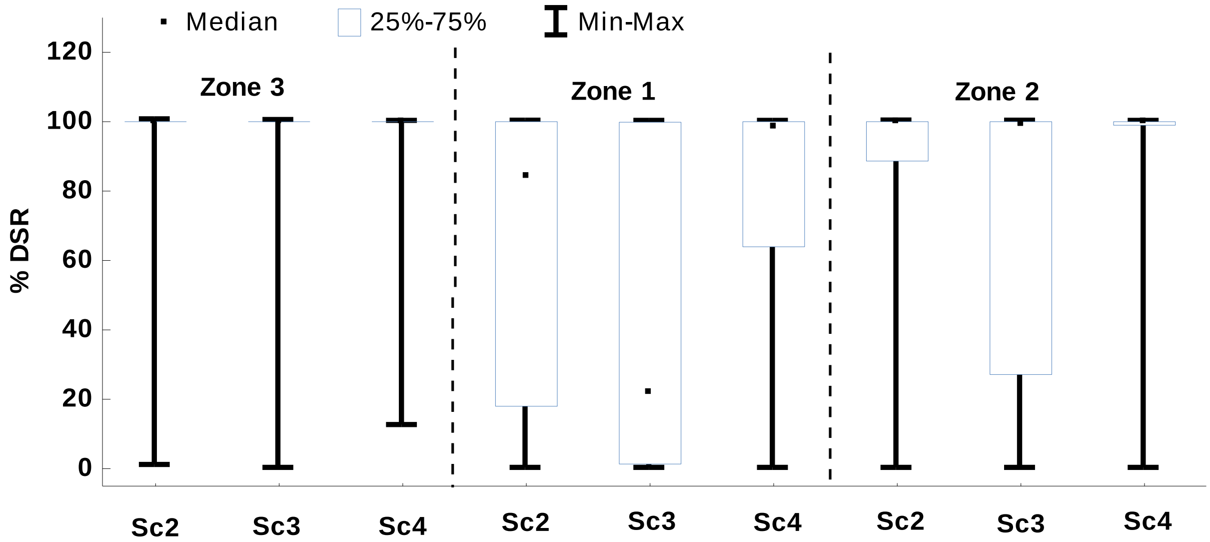


Figure A-1 Percentage of demand satisfaction for different pressure-deficient scenarios.

APPENDIX B IMPROVEMENT OF ACCIDENTAL INTRUSION PREDICTION DUE TO SUSTAINED LOW-PRESSURE CONDITIONS: IMPLICATIONS FOR CHLORINE AND *E. COLI* MONITORING IN DISTRIBUTION SYSTEMS

Journal: Water Resources Planning and Management (submitted)

Title: Improvement of accidental intrusion prediction due to sustained low-pressure conditions: implications for chlorine and *E. coli* monitoring in distribution systems

Authors: Fatemeh Hatam, Marie-Claude Besner, Gabrielle Ebacher, Michèle Prévost

Numerical modeling

The Tanyimboh and Templeman (2010) pressure-demand relationship is selected for the pressure-driven model (WaterGEMS V8i, SELECTseries 5) (Bentley Systems 2014). The desired pressure head in this equation is 15 m (21 psi) at all nodes. Nodes with pressure heads equal to or lower than zero have no demand available. Demand satisfaction ratio (DSR) at each node is the ratio of the demand that can be supplied under PDCs to the corresponding required demand. Pressure values under DDA and PDA are compared. Hydraulic time steps of 30 minutes and water quality time steps of 30 seconds were used.

To simulate chlorine decay the simple first-order model is used:

$$\frac{dC}{dt} = -k_1 C \qquad \text{Eq. B-1}$$

where C is the disinfectant residual concentration (mg/L), and k_1 is the chlorine decay coefficient (h^{-1}). For chloramine, the second-order model is used as follows:

$$\frac{dC}{dt} = -k_2 C^n \qquad \text{Eq. B-2}$$

in which n is the order of power law decay and k_2 is the chloramine decay coefficient $(\mathrm{L/mg \cdot h})$. Here, n is assigned a value of 2 (LeChevallier et al. 2011). For both disinfectants, the impact of reactions with biofilm, corrosion materials, etc. on disinfectant residuals are ignored. The Chick-Watson model is applied for the inactivation of *E. coli* (Betanzo et al. 2008):

$$\frac{dP}{dt} = -k_p CP \qquad \text{Eq. B-3}$$

where P is the *E. coli* concentration (CFU/L) and k_p is the inactivation constant $(\mathrm{L/mg \cdot h})$.

For the nodes prone to intrusion (internal pressure head less than 1 m), the maximum calculated C_{leak_i} are shown in Figure B-1.

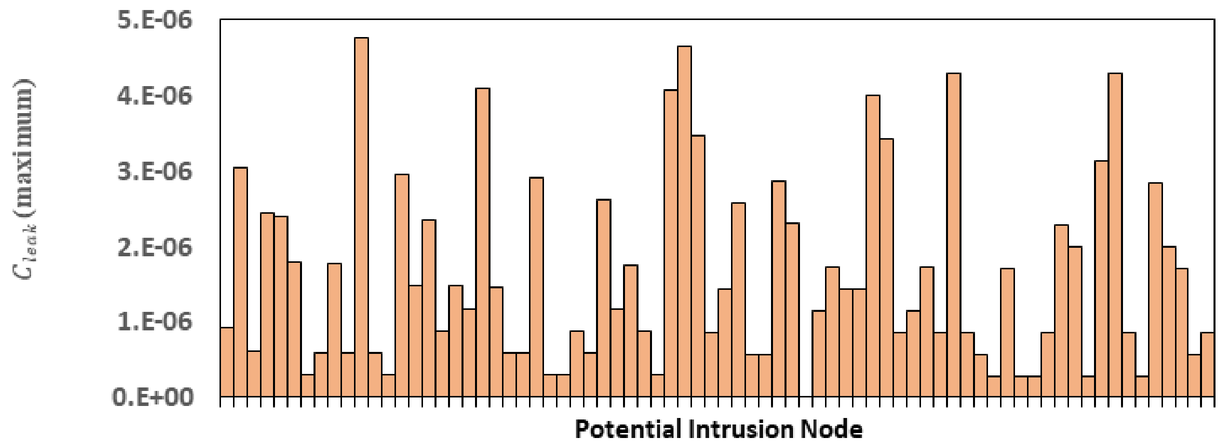


Figure B-1. Maximum estimated C_{leak} at each of the 74 nodes prone to intrusion used for calculating intrusion flow rates.

Intrusion flow rates and pressure values at the Intrusion Nodes

Figure B-2 shows the corresponding pressure values for potential intrusion nodes and intrusion flow rates. The variation of intrusion flow rate does not follow the pressure trend because of the variable leakage constants. The intrusion flow rate varies from 0 to 0.4 L/min per node (Figure B-2).

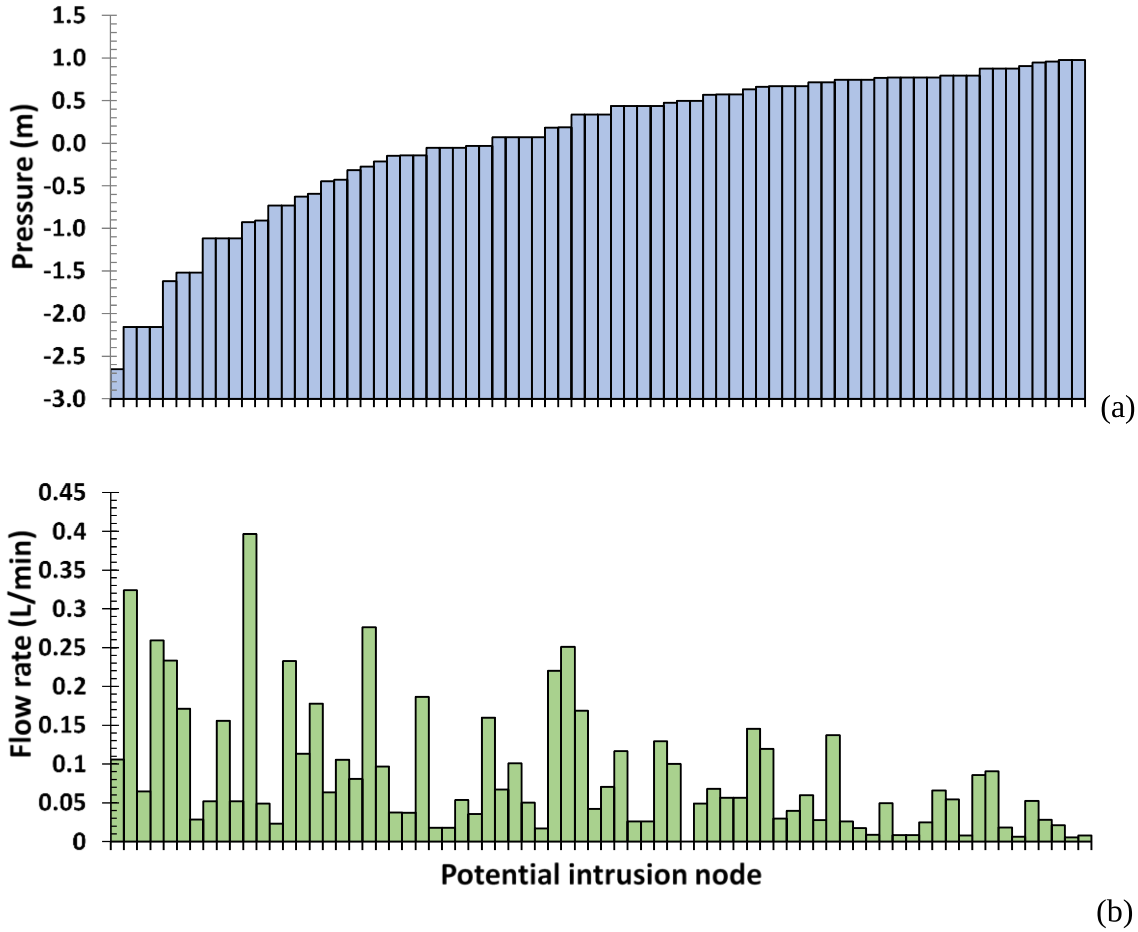


Figure B-2. (a) Pressure values at potential intrusion nodes, and (b) corresponding intrusion flow rates.

Water Quality Variations without Intrusion Effects

Figure B-3 shows distribution of water age and chlorine residual throughout the network (grouped based on node pressure under PDC) before and after the pressure drop without any intrusion event. The results illustrate that it may take a while, more than 10 hours at some nodes, for the water quality to stabilize again following the 5-hour pressure loss. The results show that the variations of median water age and chlorine residual values are generally higher for nodes with pressure lower than 15 m, as compared comparing to nodes with pressure greater than 15 m. The reason of these variations is only due to hydraulic conditions, for example changing water paths. This means that even without considering the impact of intrusion demand, pipe surfaces and corrosion by-products, lower chlorine residuals may be found in some areas during PDCs. For the studied PDCs, there is a sharp decrease of the median chlorine concentration from 0.8 to 0.6 mg/L at nodes with pressure less than 1 m (Figure B-3, b) reflects the increased water age (Figure B-3, a). Losses of chlorine residuals may decrease the level of protection against intrusion, especially considering that the nodes with lower pressure generally experienced higher losses compared to normal conditions. Another approach to interpret residual losses is to examine the impact of the PDCs on the ability to maintain a minimum reference chlorine residual across the DS. North American practice prescribes the maintenance of a measurable disinfectant residual (> 0.2 mg/L) at all points of the DS to maintain a barrier against microbial contaminants (Propato and Uber 2004). It is interesting to note that chlorine residual are below 0.2 mg/L at 2,099 nodes even under normal operating conditions for the studied model (Figure B-3, b). Less than 1% (6 nodes) of these nodes have pressure less than or equal to 1 m, about 6 % (123 nodes) have pressure less or equal to 15 m but more than 1 m, and about 94 % (1,970 nodes) of them have pressure more than 15 m under the PDCs. At the end of the event, five hours after the start of PDCs (9 PM), a similar number of nodes (1993) have chlorine less than 0.2 mg/l while among them, less than 1% (4 nodes) have pressure values lower than or equal to 1 m and about 94 % (1877) have pressure more than 15 m. When using chloramines, the decay is slower and all the intrusion nodes ($P \leq 1$ m) experience a residual of higher than 0.4 mg/L (Figure B-3, c).

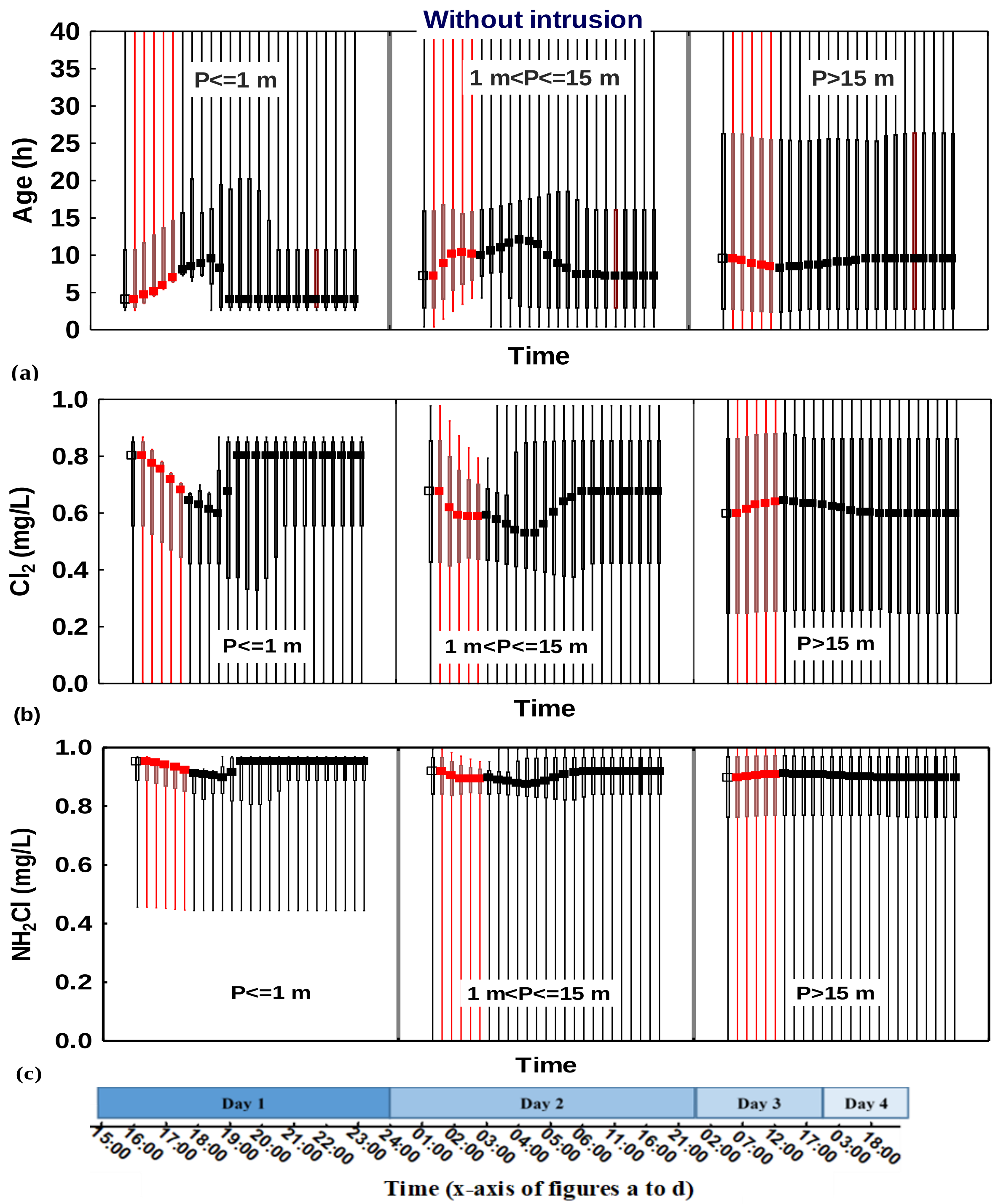


Figure B-3. Distribution of (a) water age with y-axis limited to 40 hours (b) chlorine (Sc5), and (c) chloramine (Sc8) without considering any intrusion; for all the nodes in the network categorized by pressure values under PDCs (at 16:00) with respect to time; Time intervals are not equal; Square: Median; Box: 10%-90%; Whisker: Min-Max.

Propagation of *E. coli* throughout the Network

Figure B-4 shows the spatial distribution of *E. coli* in the presence of chloraminated 9 hours after the end of intrusion events. The maximum *E.* coli in the color map is limited to 1 CFU/100mL for a closer examination of lower concentrations. Cyan in this map shows very low concentrations (≤ 0.01 *E.coli*/100mL).

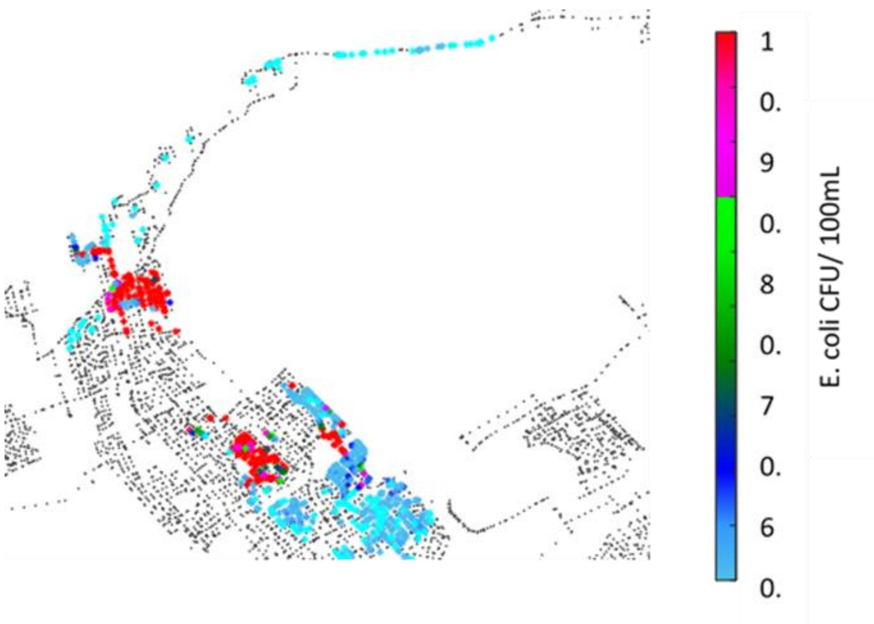


Figure B-4. *E.coli* distribution at 06:00 day 2 in chloraminated system; Concentrations higher than 1 CFU/100mL are demonstrated in red.

APPENDIX C USING NODAL INFECTION RISKS TO GUIDE INTERVENTIONS FOLLOWING ACCIDENTAL INTRUSION DUE TO SUSTAINED LOW PRESSURE EVENTS IN A DRINKING WATER DISTRIBUTION SYSTEM

Journal: Water

Title: Using nodal infection risks to guide interventions following accidental intrusion due to sustained low pressure events in a drinking water distribution system

Authors: Fatemeh Hatam, Mirjam Blokker, Marie-Claude Besner, Gabrielle Ebacher, Michèle Prévost

Accidental intrusion modeling

Pressure values resulted from PDA are used to define the intrusion nodes and intrusion volumes. Tanyimboh and Templeman (2010) equation is selected as the pressure-demand relationship. It is assumed that when nodal pressure head is more than 15 m the demand is completely satisfied and at nodes with pressure head less than the nodal elevation the demand cannot be supplied at all. For calculating the intrusion volume, the negative pressure values are calculated using the method presented in Hatam et al. (2018a). However, if one uses the recent version of WaterGEMS the issue described for the version used in our previous study regarding reporting negative pressure as zero is solved.

To simulate time-varying conditions, an extended period simulation is carried out for 336 hours. Normal hydraulic operating conditions are simulated for the first 240 hours to stabilize the water quality. Then, the unplanned shutdown of one WTP is simulated. The hydraulic and water quality time steps are 30 minutes and 30 seconds, respectively.

The orifice equation is applied to calculate the intrusion flow rate at each node using the nodal pressure value from PDA when the pressure head above the pipe is below 1 m. In this equation, for each node, the product of discharge coefficient and area of the orifice is calculated based on nodal leakage demand of the calibrated model under normal operation conditions. For each intrusion node, the contamination mass rate is calculated based on the intrusion flow rate at the node and the concentration of *Cryptosporidium* outside the pipe. More details on accidental intrusion modeling can be found in Hatam et al. (submitted). For the studied scenarios, after implementing the intrusion flow rates into the hydraulic model, the maximum nodal pressure variation was less than 0.006 m. Therefore, there is no need to recalculate the intrusion volumes based on the adjusted pressures.

In this paper, the intrusion duration concurs with the time of pressure loss and contaminant intrusion stops once the pressure is back.

Consumption time

Probability of consumption of contaminated water depends on the time of filling a bottle or glass from tap even if the water is not consumed immediately. In this paper, the terms of consumption time and filling time are used interchangeably. Figure C-1 shows the modified kitchen tap use (in blue) that is set to zero at the time when there is no demand available under PDCs to account for demand satisfaction as computed by PDA.

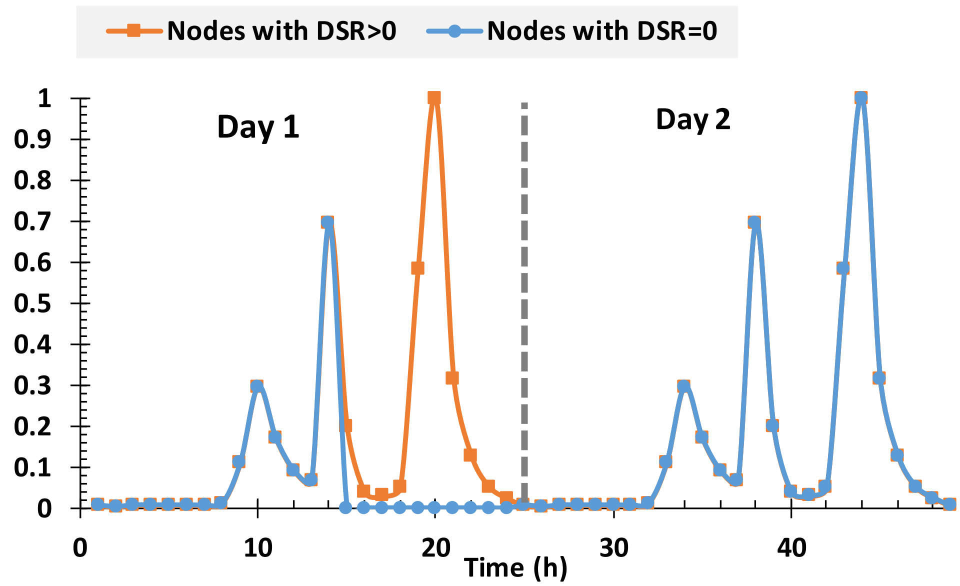
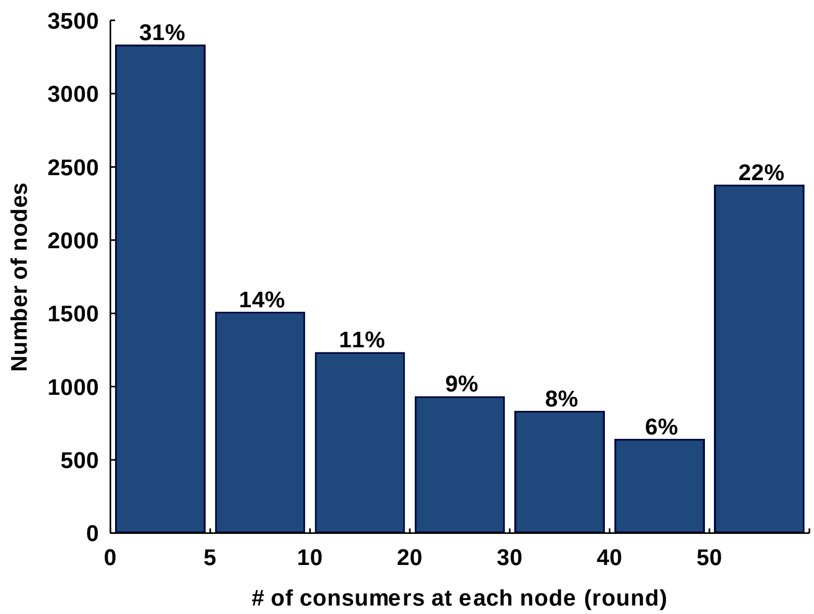


Figure C-1. Probability of filling a glass or bottle for consumption over the 2 days. Consumption at kitchen tap use (Blokker et al. 2018) (orange, square); modified kitchen tap use for this study for the residential nodes with no available demand for consumption based on PDA results at days 1 and 2 for the 10 hours scenario (blue, circle); days 3 and 4 are the same as day 2.

Nodal Population

Population spatial distribution of 400,000 population supplied by the three WTPs in the studied network is demonstrated in Figure C-2. The minimum person at a node is one and the maximum is 1352. The number of people on a node is determined only based on residential demand as other demand types are usually used for other purposes such as processing, cooling or cleaning. Also, for example for school it happens that children bring bottles of water from home. Therefore, in this study only the residential exposure from tap water is investigated. To obtain the number of people at each node, the daily residential demand of that node is divided by the daily average demand per people. The daily average demand is estimated by dividing the total residential demand of the studied network by total population (400,000). For population calculation, the nodal demand under normal operating condition is used and the daily pattern is considered.

(a)



(b)

Figure C-2. (a) Geographical distribution of population, and (b) histogram of number of people at each node; Exclude nodes with zero population.

One-hour event with daily demand patterns

The cumulative probability distribution of the number of infected people for 200 random consumption behaviors and the spatial distribution of risky areas are shown in Figure C-3 for one-hour event with daily demand patterns in the hydraulic model.

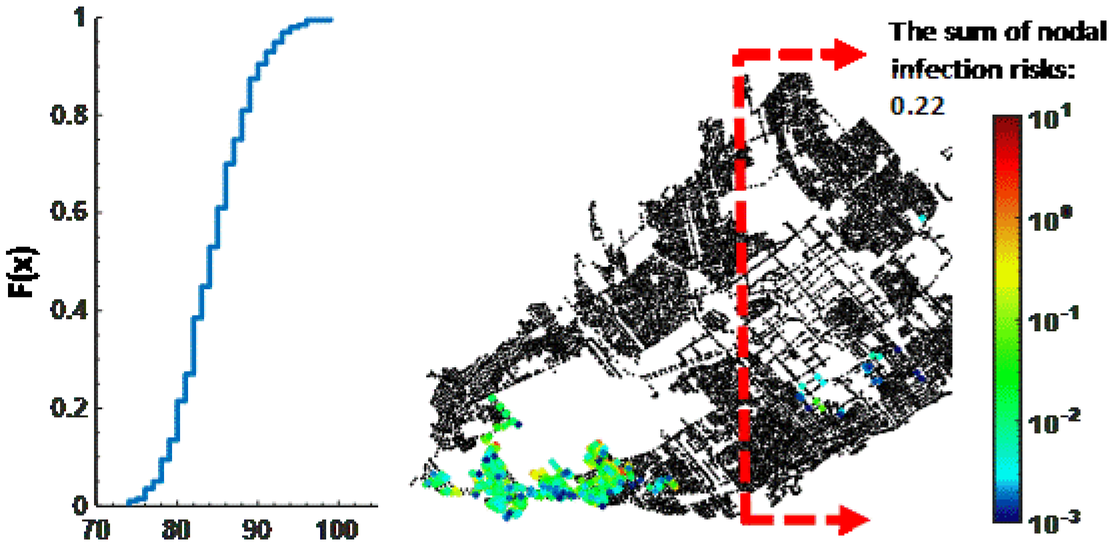


Figure C-3. The probability distribution of the number of infected people during 4 days of simulation; 200 Monte Carlo simulations; 1 hour intrusion (a). The spatial distribution of the nodal risk corresponding to consumption event with F(x) =1 (b). Daily pattern in the hydraulic model.

Pressure distribution under PDCs

Geographical distribution of nodal pressure is demonstrated in Figure C-4. Nodes with pressure values less than 1 m are the nodes prone to intrusion in this study.

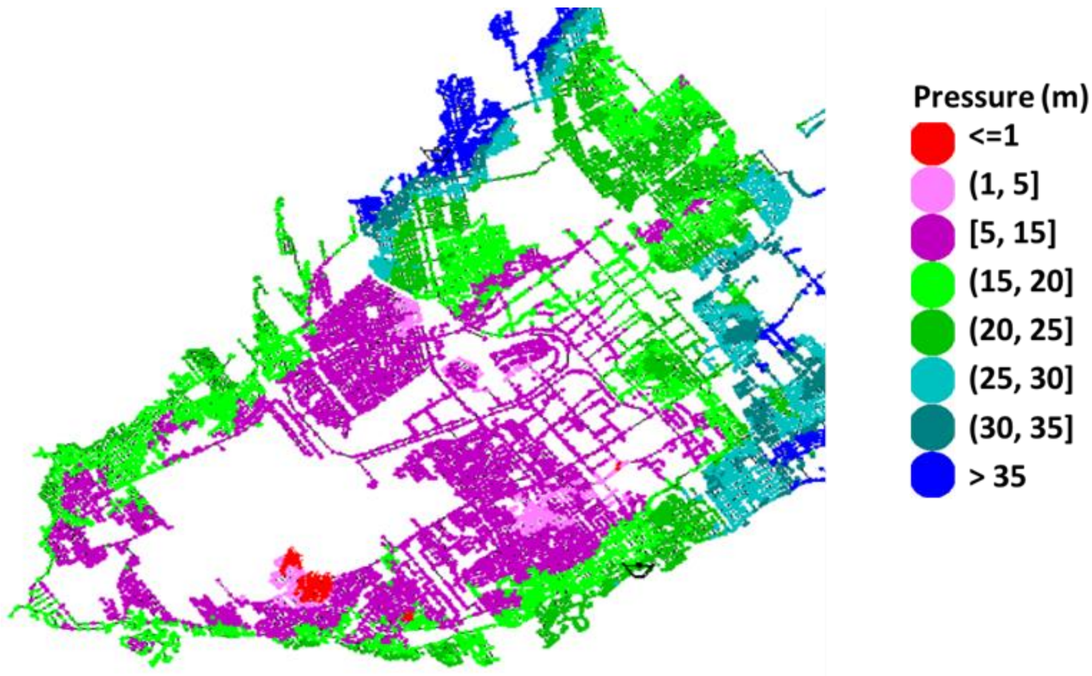


Figure C-4. Spatial distribution of pressure using PDA under low/negative pressure event, at 7:00 PM.

APPENDIX D DISCUSSION ON ISSUES OF REPORTING NEGATIVE NODAL PRESSURE VALUES AS ZERO IN PDA MODELS

Lee et al. (2015) have claimed that the existing tools for preforming PDA may produce unacceptable results such as total head reverse occurrence. They have demonstrated this problem by modeling two simple networks. In both networks, they have shown that at some pipes the flow direction is from lower total head to higher total head. However, as the authors have also mentioned this is not theoretically possible. Therefore, they tried to resolve this problem by proposing a modification technique. However, the suggested methodology needs change in the system reconfiguration and it would be difficult and time consuming for large distribution system and more complicated in the case of EPS.

Negative pressure values were not allowed in the PDA model used by Lee et al. (2015). In the following, we have demonstrated that this limiting assumption can be the reason of total head reversal problem in the PDA model. Table D-1 demonstrates the hydraulic results, based on PDA, for the same networks and the same pressure-deficient condition defined in the authors' paper (Lee et al. 2015). Columns 4, 6 and 8 (in both tables) are our simulation results when negative pressures are considered. In column 6 of Table D-1, the total head at node 3 (72.45 m) is less than node 2 (78.48 m) which is consistent with flow direction. While, column 7 (the results from discussed paper) indicates that flow direction does not match total head differences between nodes 2 and 3. Same explanation holds for node 2 and 3 of network 2 (Table D-2). These results reveal that when negative pressure values are considered there would be no total head reversal problem, which was reported as a deficiency for the PDA model in Lee et al. (2015). This also eliminates the need of applying the proposed modification technique by the authors, for PDA models, in which changing the configuration of the system was required. Also, the results underline the importance of improving PDA models by allowing negative pressures; otherwise the assumption of not considering below zero pressure may lead to some misinterpretations. Moreover, negative pressure values may become important during modeling the risk of intrusion events in distribution systems, and estimation of intrusion volume and health impact associated with low/negative pressure events.

Table D-1. Modeling results for network 1 under abnormal condition (pump outage).

Node ID	Elevation (m)	Base demand (L/*s*)	Available demand (L/s)		Total Head (m)		Pressure (m)	
			This study	Lee et al. 2015	This study	Lee et al. 2015	This study	Lee et al. 2015
Junc2	78	3	0.52	0.53	**78.48**	**78.47**	0.48	0.47
Junc3	80	3	0	0	**72.45**	**80**	-7.55	0
Junc4	20	3	3	3	70.78	70.78	50.78	50.75
Junc5	0	3	3	3	70.32	70.32	70.32	70.28
Junc6	20	3	3	3	70.78	70.78	50.78	50.75
Junc7	0	3	3	3	70.32	70.32	70.32	70.28

Table D-2. Modeling results for network 2 under abnormal condition (nodal demand is increased at Junc2).

Node ID	Elevation (m)	Base demand (L/*s*)	Available demand (L/s)		Hydraulic grade (m)		Pressure head (m)	
			This study	Lee et al. 2015	This study	Lee et al. 2015	This study	Lee et al. 2015
Junc2	33	14	9.66	9.66	**40.14**	**40.14**	7.14	7.13
Junc3	42	2	0	0	**39.69**	**42**	-2.31	0
Junc4	10	2	2	2	39.65	39.65	29.65	29.64
Junc5	10	2	2	2	39.46	39.46	29.46	29.44
Junc6	0	2	2	2	39.45	39.46	39.45	39.44

APPENDIX E IMPACT OF THE CUMULATIVE IMPACT OF INGRESS ON CHLORINE DEMAND DURING EXTENDED PDCS

The cumulative impact of chlorine demand for two intrusion nodes is shown in Figure E-1 for a simple situation where node (b) is located downstream of node (a) with a travel time of 77 minutes between the nodes during the PDCs. As the travel time is shorter than the duration of the simulated PDCs, the cumulative effect of the chlorine loss can be seen distinctly at the down-flow node. However, in the case of extended travel times between nodes and flow reversal after NOCs are restored, such trends may not be seen at all nodes. Clearly, the intrusion duration is a key factor to determine the extent of chlorine decay, affecting the ability to maintain minimum chlorine residuals after intrusion.

For health risk modeling of intrusion during negative pressure transients, some researchers have proposed modeling a single intrusion node at a time, establishing system responses and integrating adjusted random virus concentrations in intrusion water in the hydraulic and water quality models. Then, all separate system responses are summed at each node by assuming the operational conditions remain the same in the system and the intrusion flow rate is small compared to the pipe flow rate at that node (LeChevallier et al. 2011, Teunis et al. 2010). For linear superposition to be valid, it should be assumed that the decay kinetics are first-order and that hydraulics of the network are known (Boccelli et al. 1998). These assumptions may not hold for extended low-pressure conditions as modeling each intrusion node separately cannot consider the cumulative effect of chlorine losses at down-flow nodes, which is shown in Figure E-1. Moreover, in the simulated sustained PDCs, the impact of intrusion flow rates on both hydraulic and water quality of the network is considered, as intrusion flow rates may be considerable compared to some pipe flows at intrusion nodes. In addition, selectively increasing the decay based on the presence of conservative species is more realistic.

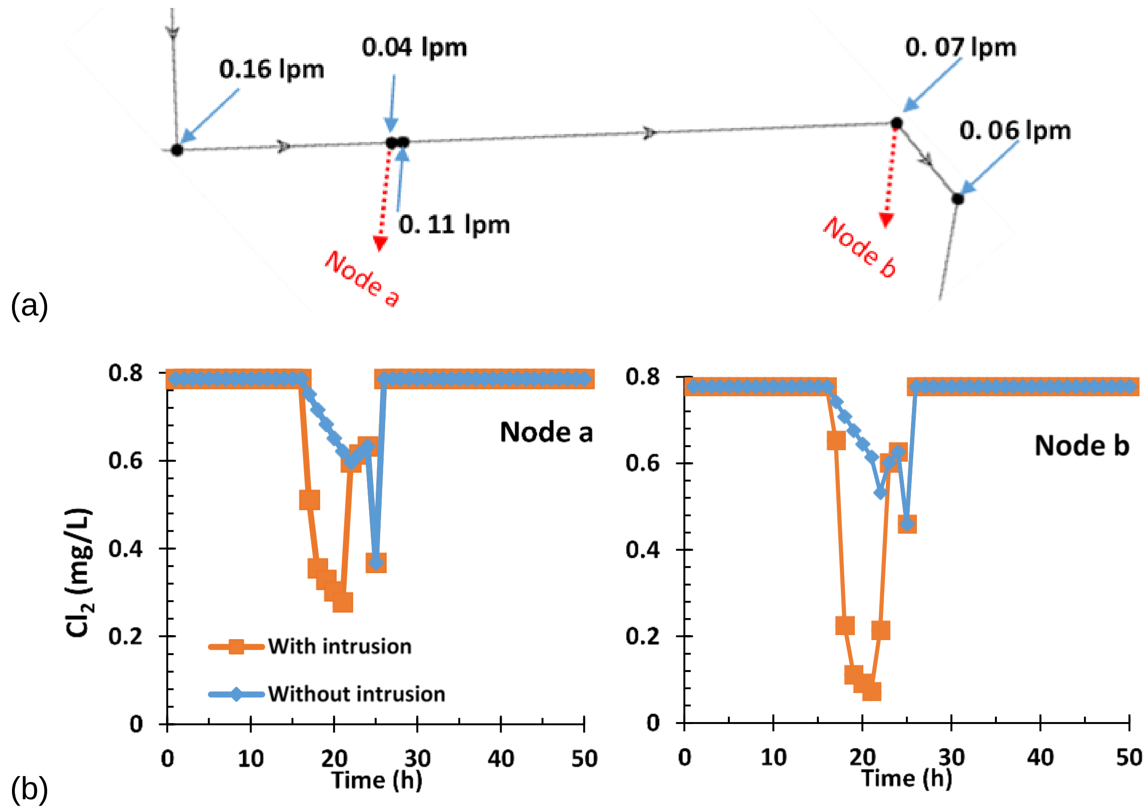


Figure E-1. (a) Change of water path during PDCs; all the nodes are intrusion nodes (b) Chlorine residuals variation due to PDCs at nodes a and b with and without intrusion (travel time of 77 minutes between nodes).