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POLYTECHNIQUE MONTRÉAL
affiliée à l'Université de Montréal

Two-Stage Stochastic Optimization for Peak Load Reduction in Smart District Microgrid

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Mémoire présenté en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

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Ce mémoire intitulé :

Two-Stage Stochastic Optimization for Peak Load Reduction in Smart District Microgrid

présenté par **Fatemeh BAGHERI**
en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*
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Luc ADJENGUE, président
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DEDICATION

To my parents.

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I would like to express my deepest thanks to my advisors, Professor Hanane Dagdougui and Professor Michel Gendreau, for their valuable guidance, mentorship, patience, encouragement, sharing their professional experience, and providing me with financial support throughout this project.

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Last but first in my heart, I thank my parents, who always encouraged me to go further in knowledge.

RÉSUMÉ

Les microréseaux offrent une diversité de ressources énergétiques distribuées pour fournir de l'électricité aux propriétaires de bâtiments, et ainsi contribuer à la réduction de la facture énergétique et les émissions de gaz à effet de serre. En effet, les sources d'énergies renouvelables sont propres et peu coûteuses, mais elles ont la particularité d'avoir un caractère intermittent. Pour la clientèle de grande puissance, les microréseaux peuvent également contribuer à l'écrêtage de la demande de pointe locale. Cependant, définir le dimensionnement et l'opération optimaux d'un microréseau compte tenu des incertitudes liées à la génération et à la consommation est un grand défi. Ces incertitudes doivent être adéquatement modélisées pour la gestion optimale d'un microréseau. L'optimisation stochastique offre un cadre approprié pour l'ople dimensionnement et l'opération du microréseau dans un contexte incertain. Cependant, il existe un besoin accru pour le développement d'approches de génération et de réduction de scenarios pour limiter le temps de calcul de tels problèmes. Dans cette étude, un problème d'optimisation stochastique en deux étapes comprenant le dimensionnement et le fonctionnement d'un microréseau pour la réduction de la charge de pointe est proposé. Un réseau antagoniste génératif (GAN) a été proposé pour générer des scénarios de profils de puissance PV et de demande électrique. En raison d'un grand nombre de scénarios, la technique de réduction de scénarios K-medoids a été appliqué. Les résultats du cas d'étude d'un campus canadien ont démontré que la méthode proposée réduisait les coûts ainsi que la demande de pointe en utilisant des systèmes de production d'énergie PV et du stockage sur batterie.

ABSTRACT

Microgrids offer a diversity of distributed energy resources to supply electricity to building owners, and thus contribute to the reduction of energy bills and greenhouse gas emissions. Indeed, renewable energy sources are clean and inexpensive, but they have the particularity of being intermittent. For large-power customers, microgrids can also contribute to local peak-shaving. However, defining the optimal sizing and operation of a microgrid considering generation and consumption uncertainties is a big challenge. These uncertainties must be adequately modeled for the optimal management of a microgrid. Stochastic optimization provides an appropriate framework for microgrid sizing and operation under uncertainty. However, there is an increased need for the development of scenarios generation and reduction approaches to limit the computation time of such problems. In this study, a two-stage stochastic optimization problem including sizing and operation of a MG and peak load reduction has been solved. A generative Adversarial Network (GAN) was proposed to generate PV power and electrical load demand scenarios. Due to a large number of scenarios, the K-medoids scenario reduction technique has been applied. The results of the case study of a Canadian university campus, showed that the proposed method decreased costs and properly shaved peak loads using PV power generation and battery storage systems.

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LIST OF SYMBOLS AND ACRONYMS

MG	Microgrid
PV	Photovoltaic panel
ESS	Energy storage system
SP	Stochastic programming
RES	Renewable energy sources
DER	Distributed energy resources
EMS	Energy management system
GHG	Greenhouse gas
WT	Wind turbine
PLS	Peak load shaving
EV	Electric vehicle
DMS	Demand side management
C-GAN	Conditional Generative Adversarial Network
MILP	Mixed-integer linear programming
HEM	Home energy management
NN	Neural network

CHAPTER 1 INTRODUCTION

1.1 Background and Motivation

Nowadays, environmental issues have been highlighted due to the increase of the global greenhouse gas (GHG) emissions from fossil fuels. As long as the world's population grows, the side effects of using fuel-based energies increase due to the growth of energy demand. Environmental and economic issues caused by increasing fuel-based energy usage led to the integration of other energy resources into the power systems. Solar radiation and wind energy are two renewable energy sources (RES) that can generate power through Photovoltaic (PV) panels and wind turbines (WT). RES are free, clean and have significant economic and environmental advantages. However, RES suffer from uncertainties in their nature. They are hard to predict, and they are highly dependent on meteorological conditions. The integration of RES needs energy management systems that can properly manage the available resources and their interactions with the grid to satisfy the power demands. The presence of distributed energy resources (DER) to supply the demand creates a need for a new technology named microgrid (MG) to integrate different power resources and control them in a power system [1–3].

MG is a small power system composed of DER, energy storage system (ESS) and local loads. It can operate in grid-connected or in island modes. MGs have been widely used in the recent decade due to their environmental and economical advantages for power suppliers and consumers. For the power suppliers, MGs help to increase the grid's flexibility and decrease the losses in the network. They offer the possibility to provide power locally, and increase the grid reliability. For the users, MGs provide local power for consumers and reduce the electricity bill, especially in peak hours when purchasing power from the main grid may lead to some penalties [2, 4]. MG can operate as a backup system for the utility grid when the demand is high in peak hours. The power generated from DER are uncertain and not available all the time. Hence, when power generation is insufficient, the ESS provides electrical energy to the load, and if necessary, purchases electricity from the main grid ; when the power generation is higher than the load demand, the excess energy is stored in the ESS or sold to the main grid to ensure reliable operation of the system [5].

Sizing and operation of MG are two critical factors of the MG system. Oversizing MG will lead to an increase of the investment costs, that cause cost overruns related to the excess in infrastructure capacity. From another viewpoint, undersizing MG will lead to a large mismatch between power generation and demand that causes deficit in power supply in

MG. PV power generation are time-varying, that highly rely on weather conditions and are challenging to predict [6]. Hence, problems of MG sizing and operation become more difficult to solve due to the the uncertainties of these parameters [4].

The problems of MG sizing and operation are solved using optimization approaches that are restricted by many constraints. The type of optimization problems relies on the nature of the modeling MG components and the objectives. Stochastic programming (SP) is one of the techniques used to integrate uncertainties in the modeling when uncertain parameters are accessible in MG [7, 8]. Scenario generation is one of the main feature of stochastic optimization [9] that allows capturing the uncertainties and considering the probability of occurrence for each scenario [10] in the optimization problem. Solving stochastic optimization with a large number of scenarios led to introducing scenario reduction approaches, that help reducing the computational aspect of solving stochastic optimization. These optimization problems are solved to achieve various goals for the MGs.

One of the objectives of the MG problems is peak load shaving (PLS) in buildings. PLS strategies might use on-site generation and storage to satisfy the load in peak hours. PLS strategies have economic and environmental advantages for many buildings. It allows them to reduce the electricity bills, and to decrease the GHG emissions through energy efficiency measures. PLS could be performed using demand-side management (DMS) programs, local ESS, electric vehicle (EV) through V2B concept, or a combination of many mechanisms. Each PLS strategy has both advantages and drawbacks ; however, the advantages of the RES-ESS approach are more than its disadvantages among other available approaches. Using renewable energy sources helps buildings' energy management system (EMS) to take the exceeding energy from these resources instead of buying from the primary grid. This lead to producing lower fuel-based generations and lower production of GHG. Along with RES benefits, ESS helps the MGs to shave the peak by storing the power in off-peak hours to use during peak and avoiding the waste of RES powers in off-peak hours [11, 12].

1.2 Problem statement

As discussed above, it is well-known that RES have advantages for MGs due to providing cheap and clean energy. However, RES generations are not available at all times. RES depend on weather conditions such as temperature, humidity, the season of the year, etc. The uncertainty of these types of energies is a big challenge. The uncertainties of demand load also make another problem since it is hard to predict the consumer's energy usage. Including the uncertainties in MG operation is critical.

Consequently, due to selected MG components, sizing MG and operation of energy flow in MG is critical. In terms of oversizing, the user should pay more investment costs while the produced energy is wasted more than the principal usage for MGs in island mode. If the MG is undersized, the available power can not satisfy the demand, creating additional costs for the users to provide energy from the network.

PLS with RES-ESS technologies is challenging due to the uncertain nature of RES and loads. The scheduling of MG for PLS using RES is hard to achieve since the EMS of MG can not rely on a predetermined and specific power to satisfy the demand. In addition, predicting the peak loads is another challenge since the program can not detect peaks properly to manage the demand. So considering the uncertainties of loads and RES in the problem of PLS makes a big challenge. PLS using renewable energies and batteries is a way to encourage building owners to use RES-ESS technologies.

Stochastic programming is critical to solving the optimization problem with RES and load uncertainties. There is a need for a proper scenario analysis method with a reliable ability to capture possible scenarios in the future. The more accurate scenario generation methods, the better MG scheduling. A large number of scenarios could capture more future fluctuations. However, a more extensive scenario set makes the stochastic problem more complex since the optimal solution must be found for all scenarios. The importance of scenario reduction techniques shows here. The scenario reduction must be appropriate to capture the main structure of the initial scenario set in the reduced set.

The problem of peak shaving using stochastic optimization is solved in [13] ; however, the microgrid sizing is not included in their modeling. Sizing MG has benefits for MG operation by defining the proper size of available components so the problem of stochastic optimization. Another study considering two-stage stochastic optimization for sizing microgrid and operation in-home energy management is proposed in [14]. However, the previous work does not discuss the scenario generation and reduction approaches. Scenario generation using GAN is proposed in [15–23] for renewable energies and in [24] for load forecast error. Except [16] which uses generated wind power scenarios for scheduling MG operation, other papers do not use the generated scenarios in the field of MG.

Generally, the solution to the problem is based on sizing MG, defining the optimal operational power flows, and considering peak shaving. Due to uncertainties associated with MG components, this is typically a complex problem. There is a need for a way to capture uncertainties adequately. The problem becomes even more complicated in the presence of a large number of scenarios. Here a scenario reduction approach must be entered and explore whether the solving procedure is more straightforward.

1.3 Research objectives and Contributions

This study proposes a two-stage stochastic optimization approach to minimize microgrid investment and operation costs, considering shaving the peak loads. It includes both sizing and operation. The proposed method applied the scenario generation technique of conditional Generative adversarial network (C-GAN) and the k-medoids scenario reduction to decrease the complexity of the scenario analysis part. The method was tested on an actual case study related to a university campus.

1. Develop a two-stage stochastic optimization strategy for reducing peak loads on a university campus, considering MG investment and operational costs.
2. Develop a scenario generation technique incorporating conditional GAN for PV power and load uncertainties.
3. Propose a scenario reduction strategy based on the K-medoids approach to lower the stochastic optimization problem's computing time.
4. Implement the suggested technique on a university campus in Montreal.

1.4 Outline of Dissertation

Chapter 1 of the thesis defines the background and motivation, problem statement, research objectives and contributions, and the outline of the dissertation. In chapter 2, a literature review is presented consisting of microgrid definition, sizing microgrids, energy management system including available optimization approaches, stochastic optimization for microgrids, and scenario generation and reduction. Chapter 3 includes the article of this work. A conclusion and discussion, limitations, and future research opportunities are presented in chapter 4.

CHAPTER 2 LITERATURE REVIEW

2.1 Microgrid definition

By increasing the world population, the energy demand raised. The conventional sources of energy are limited, and due to increasing demand, the price of supplying energy using these sources has also increased. Moreover, using fuel-based energy sources cause environmental issues such as increasing greenhouse gas (GHG) emissions and global warming. These issues inspired decision-makers to find new ways to include the available power resources in nature to supply energy. A definition of the microgrid is widely used in the literature which is developed for the U.S. Department of Energy by the Microgrid Exchange Group as : "[A microgrid is a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can operate in both grid-connected or island mode [25]."

MGs are a group of distributed energy resources (DER), local loads, and storage systems. Diesel generators, microturbines, fuel cells, and renewable generators (photovoltaic panels, wind turbines, etc.) might be used as generation resources in microgrids. Moreover, electric vehicles (EVs) can play an important role as energy providers and storage system. The storage systems help MG consider the mismatches between available power generations and demand [1, 4, 26]. Fig.2.1 shows a sample of a microgrid with different DER.

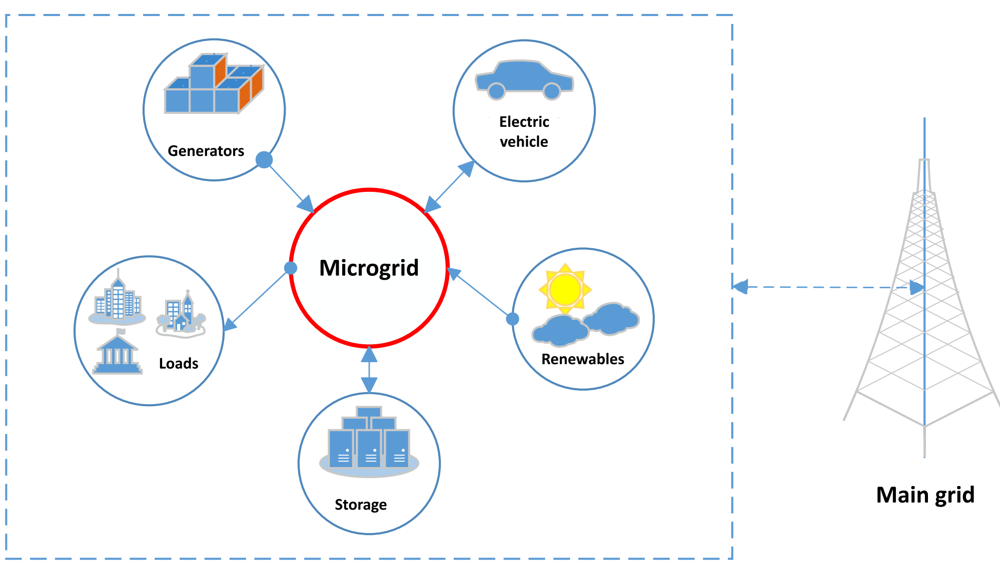

Figure 2.1 Microgrid distributed resources

Microgrids have been widely used in recent years. Energy security, economic benefits, and clean energy integration are the three primary factors pushing the microgrid integration in buildings. MGs help increase networks and buildings' ability to provide reliable energy and flexibility at each moment [1, 4].
MGs have advantages for both utility providers and building owners. For utility providers, MGs send the additional local generated power to the main grid. Moreover, during high-demand hours, MGs assist the main grid in managing power flows. For the building owners, MGs help to shave the peak and reduce electricity bill by providing power from on-site generation and storage and reducing the power bought from the main grid [4].
MGs studies have two main components : sizing and operation [27]. The following literature will discuss state-of-the art related to sizing MGs.

2.2 Sizing microgrids

MGs include renewable generation units (e.g., PV panels and wind turbines), conventional power generation systems, electrical storage system (ESS), thermal storage system (TSS), electrical and thermal loads [28]. PV-based MGs have been widely used microgrids in recent years due to available solar energy worldwide. However, solar power depends on the environmental conditions, and the PV-based MGs need a backup when there is no solar energy available such as on cloudy days. Batteries play an important role here. Batteries store power during off-peak hours and use it when the system needs it, especially during peak hours. To design a MG, finding the optimal size of MG components is critical [29, 30]. The current studies on MG sizing are in the form of optimization problems with the aims of minimizing the cost of investment and power generation and decreasing the greenhouse gas (GHG) emissions. Deterministic and stochastic approaches are available to solve the sizing problems. There are a lot of technical, environmental and economical constraints which are feed to the algorithm. Sizing problems are solved with a wide range of approaches. Fig.2.2 includes the available approaches in the literature to solve sizing problems. The explanation of each method along with the state-of-the art for each category is included in [29].

Table.2.1 shows some studies applying various approaches for sizing PV and battery in the MG.

A novel approach for sizing MG for a residential building was proposed in [41], which the demand response of home electrical applicants was considered. It consisted of PV panels, wind turbines, and batteries. The problem was solved as a mixed-integer linear programming (MILP) applied to a real case study in Okinawa [41].

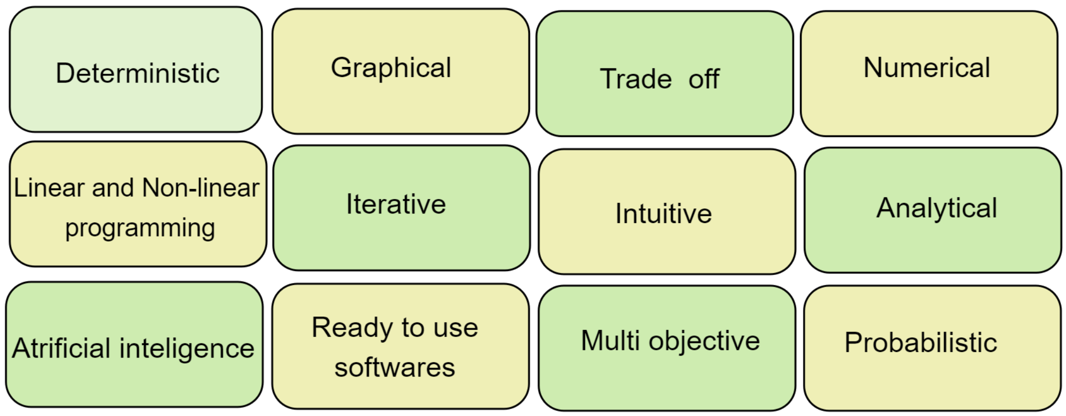

Figure 2.2 Microgrid sizing optimization methods

Table 2.1 Some literature works related to diffemt sizing approaches

Reference	Battery	PV	Method
[31]	✓	✓	Numerical
[32]	✓	✓	Probabilistic
[33]	✓	✓	Analytical
[34]	✓	✓	Analytical
[35]	✓	✓	Iterative
[36]	✓	✓	Linear programming
[37]	✓	✓	Linear programming
[38]	✓	✓	Trade off
[39]	✓	✓	Multi objective
[40]	✓	✓	Artificial intelligence

A study was developed in [42] for sizing the battery in a PV-battery MG and defining its optimal operation. The MG also includes diesel generator and wind turbine.

The sizing and placement of the battery in a PV-based MG using Genetic Algorithm Linear Programming (GALP) are investigated in [43]. The battery's daily charging or discharging schedule is proposed while minimizing the cost of energy flow. A study for optimal sizing and capacity of battery and PV is developed in [44]. The approach was implemented in a real household case study ; however, the method was not in the form of an optimization problem.

Bi-level stochastic programming was proposed to size the battery and assess its operation in a MG with the presence of PV generations. The advantages of the battery were discussed by testing the system with PV and with or without battery storage system [45].

A sizing of PV-battery system for residential households is proposed in [46] to investigate the economic aspects of applying such a system. It is shown that the profits increased if the battery was added to the PV system.

In [47], a study is conducted to find the optimal size of a PV-battery system for households. The strategy is proposed as two configurations, PV panels alone and one that combines both PV and battery. The practical operation is applied to real cases in Australia.

Another study was proposed in [48] to indicate the optimal sizing of PV and battery as the "here-and-now" decisions in addition to minimizing the operational cost as "wait-and-see" decisions. The problem has been formulated as two-stage robust optimization considering the uncertainties of PV and load for residential buildings.

Two-stage stochastic programming was proposed for optimal sizing and planning MG in a residential building. The first stage aims to optimal investment cost while the second stage solves to get to the optimal solution for system operation cost. The scenario generation method has not been discussed ; however, it is mentioned that six typical scenarios are considered for the whole year, which multiplied total stochastic formulation by 365 days [14].

2.3 Energy management system in microgrids

The energy management system (EMS) in MGs has the role of controlling the powers of the buildings. EMS in MGs is responsible for providing an optimal scheme in which the power is supplied by the available energy resources such as RES, ESS, etc. A comprehensive review of energy management system techniques from different perspectives in [7] considered the available approaches for EMS strategies in the state-of-the art as three main classes : classical, heuristic, and intelligent techniques. In this study, the classical methods applied in EMS will be discussed.

Classical methods include minimizing/maximizing an objective function formulated as linear/nonlinear problems to deal with the problem's constraints and find the decision variables. The classical methods can be categorized into certainty and uncertainty problems. The available approaches for certainty problems are linear programming (LP), mixed integer programming (MIP) and nonlinear programming (NLP) [49, 50], Mixed-integer linear programming (MILP) [51–56] and mixed integer nonlinear programming (MINLP) [57, 58]. The uncertainty problems are solved using dynamic programming (DP) [59, 60] and stochastic programming (SP) [7].

This work focuses on stochastic programming approaches applied in EMS in MGs.

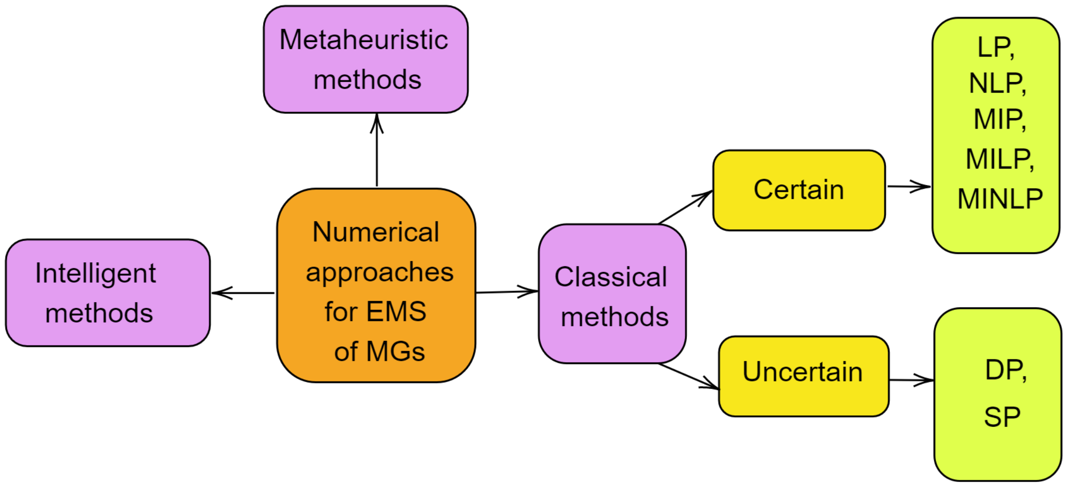

Figure 2.3 Numerical methodologies in EMS of MGs

2.4 Stochastic optimization for MGs

Stochastic programming (optimization) techniques are used to solve optimization problems tackled with uncertainties. The uncertainties are captured with scenario analysis methods. The importance of scenario realization approaches is to capture the uncertain behaviors of parameters in stochastic optimization [14].

An algorithm to address the optimal energy exchange optimization of MGs in the distribution network is proposed in [21], considering the load consumption and renewable power generation uncertainties. This work also proposed a new method for energy exchange optimization that consider the economic, reliability, and effect of different risk strategies on the operation of MGs. They generated the scenarios from PDF of uncertain parameters. They reduced the 2000 scenarios into 30 by utilizing the scenario reduction method to simplify the computations.

In [6], the combination of MILP and stochastic chance-constraint optimization is applied on EMS on MG with on-site storage, renewable sources, and electric vehicles. However, the scenario analysis is not mentioned in their work. They concluded that the stochastic approach was better than a non-stochastic model in all charging cases.

An approach consisting of deterministic model predictive control (MPC) and stochastic MPC (SMPC) to address the problem of optimal energy management in grid-connected microgrids is proposed in [61]. However, scenario generation and reduction techniques are not discussed in this work.

A new approach proposed in [62] by a two-stage hierarchical energy management system for smart homes considering both day-ahead and actual operation stages. The authors modeled the PV solar generation as the uncertainty in the research. They used Beta probability density function and formulated the PV generations, and used Wasserstein distance-based scenario generation and K-medoids-based scenario reduction for scenario generation and reduction, respectively. The case study was a home energy management (HEM) system that used MATLAB optimization toolbox to solve.

The coordination problem between the plug-in electric vehicle (PEV) and wind power in MG is assessed in [63]. A two-layer stochastic control method that balances the power supply and demand in the first layer and then sends the power references to the second layer to control the system is proposed. An online probabilistic wind power forecasting method is proposed to manage the uncertainty of wind power in the controller design.

A stochastic model predictive control (SMPC) method for optimal scheduling of microgrid considering the uncertainties of both supply (renewable generation uncertainties) and demand (utility of load demand uncertainty) is presented in [64]. They modeled the uncertainties of wind power by the non-Gaussian predictive distribution.

A stochastic optimization model considering the uncertainties of PV and load for day-ahead scheduling of distributed energy resources in a microgrid is proposed in [65]. They used the Monte-Carlo technique for scenario generation by using a three-month historical period to calculate the quantiles and the covariance matrix to generate Normal Gaussian scenarios. They also used probabilistic distance and fast forward selection methods for scenario reduction.

A two-stage robust optimization model to address the joint optimization of day-ahead and uncertain near the real-time operation of microgrids is presented in [66]. They used Mixed Integer Linear Programming (MILP) in the first stage to model the day-ahead problem. They also used robust modeling of the uncertainties to model the uncertain real-time operation in the second stage. They considered the uncertainties of renewable energy resources (in their case studies, they just considered wind turbines) and real-time market price without discussing scenario generation or reduction approach.

A two-stage stochastic optimization method for optimal scheduling of microgrids in the short-term time scale with interdependent electricity and natural gas networks is proposed in [67]. They used the PDFs of renewable energies to capture the uncertainties, define the scenarios, and use the SCENRED tool/GAMS method to reduce the number of scenarios.

Optimal operation of microgrids with the presence of renewable energy sources and demand response using stochastic optimization is studied in [68]. The authors used a scenario tree to create the scenarios using the probability density function of Weibull, Beta, and Normal distribution,. A scenario reduction method based on DE (Differential Evolution) was used to reduce the number of scenarios.

Another study is proposed in [69] in which the uncertainty of electricity consumption in a microgrid is presented. The two-stage stochastic programming is addressed in which the battery capacity and operational decisions were considered in the first and second stages, respectively. They considered wind, PV, and electricity demand uncertainties in the optimization model. The authors did not use any specific scenario generation or reduction method.

A two-stage approach for an energy management system to minimize the operation cost of a network of microgrids is developed in [70]. The first stage is an hour ahead, and the second stage is related to a 5-min time resolution schedule, respectively. The authors considered the uncertainties of wind and solar power as Beta distribution and the uncertainties of load and price as a Gaussian distribution function and used the backward method for scenario reduction.

As discussed so far, uncertainty modeling in stochastic optimization approaches applied to MG is critical. Uncertainty modeling supports the energy management system to present uncertainty of parameters including output power of RES, loads, electricity price and fossil fuel price [71] which affects both planning and operation of EMS. Probabilistic, possibilistic, interval analysis, and scenario analysis methods are available for modeling uncertainties. Scenario analysis is the most effective method among all other approaches. Scenario analysis methods provide a scenario set made by the possible values of the uncertain parameters in the future assigned with a probability of occurrence. Scenario generation and scenario reduction are subsets of scenario analysis [10]. In the following sections, scenario generation and reduction methods will be discussed.

2.4.1 Scenario generation techniques

A comprehensive review of scenario generation methods is presented in [10]. Scenario generation methods are divided in two main subsets : Parametric and non-parametric scenario generation methods [10]. However, in [72] another subset entitled learning-based methods, is presented including NN-based models. Figure.2.4 shows a summary of available scenario generation methods.

Parametric methods are specified by the characteristics of the input (historical data). It is divided into two main groups : uncertain feature modeling and scenario sampling. Due

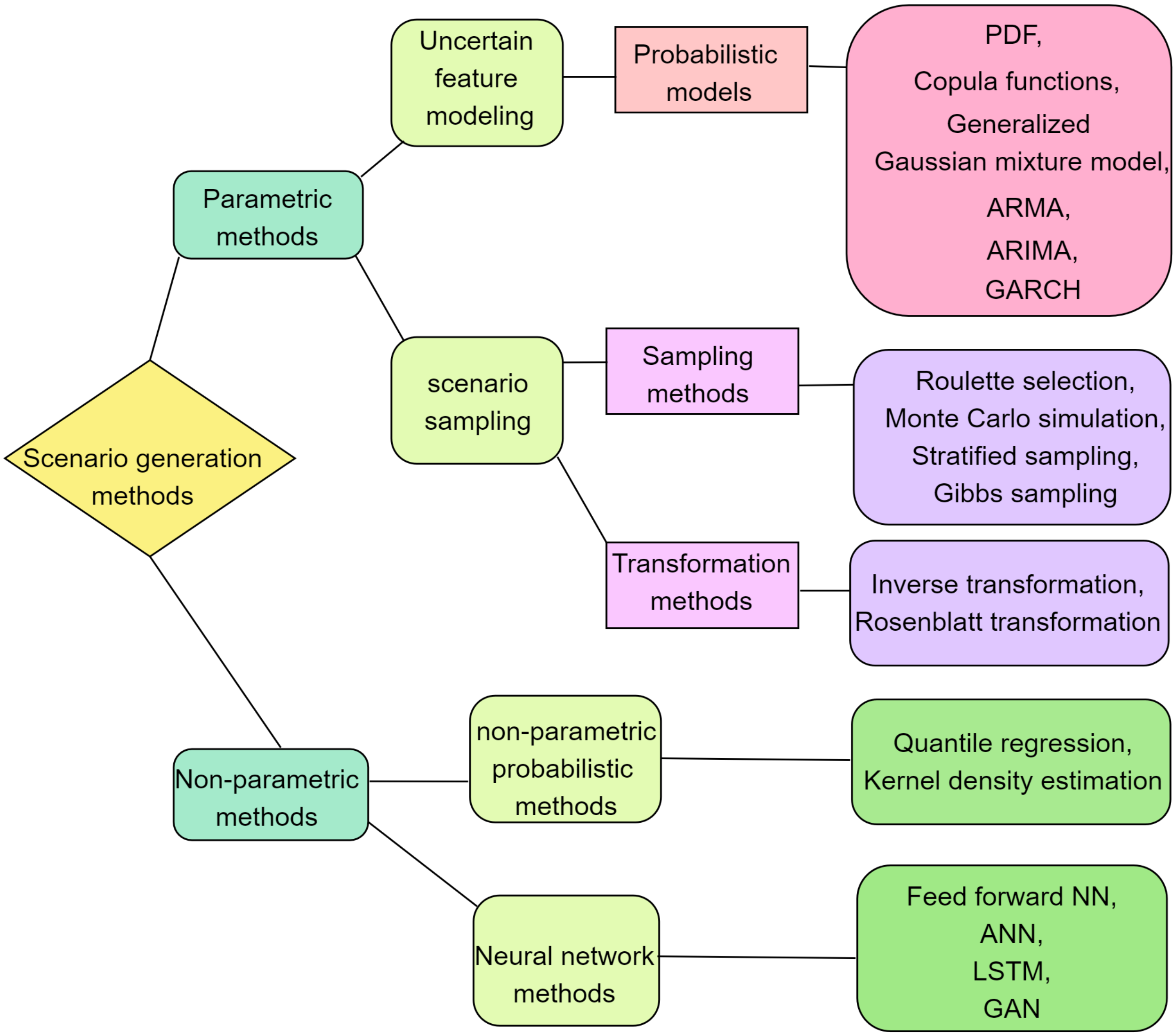

Figure 2.4 Summary of scenario generation methods

to uncertain model features, some methods use probability distribution functions (PDF) of uncertain parameters to generate scenarios. Weibull, Beta, Gamma, lognormal and normal distributions are the PDFs introduced to capture the uncertainty of one parameter in the literature [21, 67, 68, 70]. Other probabilistic methods are developed to include the joint uncertainties of more than one parameter in cases of correlation between uncertain parameters, for example, wind and solar, solar and load, etc. [6, 65]. More information on such methods is available in [10]. The references [65] and [6] proposed Monte Carlo scenario sampling methods for scenario generation in smart grid. The probabilistic methods cannot capture the uncertainties well since the predetermined distributions are limited, and in some cases, they need massive data set to be considered as inputs [10].

Non-parametric methods assign each input data to a scenario using distribution-free approaches such as quantile regression, kernel density estimation, and Markov chain [72].
Neural network (NN) based models are a subset of non-parametric approaches in [10] and in [72] in the group of learning-based models. The accuracy of NN-based methods is high, and they are mainly applied to generate RES scenarios than load. Feed-forward NN, artificial NN, Long-short term memory (LSTM), and Generative adversarial network (GAN) are NN-based models for scenario generation. Compared with probabilistic sampling and available non-parametric methods, NN-based models can illustrate the non-linearity aspects of scenarios ; however, it is more complex to learn a fitted model well [10].

In [23], GAN was applied for scenario generation of wind power and solar radiation for the first time. In [73], and [19], GAN was applied to generate wind power scenarios. Another study proposed to generate wind power scenarios for multiple wind farms using conditional Wasserstein GAN (C-WGAN) [18]. In [74], GAN proposed to generate PV power forecasting and concluded that GAN performs well in generating new data for the day-ahead prediction horizon. GAN proposed to generate scenarios of wind power and solar radiation in [17], [20] and [75]. However, the application of the generated scenarios is not shown in the optimization problems of smart grids in the previous papers.
A sequence GAN was proposed in [16] to generate wind power scenarios and analyze a MG operation case study. However, the stochastic modeling of the optimization problem as well as the modeling of the constraints is not discussed in detail. The results showed the performance of GAN besides kernel density estimation and Gaussian distribution.
Compared to applications of GAN to RES scenario generation, a few studies proposed GAN for scenario generation of load. [24] used C-GAN to capture load forecast uncertainties. However, the generated scenarios have not been analyzed in MG scheduling case studies.

It is worth mentioning that a few studies use scenario generation techniques for weekly, monthly, or yearly time horizons, and most of them are for day-ahead simulations. In addition, due to the vast computational time of solving stochastic problems in the presence of scenarios, scenario reduction techniques must be used to decrease the complexity of problems [10].

2.4.2 Scenario reduction techniques

Scenario reduction is the technique that allows reducing the original number of scenario set into a smaller set so that the characteristics of the original set are saved. Scenario reduction methods are needed to computationally enhance solving the optimization problems when the scenario set is extensive. However, the reduction method must be efficient and properly capture the uncertainties [10]. The available reduction techniques include reduction based on scenario-distance [21,76], scenario tree [67,70], clustering reduction [14,62,68] techniques, and reduction using optimization methods. All methods other than clustering-based techniques are still time-consuming and expensive in terms of reducing the large scenario set [10].

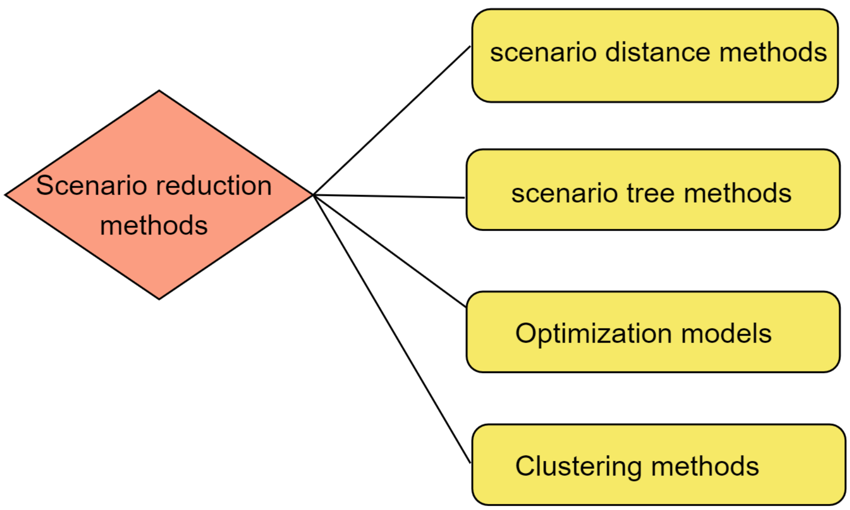

Figure 2.5 Summary of scenario reduction methods

CHAPTER 3 GENERAL ORGANIZATION OF THE DOCUMENT

In this chapter, the general organization of the dissertation according to research objectives is presented.

Chapter 1 includes the introduction of the dissertation in which the background and motivation of the research, as well as the problem and research objectives, are presented. In chapter 2, microgrid context, sizing of MG's components, and various optimization approaches to solve the problem were reviewed. In particular stochastic optimization for MGs along with scenario generation and reduction techniques have been reviewed. In chapter 4, the main body of this study is included. It is stochastic optimization for peak load shaving in MG of district buildings with a focus on scenario generation and reduction methods, including both sizing and operation in MG.

In the existed studies, the problem of sizing and operation of MG was presented. Some studies considered the uncertain parameters in MG operation. Peak shaving was a part of objectives in some previous works. But managing all these aspects of MG is critical. Hence in chapter 4, a novel approach that provides sizing, operation, scenario generation, and reduction with the aim of extending the method to a real case study of district buildings has been proposed.

In chapter 5, the general discussion of the proposed methodology and the extracted results have been conducted. In chapter 6, the summary of works as well as the limitation and future research opportunities have been presented.

CHAPTER 4 ARTICLE 1:STOCHASTIC OPTIMIZATION AND SCENARIO GENERATION FOR PEAK LOAD SHAVING IN SMART DISTRICT MICROGRID:SIZING AND OPERATION

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Abstract : Microgrids play an essential role in the integration of multiple distributed energy resources in buildings. They can meet critical loads in buildings while reducing peak loads and congestion and providing other types of ancillary services to the main electrical grid. Sizing the components of microgrids and scheduling their optimal operation while jointly integrating uncertain renewable energy generation and loads can significantly affect its ability to meet these objectives. In fact, microgrids face great challenges due to renewable energies and load uncertainties. In this paper, a two-stage stochastic programming model for optimal sizing and operation of various distributed energy resources for peak load shaving in district buildings is proposed. The first stage is related to the planning of photovoltaic panels and batteries, while the second stage aims to find the optimal operation of the system in grid-connected mode. The uncertainties are related to photovoltaic power generation and loads. The Generative Adversarial Network (GAN) is implemented to generate the scenarios of uncertain parameters, and the k-medoids classical method for scenario reduction is applied to decrease the number of scenarios. The proposed two-stage stochastic optimization is tested for a real case study of a university campus in Canada.

Keywords : Energy Management, Microgrid, Sizing, Operation, Scenario generation, Scenario reduction, Peak load shaving, Two-stage stochastic optimization

4.1 Introduction

Distribution systems around the world are undergoing significant transformations in their operation, portrayed by significant active asset driven entities, integration of Distributed Energy Resources (DER), and digital and cloud computing technologies. In this regard, buildings are important to grid modernization, playing a vital role to help balance energy use during the time of peak demand through appropriate aggregation and coordination mechanisms. The growing integration of on-site assets like solar photovoltaic (PV) panels and storage systems into buildings has demonstrated its enormous economical and environmental

Nomenclatures

Symbols

PV : Photovoltaic panel
ESS : Energy storage system
STC : Standard Test Conditions
MG : Microgrid
EMS : Energy management system
RES : Renewable energy sources
B : Battery energy storage system
C : Cost
i/I : Time slot set i=1,...,I
s/S : Scenario set s=1,...,S

Parameters

C^{PV} : The investment cost of PV panel ($\$/m^2$)
C^{B} : The investment cost of battery ($\$/KWh$)
$L_{i,s}$: Building load at time slot i and scenario s
$P^{PV}_{i,s}$: The PV output power of unit panel ($1m^2$) rated at 200 W
ρ_s : The probability of scenario s
A^{Max}_{PV},B^{Max} : Limit size of PV installation area and battery energy capacity
ΔT : Controlling time interval
η_{ch},η_{dch} : The battery charging and discharging efficiency

Variables

S^{B} : The installation energy capacity of the battery
S^{PV} : The installation size of the PV panel
$P^{PV,G}_{i,s}$: The power flow from PV to the grid at time i in scenario s
$P^{PV,B,ch}_{i,s}$: The power flow from PV to the battery at time i in scenario s
$P^{PV,L}_{i,s}$: The power flow from PV to the load at time i in scenario s
$P^{BL,dch}_{i,s}$: The power flow from battery to the load at time i in scenario s
$P^{GL}_{i,s}$: The power flow from grid to the load at time i in scenario s
$P^{GB,ch}_{i,s}$: The power flow from grid to the battery at time i in scenario s
$P^{GLP}_{i,s}$: The power flow from grid to the load at time i in scenario s during peaks when the battery and PV can not satisfy all loads

benefits [77,78]. Consequently, the local flexibility should be efficiently managed by buildings' operators in a way that minimizes the adverse effects on the power system and reduces energy consumption. When the pricing mechanism depends on the declared maximum peak load, such as for industrial, commercial and institutional buildings, the reduction of peak demand is a powerful solution for the grid and buildings operators. There are various approaches to Peak Load Shaving (PLS), they usually depend on pricing mechanisms and the deployed DER and demand side-management strategies. In [67,79,80], three PLS strategies are discussed based on energy storage system (ESS), electric vehicles and demand side management. In particular, Building MicroGrid (BMG) with PV and energy storage systems is a key solution that enables buildings to fully employ the available ressources to reduce/shave the peak load, while maintaining the local comfort. MG is a group of DER together with energy storage systems (ESS) and loads that can be operate in islanded or grid-connected modes [81]. The main purpose of using MG is to enhance the flexibility of buildings to reduce their peak load and thus minimizing the electricity bill. In this regard, the available flexibility of the MG is also highly dependent on the size of microgrid's components. The desire of building operators is to decrease the investment costs of MG while, ensuring significant peak shaving. Hence, it is of high importance to reach an optimal system configuration to avoid oversizing or undersizing microgrids and reach an overall system size and cost. The high uncertainties related to RES [82] and loads [83], makes the sizing and operation of MGs in the context of buildings a challenging task.

Several methods have been proposed to size [84–86] and control microgrids [87–90]. In this perspective, the RES and loads have uncertainties which must be considered to define the optimal sizing of the renewable generators [91]. In this case, deterministic optimization approaches could not be used to solve such problem since uncertainties are made of probabilities and it needs to handled with appropriate tools such as stochastic methods [92]. One of the main characteristic of solving stochastic optimization is the existence of a probability distribution of the uncertain parameter. The high computational complexity of stochastic optimization is related to the number of uncertain parameters, which increases dramatically the number of scenarios involved in the optimization [93]. To avoid the large computational complexity, scenario reduction techniques are required to decrease the number of scenarios [94].

There is a vast body of literature on the application of stochastic optimization approaches to optimal power flow (OPF-based) problems, which is investigated and reviewed in this paper.

4.2 Literature review

This section presents the literature review covering the application of stochastic optimization in the field of MGs. The type of available uncertainties in the system is discussed as well as the scenario generation and reduction approaches. At the end of the section, research gap will be identified.

4.2.1 Stochastic optimization for MGs operation

There has been a rich number of research papers addressing the energy management issues of MGs. Stochastic optimization approaches for optimal MG operation with the presence of uncertainties have been carried out. Luo et al. [62] investigated a two-stage hierarchical energy management system for smart homes considering both day-ahead and actual operation stages. Despite of author's efforts to apply the scenario generation and reduction of PV generation scenarios, they did not include the uncertainties related to the load. Aboli et al. [66] proposed a two-stage stochastic model to address the joint optimization of day-ahead and uncertain real-time operation of MGs combining mixed-integer linear programming (MILP) and robust optimization. They considered the uncertainties of RES and real-time market price with no implementation of scenario generation or reduction techniques. Sedighizadeh et al. [68] addressed the stochastic problem of optimal operation of MGs with the presence of RES and future electricity demand. The authors made scenario tree using probability distribution functions (PDFs) and reached a logical number of scenarios using differential evolution scenario reduction method. The majority of their work was focused on the operation of MGs and not sizing. Wang et al. [70] developed a two-stage approach for an energy management system considering the uncertainties of RES and load. PDF and Backward method are applied for scenario generation and reduction respectively. Zhang et al. [95] developed an online learning-based control algorithm to address the MG energy dispatching problem with random renewable generation and EVs usage pattern. In their work the patterns of energy generation, consumption and storage availability are all random and unknown at the beginning, and the MG controller is formulated as a Markov Decision Process (MDP). Shams et al. [67] presented a two-stage stochastic optimization method for optimal scheduling of MGs. Authors considered RES as well as electrical and thermal demands. PDFs related to RES are used to capture the uncertainties and define the scenarios. Kou et al. [64] proposed a stochastic model predictive control method to optimally schedule MGs considering the joint uncertainties of RES and load. In [63], authors addressed a similar problem with the existence of RES and plug-in electric vehicles (PEV) uncertainties, where an assessment of the coordination between the PEV and wind power in MGs is considered. They proposed a two-layer stochastic control method which balances the power supply and demand in the first layer and then sends the power references to the second layer to control the system. An online probabilistic wind power forecasting method is implemented to manage wind power uncertainty. Gazijahani et al. [21] proposed an algorithm for optimal energy exchange optimization of MGs in 24 hour-ahead using stochastic formulation. The stochastic modelling of RES and load consumption are considered in their three risk-based strategies. The main focus in their objective function is assessing various risk strategies in MGs considering the financial and economical ones.

Ravichandran et al. [6] proposed a MILP and a stochastic chance-constrained optimization for online optimal power control in MGs. They considered uncertainties related to electric vehicles connection and disconnection times to MGs as well as RES. Scenario reduction methods has not been applied in this work. Silve et al. [65] proposed a stochastic optimization model considering the uncertainties of RES and load. Monte Carlo technique for scenario generation, probabilistic distance and fast forward selection methods are used. Lazaroiu et al. [96] used both stochastic and deterministic approaches to solve an optimization problem in MG in the presence of uncertainties related to RES. However, scenario generation or reduction techniques are not deployed in this work. Cominesi et al. [97] proposed a two-layer method consisting of deterministic model predictive control (MPC) as the higher level and stochastic MPC as the lower level. The stochastic MPC (online) is applied each 1 min and with time step of 15 min to control the uncertainties effect on the optimization problem while the higher level (offline) economically optimize the problem. However, the potential of scenario generation was not exploited in their work.

4.2.2 Planning and sizing MGs

Some works in the literature investigated both sizing and optimal operation of microgrids. Prathapaneni and Detroja [98] proposed an integrated planning and operation approach for an islanded MG with the presence of distributed renewable energy generators. They employed sizing to find the optimal sizes of diesel generators, PV panels and batteries. The approach was not stochastic optimization but considered the uncertainties of load and RES in sizing MG. Zheng et al. [14] proposed a multi-year two-stage stochastic optimization problem considering both sizing and operation. Their paper comprises work concerned with developing a method for maximizing benefit for residential building owners taking into account the inflation rates in prices during the years. The approach was tested on public IEEE data set and does not fully consider the problems that can appear in real situations. In [27], the authors investigated a method for sizing MG in order to minimize the annual costs, greenhouse gas emissions and energy losses, while maximizing the annual benefit due to the deferral of upgrades. The MGs' components were sized and applied on scheduling MG operation using Gray Wolf Optimizer approach. In [99], the authors constructed an algorithm to optimize the size of PV panels, wind turbines, fuel cell and diesel generator aiming to minimize the total costs and the total greenhouse gas emissions of the MG. However, the uncertainties of the RES parameters is not considered. The method presented in [100] is about optimal sizing and planning of PV-battery systems using non-stochastic method. It was worth mentioning that the method performs well for different tariff structures which are considered in their work. In [101] the objective of the investigation is to size a hybrid system based on PV, wind turbine, diesel and battery with the aim of minimizing the net present and emission costs while the uncertainties of the components is not included in their work.

4.2.3 Uncertainties modelling in MGs

Scenario generation methods are divided in two main subsets : parametric and non-parametric scenario generation methods [10]. However, in [72] another subset entitled learning-based method, is presented including NN-based models. Parametric methods are specified by the characteristics of the input (historical data). It is divided into two main groups : uncertain feature modeling and scenario sampling. Due to uncertain model features, some methods use probability distribution functions (PDF) of uncertain parameters to generate scenarios. Weibull, Beta, Gamma, lognormal and normal distributions are the PDFs introduced to capture the uncertainty of one parameter in the literature [21, 67, 68, 70]. The probabilistic methods cannot capture the uncertainties well since the predetermined distributions are limited, and in some cases, they need massive data set to be considered as inputs [10]. Non-parametric methods assign each input data to a scenario using distribution-free approaches such as quantile regression, kernel density estimation, and Markov chain [72].
Neural network (NN) based models are a subset of non-parametric approaches in [10] and in [72] in the group of learning-based models. The accuracy of NN-based methods is high, and they are mainly applied to generate RES scenarios than load. Feed-forward NN, artificial NN, Long-short term memory (LSTM), and Generative adversarial network (GAN) are NN-based models for scenario generation. Compared with probabilistic sampling and available non-parametric methods, NN-based models can illustrate the non-linearity aspects of scenarios ; however, it is more complex to learn a fitted model well [10]. It is worth mentioning that a few studies use scenario generation techniques for weekly, monthly, or yearly time horizons, and most of them are for day-ahead simulations. In addition, due to the vast computational time of solving stochastic problems in the presence of scenarios, scenario reduction techniques must be used to decrease the complexity of problems [10]. A number of uncertainties models are proposed to include RES and load uncertainties in MGs. In [102], the interval prediction technique, which includes point forecast combined with a forecast error, is used to model the lower/upper bounds of uncertainties. The authors proposed orthogonal array (OA) to find the possible scenario set. Defining the PDF of forecast error in addition to finding suitable OA matrix are the challenges of their method. In [62], a Wasserstein distance-based scenario generation attached with the PDF of the PV solar power is employed for generating scenarios. The beta distribution is selected to define the characteristics of solar radiation and is discredited by Wasserstein method. In [21, 67, 68, 70], PDFs of uncertain parameters are used for generating scenarios. In [6, 65], the authors proposed Monte Carlo simulation in order to

generate the scenarios.
It is worth that the aforementioned approaches depend on the distributions of the uncertain parameters. Defining the most exact distribution applied to historical data is critical specially in planning and operation of MGs. Using the predetermined PDFs leads to apparent losses in generating realistic scenarios. Most of the approaches can not capture the non-linearity of historical data. GAN is a type of Neural Network-based model which is distribution-free, and there is no need to know the PDFs of uncertain parameters before scenario generation. In GAN, the randomness of the parameters is described well due to generating scenarios. Moreover, the non-linearity correlations could be considered to generate realistic scenarios [10]. Chen et al. [23] used GAN to generate scenarios of RES consisting of wind speed and solar radiation for the first time. Jiang et al. [73] and Yuan et al. [19] used GAN for generating wind power scenarios. Zhang et al. [18] proposed a conditional GAN to generate wind power scenarios for muti-locations. Wang et al. [74] proposed GAN to generate PV power forecasting and concluded that GAN performs well in generating new data for the day-ahead prediction horizon. Dong et al. [17], Qiao et al. [20] and Chen et al. [75] proposed GAN to generate scenarios of wind power and solar radiation. However, the application of the generated scenarios is not shown in the optimization problems of smart grids in previous literature. Yang et al. [103] generated the electric vehicle charging uncertainties via GAN. Wang et al. [24] modeled the load uncertainty using conditional GAN. Liang et al. [16] generated wind power scenarios and studied the performance of generated scenarios in a MG operation case study. However, the stochastic modeling of the optimization problem is not discussed. As far as we know from the literature, no work used GAN scenario generation in MGs for peak shaving using stochastic optimization.

4.2.4 Peak load shaving and reduction

One of the most critical energy management strategies in the context of buildings is peak shaving (or reduction). Various peak shaving strategies have been proposed in the literature. These studies focused on presenting a set of options to better control the building's peak load. In [104], the authors presented a MPC approach to shave the peak using battery for a household with the presence of PV system in a low voltage grid. The main objective of their work is to maximize the contribution of the battery and peak shaving in a single electricity price scenario. They implemented uncertainties related PV generation in the modeling, however the approach did not include finding the suitable sizing for technologies. In [105], the role of battery, i.e. size and operational decisions, on peak shaving is evaluated simultaneously with the goal of reducing the load demand. The problem was solved using a linear programming without considering effects of uncertainties in the proposed model. In [106], the authors proposed modeling, simulation, and sizing problem of an energy storage system for residential electricity peak shaving. Despite considering sizing problem, authors did not exploit the potential of RES as a complimentary option to support peak shaving and charge the batteries. In [107], the authors released a method to size MG with the prediction of load and PV generation. However, the uncertainties of PV generation and load were not discussed in their work. In [108], authors proposed a mathematical model to shave the peak by scheduling the charging/discharging process in EV. The model considered EV energy requirements, arrival and departure times, power charging/discharging and battery constraints without any RES integration. A method to shave the peak in a local electricity system in the presence of RES and energy storage system is proposed in [109]. A scenario tree approach is used for scenario generation while assuming equal probabilities.

4.2.5 Research gap and major contributions

A closer look to the literature reveals a number of gaps and shortcomings in the topic of MGs. Table.4.1 includes a summary of literature. There is clearly an increasing need and scope for simultaneously sizing and operating MGs with the aim of peak shaving in buildings. Given the rising prevalence of stochastic optimization, there is an essential need to generate accurate scenarios, while reducing the computational complexities. To the best of our knowledge, this study is the second attempt to use GAN scenarios generation technique for the two-stage stochastic programming in MGs. The first attempt was in [16], which uses sequence-GAN to generate wind power scenarios and use them for MG scheduling. This work is conducted in response to the need to an approach which includes sizing, operation, peak shaving, stochastic optimization and scenario generation and reduction in the field of MGs. The major contributions of our work are as follows :

1. Develop a two-stage stochastic optimization approach for a university campus to reduce peak loads, while considering MG investment and maintenance costs.
2. Develop a scenario generation approach utilising conditional GAN to capture the uncertainties of PV power and load.
3. Propose a scenario reduction approach based on the K-medoids approach to reduce the computing time of the stochastic optimization problem.
4. Simulate the proposed approach using real-world data on a University campus in Montreal region.

Table 4.1 Summary of literature

Reference	Publication year	MG characteristics			Grid connection mode	Sizing and operation	Uncertainty		Scenario generation	Scenario reduction	Peak Shaving	Objective function
		RES	ESS	Industrial/ residential load	Connected		RES	Load				
Cominesi et al. [97]	2015	✓	✓	✓	✓	—	✓	✓	—	—	—	minimize the operational cost
Lazaroiu et al. [96]	2016	✓	✓	✓	✓	—	✓	—	—	—	—	minimize the operational cost
Kou et al. [63]	2016	✓	—	—	✓	—	✓	—	—	—	—	minimize the power exchange between MG and main-grid
Silva et al. [65]	2018	✓	✓	✓	✓	—	✓	✓	Monte Carlo	—	—	minimize the operation cost
Wang et al. [70]	2018	✓	✓	✓	✓	—	✓	✓	PDF	Backward selection method	—	minimize system operation cost
Gazijahani et al. [21]	2018	✓	✓	✓	✓	—	✓	✓	PDF	Kantorovich distance	—	minimize operation and maintenance cost/ minimize the energy not-supplied
Ravichandran et al. [6]	2018	✓	✓	—	✓	—	✓	—	Monte Carlo	—	—	maximize the economical benefit
Zhang et al. [95]	2018	✓	✓	✓	✓	—	✓	—	—	—	—	minimize the operation cost
Shams et al. [67]	2018	✓	✓	✓	✓	—	✓	✓	PDF	Forward selection method	—	minimize the operation cost
Kou et al. [64]	2018	✓	—	✓	✓	—	✓	✓	—	—	—	minimize the operation cost
Luo et al. [62]	2019	✓	✓	✓	✓	—	✓	—	Wasserstein distance metric	K-medoids	—	minimize the home electricity cost
Aboli et al. [66]	2019	✓	✓	—	✓	—	✓	—	—	—	—	minimize operational cost of controllable units
Sedighizadeh et al. [68]	2019	✓	✓	✓	✓	—	✓	✓	PDF	Deferential Evolution (DE) clustering	—	minimize operational cost and emissions
Liang & Tang. [16]	2020	✓	—	✓	—	—	✓	—	SeqGAN	—	—	minimize operation cost
Nieta et al. [109]	2021	✓	✓	✓	✓	—	✓	✓	—	—	✓	minimize operation cost
Zheng et al. [14]	2021	✓	✓	✓	✓	✓	✓	✓	—	K-means	—	maximize net benefit
Current work	2022	✓	✓	✓	✓	✓	✓	✓	C-GAN	K-medoids	✓	minimize operational cost and peak shaving

4.3 Methodological approach

4.3.1 Uncertainty modeling

For handling the uncertainties related to the stochastic programming approach, two main procedures are required. First, the scenarios associated to PV power generation and loads are generated using Generative Adversarial Network (GAN). Second, given the large number of generated scenarios, an approach for scenario reduction is employed.

Scenario generation : Generative Adversarial Networks (GANs)

The theory of Generative adversarial networks (GAN) was originally proposed by Goodfellow [110]. A review of the theoretical part of GAN is presented by Li et al. [111]. The idea of GAN is to launch a MinMax game between two interconnected networks i.e., generator (G) and discriminator (D). Fig.4.1 shows the structure of GAN. Compared with the classical scenario generation methods, GAN does not need to know the predetermined distributions of the inputs (historical data). The generator (G) learns the distribution of real samples in order to generate new samples based on noise inputs that comes from a known random distribution such as Gaussian or Uniform. The discriminator (D) tries to find out if the data is categorized in real historical data or generated data by GAN.

The generator and discriminator train simultaneously. The generator tries to minimize the difference between generated and real samples. Hence, the samples become more realistic while the discriminator tries to maximize the probability of distinguishing whether a sample is real. Meanwhile, the discriminator aims to minimize the probability of indicating that the sample is generated.

The conditional GAN (C-GAN) is a development of GAN which is proposed by [112]. In C-GAN, the input data to the generator is in the form of the historical data in addition to a label. The labels indicates the information of the classes. Discriminator also takes the generated samples as well as real historical samples attached with the labels to distinguish whether a sample from a specific class is generated or real. Fig.4.1 shows the architecture of C-GAN, that includes other inputs as class labels in addition to historical data.

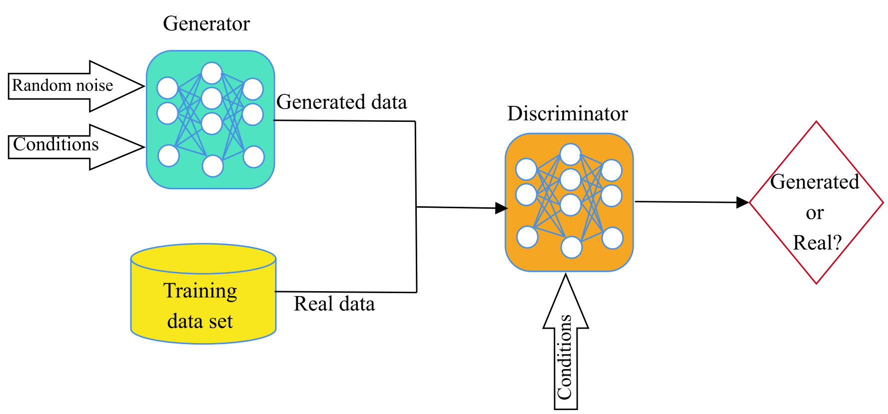

Figure 4.1 GAN basic architecture

Scenario reduction : K-medoids

Due to the large number of generated scenarios and to compromise between the solution accuracy and computational burden, scenario reduction methods are employed. Scenario reduction helps to decrease the total number of scenarios to a feasible number to decrease the run-time of the algorithm and computationally reduce the algorithm [18, 113–115]. The idea of the proposed method is to group the reduced scenarios into k clusters [18]. The reduced scenarios set will be defined by solving an optimization problem :

$$\sum_{g_m \in g_d} min_{g_n \notin g_d} d(g_m, g_n)$$

where g_m and g_n are two scenarios of total scenario set G. g_d is the reduced scenario set that has k scenarios. $d(g_m, g_n)$ is the distance between two scenarios. As indicated in [18], this method uses the idea of $k - medoids$ clustering in which the problem decreases the distance between the medoids and other scenarios in related cluster. The medoids are the points of the whole scenario set and have the lowest average dissimilarity to the entire scenario set. All other scenario data are assigned to the clusters with minimum distance with its medoids. In the clusters, a non-medoid data is selected, and the cost of substituting the new medoid with the old one is determined. This process is repeated till the most representative medoids have been selected for each cluster [116]. By solving this program, the minimum number of scenario vectors that are similar to the initial set will be obtained.

4.3.2 Mathematical modeling

In this section, the mathematical formulation of the optimization problem will be discussed. In this work, the two-stage stochastic optimization approach is proposed.

Two-stage stochastic energy management problem formulation

In the current work, a two-stage stochastic programming formulation is developed to model the load and PV uncertainties. Fig.4.3 shows the architecture of the corresponding microgrid. The determination of the optimal size of the MG components is one of the objectives of the current work. The large power consumer pricing scheme (LG) [117] is the basic price considered to supply power for the system. Fig.4.2 shows the simulation process of the proposed approach.

Objective function

The objective of the first stage is to minimize the investment costs related to MG, while for the second stage, the aim is to minimize the monthly operation costs taking into account the peak shaving strategy (Eq.4.1).

$$\begin{aligned} \text{Min}(Obj) =& CRF \times (S^{PV}C^{PV} + S^{B}C^{B}) + \\ & S^{PV}C^{PV}_{mnt} + S^{B}C^{B}_{mnt} + \\ & \sum_{s=1}^{N_s} \rho_s \times \{\sum_{i=1}^{I} C^{buy} \cdot P^{GLP}_{i,s}\} \end{aligned} \tag{4.1}$$

The two first terms of the objective are related to the first stage, i.e., the capital and maintenance costs for the selected PV and battery system. The capital recovery factor (CRF) is

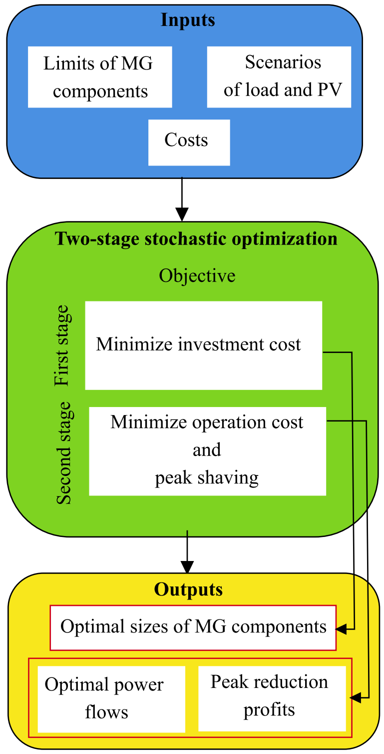

Figure 4.2 Simulation process

used to convert the initial capital cost to an annual capital cost [118], which accounts for the actual interest rate (r) and the expected lifetime of the microgrid (n_{inv}). In this study we considered $r = 0.06$ and $n_{inv} = 20$ years. S^{PV} (m^2) and S^B (kWh) are the installation area of PV panels and battery capacity respectively while C^{PV} ($\$/m^2$) and C^B ($\$/kWh$) are the initial capital costs of the PV and battery units. C^{PV}_{mnt} and C^B_{mnt} is the annual maintenance costs of PV and battery units which are considered as 10% of the investment costs.

$$CRF = \frac{r(1+r)^{n_{inv}}}{(1+r)^{n_{inv}} - 1} \tag{4.2}$$

The second stage which includes the scenarios aims to minimize the operational costs. ρ_s is the probability of scenarios, N_s is the total number of scenarios in each month, C^{buy} is the cost of purchasing power from the main grid and $P^{GLP}_{i,s}$ is the power purchased from the main grid during peak hours, i.e., after 5 MW threshold. The objective is to minimize the $P^{GLP}_{i,s}$ considering the PV power and the power stored in the battery in peak times.

The decision variables are :
$P^{PV,G}_{i,s}$: power sent from PV to the main grid
$P^{PV,B,ch}_{i,s}$: power sent from PV to charge the battery system

$P_{i,s}^{PV,L}$: power sent from PV to satisfy building load
$P_{i,s}^{BG}$: power sent from battery to the main grid
$P_{i,s}^{BL,dch}$: power sent from the battery to satisfy building load
$P_{i,s}^{GB,ch}$: power sent from the main grid to battery
$P_{i,s}^{GL}$: power sent from the main grid to building load in off-peak hours
$P_{i,s}^{GLP}$: power sent from the main grid to building during peak hours.
S^{PV} : total size of PV installation area
S^{B} : total battery capacity size

Constraints

The battery charging/discharging process is modeled by Eq.4.3 in scenario s at time i. It is assumed that the batteries can be charged from PV panels and the main grid. They are discharged to satisfy part of the building's load during peak periods. It is worth to mention that since our goal is to shave the peak, we do not allow the charging of the batteries during peak hours (when the total load exceeds the subscribed power of 5MW).

$$E_{i,s} = E_{i-1,s} + [(P_{i,s}^{GB,ch} + P_{i,s}^{PV,B,ch}) \cdot \eta_{ch} - \frac{(P_{i,s}^{BL,dch})}{\eta_{dch}}] \cdot \Delta T \tag{4.3}$$

— $P_{i,s}^{GB,ch} = 0$ if $L_{i,s} \geq 5000$
— $P_{i,s}^{BL,dch} = 0$ if $L_{i,s} < 5000$

Eq.4.4 defines that the total energy storage system at time i in scenario s cannot exceed the maximum state of charge multiplied by the total size of the batteries. Also, it is applied for the minimum state of charge of the batteries.

$$SOC_{min} \cdot S^{B} \leqslant E_{i,s} \leqslant SOC_{max} \cdot S^{B} \tag{4.4}$$

Eq.4.5 states that the product of charging and discharging powers of batteries must be 0 at each time in each scenario. This constraint allows avoiding charging and discharging simultaneously.

$$(P_{i,s}^{GB,ch} + P_{i,s}^{PV,B,ch}) \times P_{i,s}^{BL,dch} = 0 \tag{4.5}$$

Eq.4.6 states that the total charging power of the batteries, which is the sum of the power from main grid and the PV power during off-peak hours, must be positive and less than the maximum power of each battery in (kW), i.e., β, multiplied by the number of the batteries, i.e., N^{B}.

$$0 \leqslant P_{i,s}^{GB,ch} + P_{i,s}^{PV,B,ch} \leqslant \beta \cdot N^B \tag{4.6}$$

Eq.4.7 indicates that the total discharging power of the batteries cannot exceed the the maximum power of each battery in (kW), i.e., β, multiplied by the number of the batteries.

$$0 \cdot \leqslant P_{i,s}^{BL,dch} \leqslant \beta \cdot N^B \tag{4.7}$$

Eq.4.8 is the power balance constraint which indicates that the total load at time i in scenario s must be supplied from PV, main grid, battery discharging and power from main grid during peak. If the load is less than 5000 kW, there is no power flow from PV and batteries to the building.

$$P_{i,s}^{PV,L} + P_{i,s}^{GL} + P_{i,s}^{BL,dch} + P_{i,s}^{GLP} = L_{i,s} \tag{4.8}$$

if $L_{i,s} \leq 5000$ **then**
 $P_{i,s}^{PV,L} = P_{i,s}^{BL,dch} = P_{i,s}^{GLP} = 0$
else
 $P_{i,s}^{GL} = 5000$
end if

Eq.4.9 indicates that the total PV power can be used to satisfy the building load directly, to charge the battery or to sell power to the main grid.

$$P_{i,s}^{PV,L} + P_{i,s}^{PV,B,ch} + P_{i,s}^{PV,G} = S^{PV} \cdot P_{i,s}^{PV} \tag{4.9}$$

$$0 \leqslant P_{i,s}^{PV,G} \tag{4.10}$$

$$0 \leqslant P_{i,s}^{GL} \tag{4.11}$$

Eq.4.12 illustrates that the optimal capacity of battery can not be more than the maximum battery capacity, which is defined by users. Moreover, Eq.4.13 indicates that the optimal installation area for PV panels can not exceed the total rooftop area of the buildings.

$$0 \leqslant S^B \leqslant B^{max} \tag{4.12}$$

$$0 \leqslant S^{PV} \leqslant A_{PV}^{Max} \tag{4.13}$$

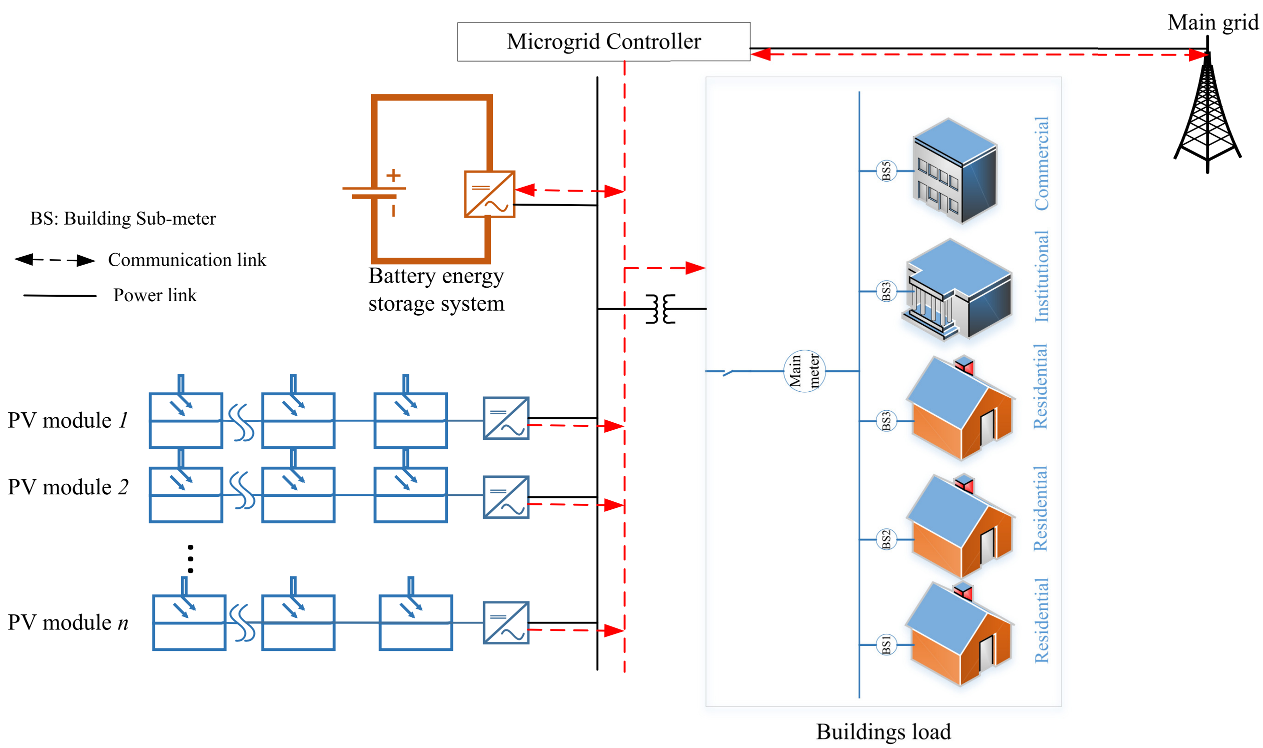

Figure 4.3 Microgrid architecture.

The output power of PV panels is calculated using Eq.4.14 [119].

$$P_{PV}(t) = N_{PV} \eta_{PV} P_{STC} \frac{G_i(t)}{G_{STC}} [1 + (T_c - T_{STC}) C_T] \tag{4.14}$$

where N_{PV} is the number of PV panels, η_{PV} is efficiency of panels, P_{STC} is the nominal power (W) under standard test conditions (STC), $G_i(t)$ is the solar radiation at operating point (kW/m^2) and $i = 1, ..., 8760$, G_{STC} is solar radiation at STC conditions (kW/m^2), C_T is the power temperature coefficient ($\%/C^\circ$), T_{STC} is the temperature at STC conditions (C°), $T_c(t)$ is the Cell temperature (C°), $T_c = T_a + \frac{(T_{NOCT}-20)}{800} \cdot G_i(t)$, T_a is the ambient temperature (C°) and T_{NOCT} is the normal operating cell temperature (C°).

4.3.3 LG pricing

In Quebec, large consumers such as campuses can follow the LG pricing scheme with a fixed subscribed power. In this scheme, the campus is charged according to the maximum amount of power during the billing period. However, if the demand is less than the subscribed power during a certain billing period, the campus will be charged for its subscribed power. The additional costs must be paid in terms of exceeding the subscribed power. According to the definition given by Hydro-Quebec utility, LG Rate applies to an annual contract whose minimum billing demand is 5000 (kW) or more, unless the contract is principally related to an industrial activity. The tariff which applies to this pricing system is 13.781($\$/kW$) and 0.3596($\$/kWh$) [117]. Hence, the total LG pricing tariff is equal to :

$$C_{LG} = max(P_{max}, 5000) \times 13.781 + E_T \times 0.3596 \tag{4.15}$$

where P_{max} is the maximum monthly power and E_T is the total monthly energy. Since our focus is on peak power shaving, we consider only the power price in the calculations.

4.4 Results and discussion

In this section, the application and numerical results are discussed. The data used in this paper are gathered from the building energy management system of a university campus in downtown Montreal. It consists of five buildings (residential, commercial and educational/office buildings) representing a diverse mix of load patterns. In this work, the generated scenarios are representative of monthly scenarios, i.e., in each month the selected scenarios are the most appropriate representation of that month. So the time resolution is $i = 1, ..., 288$ which is daily profile with 5 minutes time resolution. The monthly bills are calculated based on the maximum power called from the main grid during the month so if the peak shaving is implemented in a daily profile it could work for total month.

4.4.1 Simulation setup

The two-stage stochastic problem formulated in the previous section is solved and the numerical analysis show the capability of the optimization method. The simulation setup has three main parts : 1) scenario generation via C-GAN, 2) scenario reduction and 3) solving two-stage stochastic problem. We extended the python code of scenario generation via conditional GAN, which was available in [23]. In this work, this code has been implemented on real historical data of PV power and load of a university campus, taking into account the months labels as conditions. The total generated scenarios form the main scenario set. Then, the process of scenario reduction starts by selecting the k-medoids that have the minimum dissimilarity to all scenario sets and making the clusters. Other scenario data are assigned to one of the clusters with the minimum distance with its medoid. Once the scenario reduction techniques are completed, the most representative medoid has been selected for each cluster. The probability assigned to each medoid is calculated by counting the components of that cluster and dividing it by the total main scenario set. For scenario reduction, the K-medoids approach has been implemented via python. Then the probabilities and the scenarios for each month fed to the stochastic optimization problem. The optimization problem has been solved with JuMP programming language [120], which is open-source and is used to solve a wide range of optimization problems. The stochastic programs package has been used in the current study.

4.4.2 Data

In this study, we propose the real historical data of electrical load and solar radiation of a university campus located in downtown Montreal, Canada. The load data was recorded for five district buildings with a time resolution of 15 minutes from January 2015 to December, 24, 2016. The MG sizing and operation consider the total load of the buildings. In order to prepare data for C-GAN simulations, we transform the load data in 5 minutes resolution by triplicating each row. The available rooftop area of the total buildings is $1880m^2$. The solar radiation data is applied on unit PV panel with the area of 1 m^2 and a nominal power of 200 W to find the power of each panel at time i in scenario s. In addition, we create the calendar data to use them as conditions for GAN. We shuffled the data and 90% were used for training and 10% for testing. Fig.4.4 shows the original loads of typical scenarios in all months. It shows that in some months there is peak after 7 PM and the highest peak occurs in July for the available data set.

4.4.3 Scenario generation using C-GAN

In this paper, we propose C-GAN to generate scenarios of PV power generation and loads. In this case, we generate 2500 scenarios for both PV power generation and building loads. Auto-Correlation coefficient is considered as a metric to show the performance of C-GAN for generating the scenarios. Fig.4.5 and Fig.4.6 illustrate the real data and the generated samples of PV power and load as well as the auto-correlation coefficients for all month. The samples are selected from the validation data set that has not been used for training C-GAN. In Fig.4.5, it is shown that the C-GAN performs better in generating the scenarios in Spring

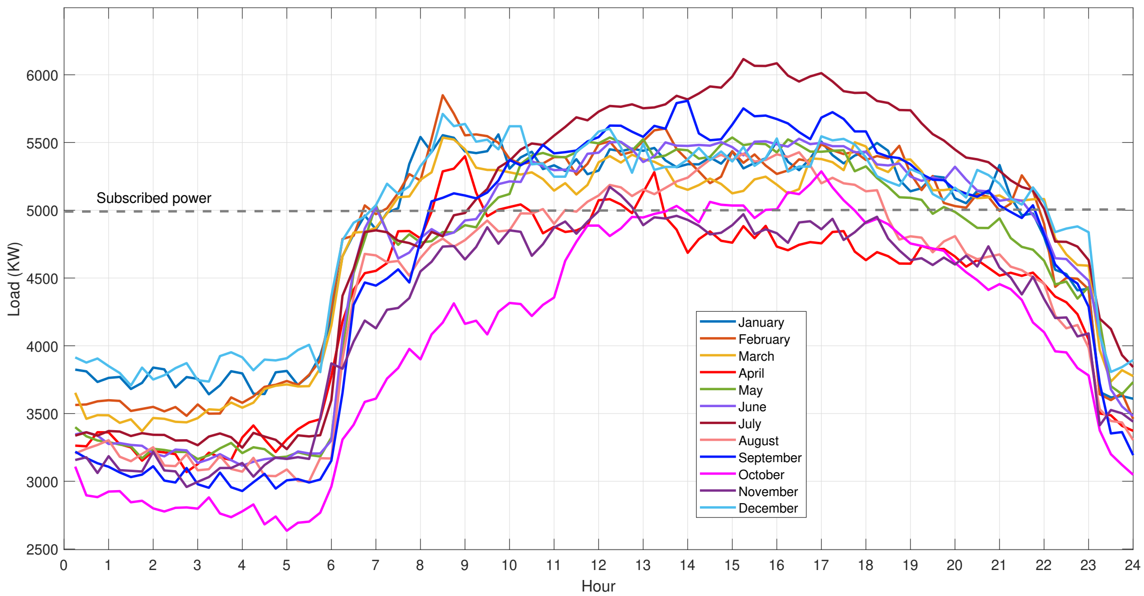

Figure 4.4 Real load profiles in typical days in all months.

and Summer. The Fig.4.6 shows similar performance for all months. It is worth mentioning that the reference paper which was selected for scenario generation using C-GAN, i.e., [23] was originally proposed for generating RES scenarios and in this work we also implement it on real historical data of load to capture the ability of the method on different data sets other than RES. In [10, 17, 121], mean, variance, skewness, and kurtosis were introduced as statistical indexes to evaluate the generated scenarios. Skewness shows whether the proposed distribution is symmetric or not compared with the Normal distribution, and it can be positive, zero, or negative. The normal distribution has a skewness of zero. Kurtosis defines the steepness of the distribution. The kurtosis of Normal distribution is 3. The values greater than 3 show the distribution is steeper than the Normal distribution and below 3 shows it is smoother than the Normal distribution. $Skewness = E(X-\mu)^3/\sigma^3$ and $Kurtosis = E(X-\mu)^4/\sigma^4$ where E is the expectation, μ is the mean of the samples of X, σ is the standard deviation of X [17]. Table.4.2 includes the four metrics mentioned above of the validation scenarios and generated scenarios for PV power and load. In spring and summer, the differences between the values for validation and generated samples are lower for both PV power and load.

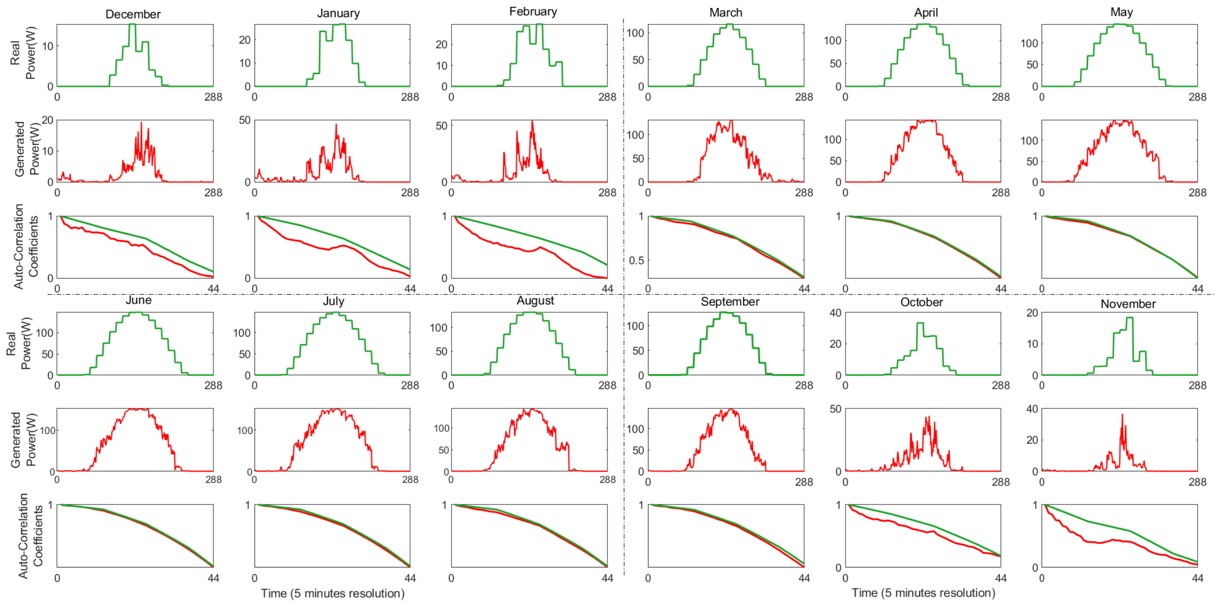

Figure 4.5 Real data vs generated samples of PV output power of a PV unit in typical days in all month which have not been used as training data. The auto-correlation functions states that the generated samples can follow the correlation to time properly

Scenario reduction using K-medoids

The K-medoids reduction technique is implemented by K=5, 10, 12, 15 for each uncertain parameter. Due to the large computational program, in this study, we use the K=5. Since the scenarios are generated monthly, hence, the reduction is also reached monthly. Thus, for each month, we reduced the scenarios into 5 among all 2500 generated scenarios. The total number of scenarios in each month is $5^2 = 25$. Fig.4.7 and Fig.4.8 show the reduced scenarios of PV and load in typical months assigned with their probabilities.

4.4.4 Numerical results

The sizing problem shows that the proposed microgrid consists of 899 kWh battery storage system and a 800 m^2 rooftop PV array. Each PV has the nominal power of 200 W and area of 1 m^2.

The second stage is solved given the optimal battery and PV sizes. The scenarios are generated monthly, and each profile with the indicated probability represented the days in that month.

Fig.4.9 shows the optimal operation in a typical scenario in July. As it is illustrated, the

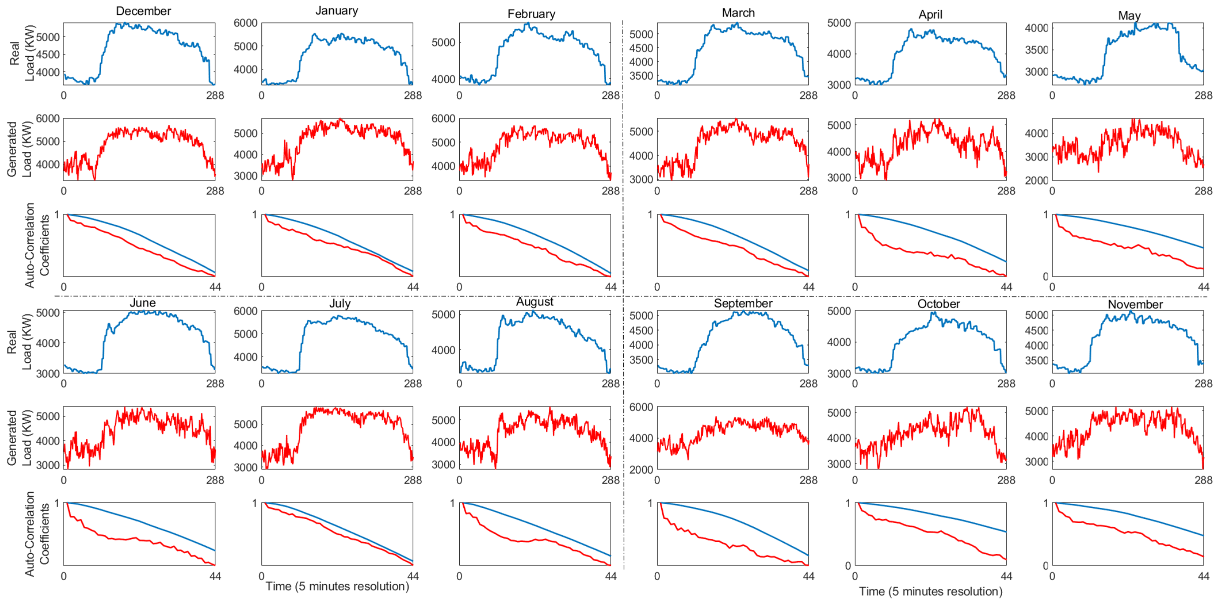

Figure 4.6 Real data vs generated samples of load in typical days in all month which have not been used as training data. The auto-correlation functions states that the generated samples can follow the correlation to time

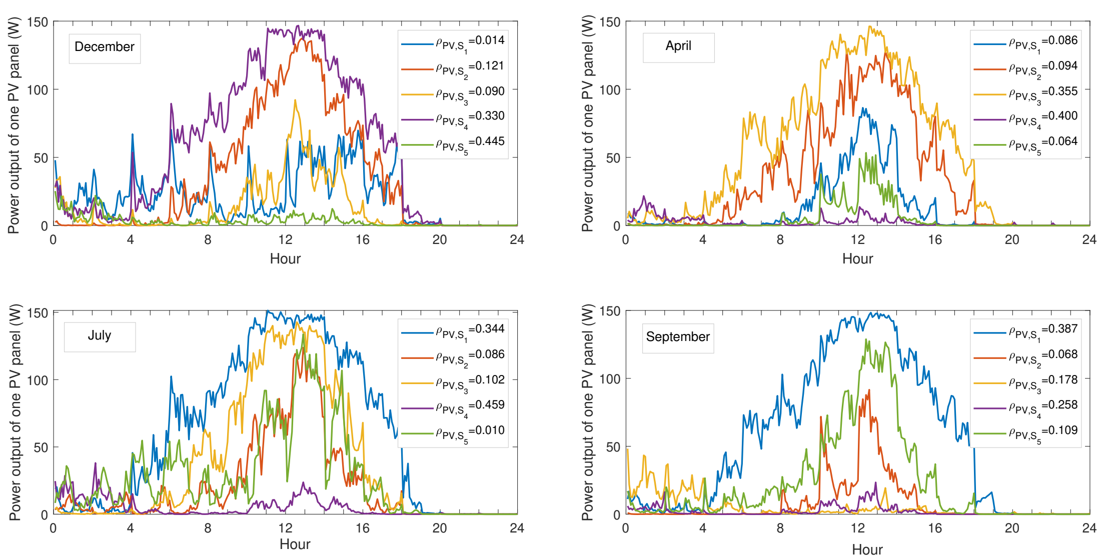

Figure 4.7 Reduced scenarios of PV power

Table 4.2 Comparison of statistical metrics of validation scenarios (Val) and generated scenarios (Gen) for all months.

		PV power				Load			
Month	Samples	Expectation (W)	Variance (W^2)	Skewness	Kurtosis	Expectation (kW)	Variance (kW^2)	Skewness	Kurtosis
Dec	Val	2.52	4.3^2	1.62	4.45	4660.20	621.99^2	-0.50	1.63
	Gen	2.07	3.6^2	2.2	7.63	4855.05	639.45^2	-0.71	2.15
Jan	Val	5.65	9.34^2	1.34	3.09	4603.45	786.12^2	-0.60	1.66
	Gen	5.72	9.17^2	1.97	6.28	4673.95	750.12^2	-0.77	2.24
Feb	Val	6.58	10.06^2	1.24	3.03	4758.13	552.48^2	-0.49	1.65
	Gen	5.51	10.21^2	2.45	9.01	4870.72	587.36^2	-0.69	2.24
March	Val	33.08	42.73^2	0.81	2.00	4454.94	772.38^2	-0.62	1.70
	Gen	33.6	43.61^2	0.90	2.21	4525.52	684.67^2	-0.71	2.22
April	Val	45.64	52.75^2	0.62	1.69	4020.81	592.91^2	-0.58	1.72
	Gen	45.38	55^2	0.72	1.87	4228.61	538.92^2	-0.39	2.32
May	Val	52.25	56.38^2	0.47	1.53	3414.94	512.87^2	0.0063	1.25
	Gen	52.79	55.36^2	0.46	1.60	3525.88	517.48^2	0.0004	1.98
June	Val	57.08	58.36^2	0.38	1.47	4229.63	770.94^2	-0.59	1.66
	Gen	56.97	59.74^2	0.42	1.51	4402.14	614.43^2	-0.53	2.19
July	Val	56.92	56.83^2	0.41	1.49	4760.14	905.38^2	-0.58	1.66
	Gen	56.56	58.82^2	0.38	1.47	4849.86	848.69^2	-0.81	2.12
Aug	Val	46.72	52.28^2	0.53	1.58	4313.53	601.97^2	-0.47	1.62
	Gen	46.83	53.34^2	0.59	1.73	4437.83	641.70^2	-0.50	2.21
Sep	Val	41.02	48.79^2	0.65	1.73	4223.13	778.82^2	-0.37	1.50
	Gen	42.2	52.86^2	0.81	2.02	4362.95	632.63^2	-0.59	2.33
Oct	Val	6.27	6.62^2	1.45	3.91	4014.83	632.63^2	-0.47	1.68
	Gen	6.14	9.61^2	1.87	6.01	4162.51	546.14^2	-0.23	2.46
Nov	Val	9.96	5.15^2	1.81	5.08	4272.29	693.66^2	-0.60	1.70
	Gen	2.44	5.06^2	3.25	15.96	4339.90	531.57^2	-0.64	2.46

battery charged in off-peak hours via main grid and PV powers. During peak periods, if the PV power is available, its power is used to satisfy peak. In addition, the battery can be discharged and if there is insufficient power in the battery system, the remaining powers can be bought from the main grid to satisfy the loads.

Fig.4.10 shows the result of the proposed method in one of the scenarios in a typical day in July without peak. In this case, the PV power generation is sold to the main grid. Fig.4.11 illustrates the optimal operation of the MG in a typical scenario in December. As it was expected, in Winter, the PV power is less available and the majority of power is coming from the battery energy storage system. In this case, an additional power needs to be purchased from the main grid during peak hours (lower than the original peak load). To show the effectiveness of using PV and batteries, we made a comparison between three cases. Case 1 considers that no PV and battery are available. In this case, the building must provide the power only from the main grid. Case 2 indicates the addition of PV panels. The PV power is fed to the building when available, and no power is saved for future uses. Case 3 defines the system when both PV and battery are available, and in this case, the battery can save

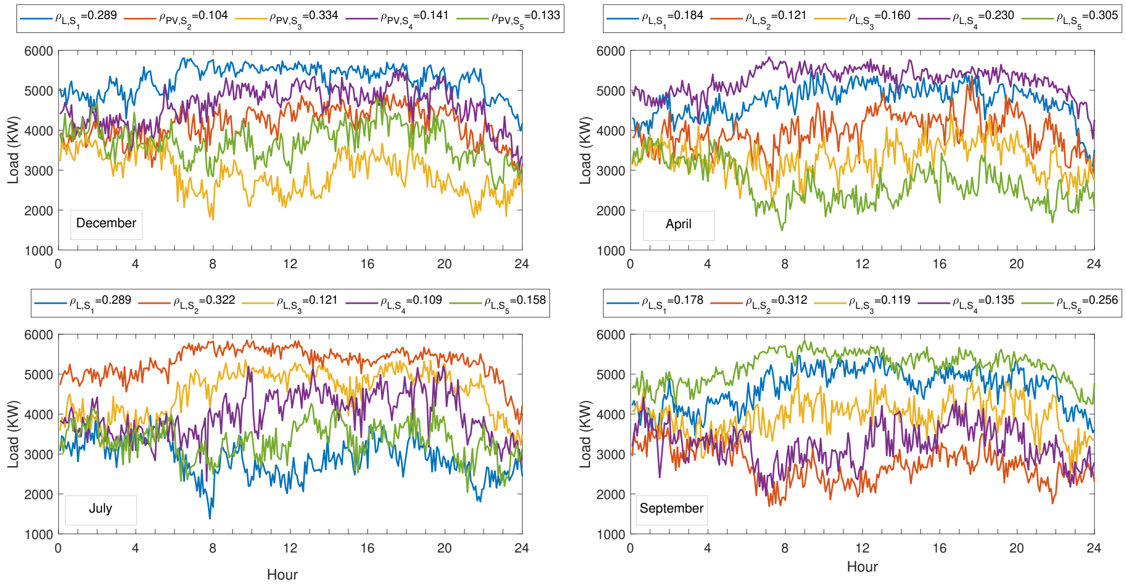

Figure 4.8 Reduced scenarios of Load

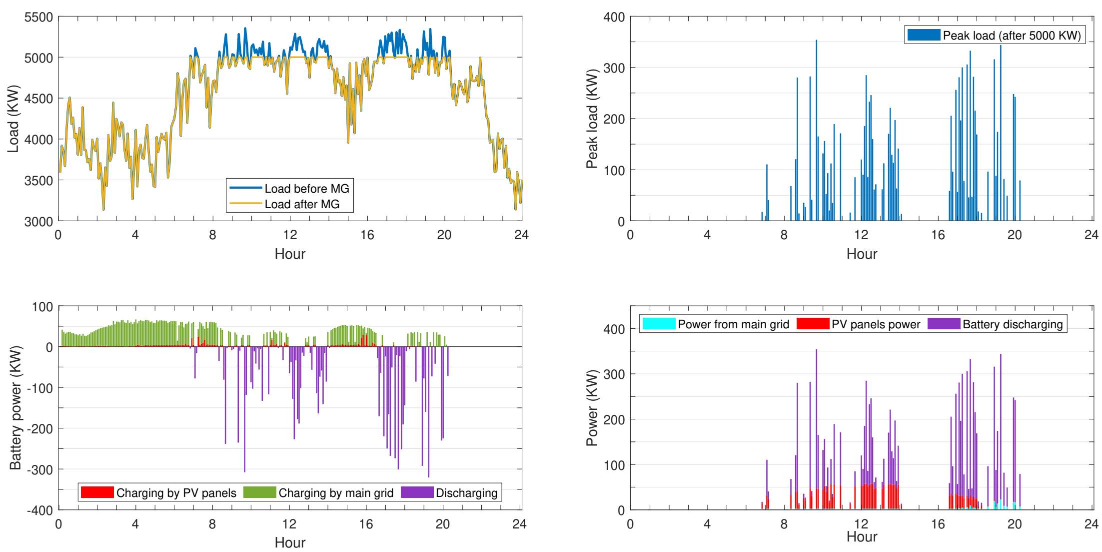

Figure 4.9 A typical scenario in July with peak

power in off-peak hours to use it during on-peak periods.

The summary of the operation in typical scenarios for the all months and following three cases is proposed in Table.4.3.

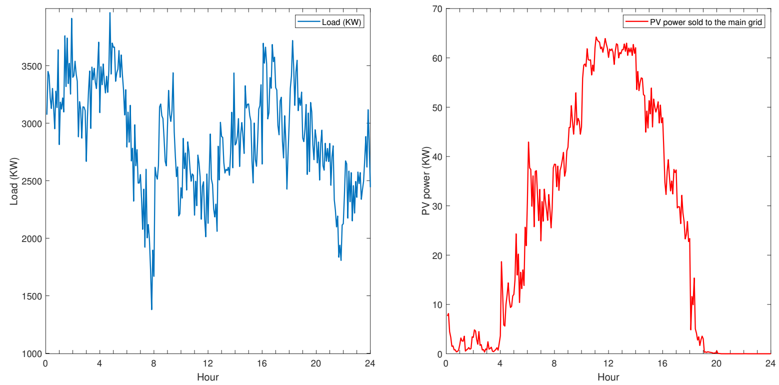

Figure 4.10 A typical scenario without peak

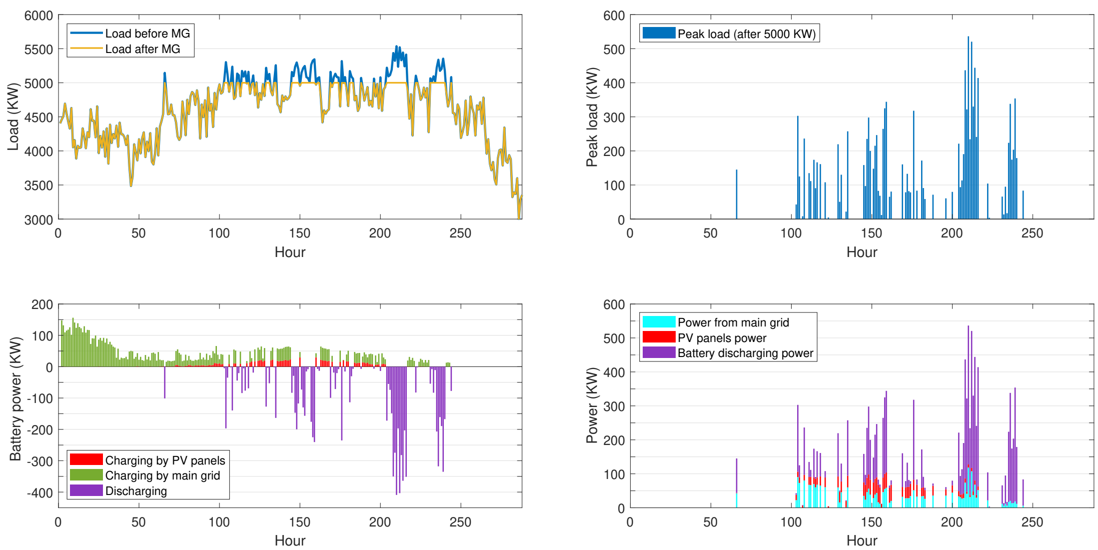

Figure 4.11 A typical scenario in December with peak

Case 1 : without PV power and battery storage

Case 1 shows the additional costs, i.e., the cost which should be paid due to peak in typical scenarios for one year. The charges in January are more than other months. December and September are in second and third degrees due to the additional costs. In December, January, and February which are winter months, the costs are $7,393.43, $8,085.04 and $4,014.98 respectively. In March the cost is lower than the winter with a value of $3,705.09. However, it is increased to reach a value of $6,215.08 in April and a value of $5,952.16 in May. In the first month of Summer i.e. June, the cost is higher than July and August (maybe because of the vacations in the campus) which reaches \$5,553.58, \$4,878.77 and \$3,885.87 respectively. With starting the next semester in September, the costs reaches a value of \$7,356.23 and for October and November it would be \$1,818.09 and \$4,712.76. It is indicated that the total penalty reaches about 63,571.14\$ for the whole year.

Case 2 : with PV power and without battery storage

Case 2 indicates the effect of PV power generation on reducing the peak. The highest PV generation is for the spring and summer months. In comparison with Case 1, PV power has \$124.44, \$93.57 and \$180.94 as saving money for December, January and February. In March, the saved money is \$384.76 and in April is \$601.95. The highest profit is for May with \$833.33. In June, July and August, it remains high with \$526.57, \$601.67 and \$593.82 respectively. In autumn the PV power decreases and the saving money reaches a value of \$390.27, \$227.11 and \$241.71 for September, October and November respectively It is showed that PV power generation could decrease the costs by 4,800.19\$ due to total peak shaving of 348.32 kW for all months.

Case 3 : with PV power and battery storage

Case 3 illustrates the importance of battery storage system in MG since it can store energy in off-peak hours and use it during peak times. The PV-battery system decreases the costs incredibly leading to a saving of \$6322.44 in September, \$6133.78 in April and \$5762.52 for December. The saved money in January and February is \$2696.53 and \$4014.95 respectively. In May, June and July the profits are \$4936.49, \$5494.62 and \$4844.84 respectively. In August, it is lower with the value of \$3859.50. In October and November the amount of saved money is \$1814.40 and 2828.82. It is showed that using battery along with the PV power could shave about 3,802.79 kW of power and decrease the costs from \$63,571.14 to \$11,164.89 and save around \$50,000 for one year. Fig.4.12 shows the power sent from the main grid during peak (P^{GLP}) in the three cases. The significant effect of the PV-Battery system in peak shaving is shown for February, March, April, June, July, and October. Fig.4.13 shows the reduction of the expenses in the three cases. It is indicated that the PV-Battery system decreased the costs.

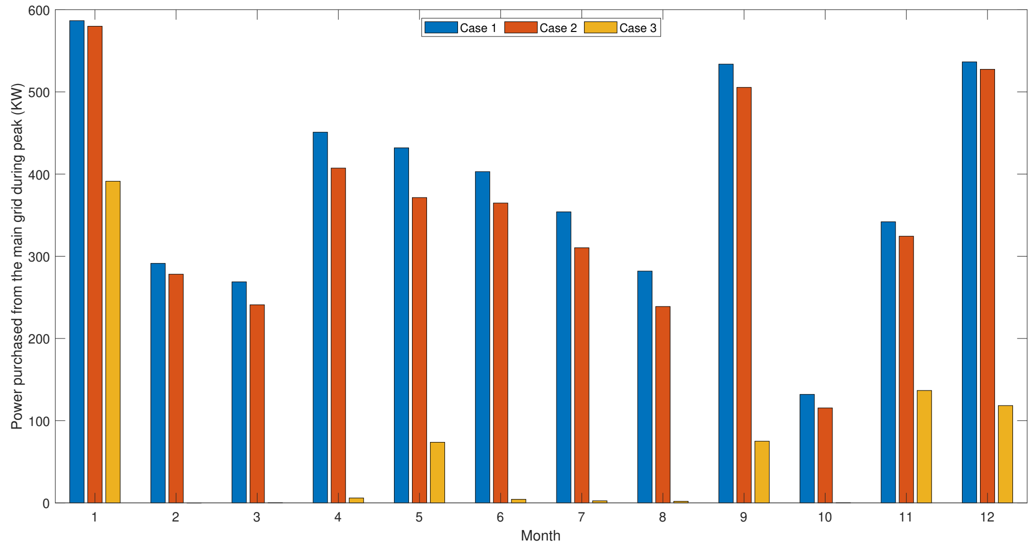

Figure 4.12 Power sent from the main grid during peak hour among three cases. Case 1 : without PV and battery, Case 2 : with PV, Case 3 : with PV and battery.

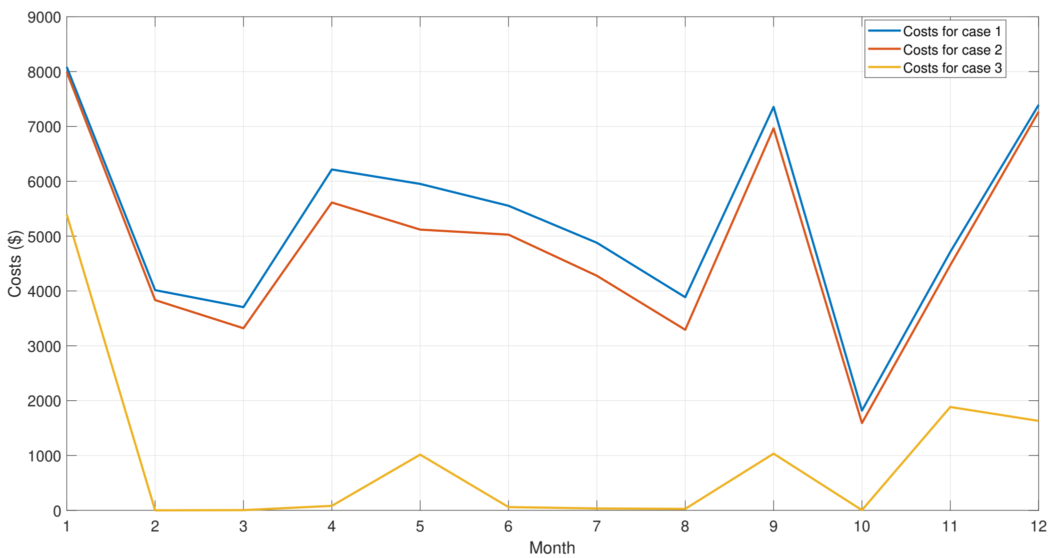

Figure 4.13 Penalties for peaks in all months for the three cases. Case 1 : without PV and battery, Case 2 : with PV, Case 3 : with PV and battery.

Table 4.3 Summary of statistics in typical scenarios in all months in three cases. Case 1 : without PV and battery, Case 2 : with PV, Case 3 : with PV and battery.

	Case 1	Case 2		Case 3	
Month	Profit ($)	PLS (kW)	Profit ($)	PLS (kW)	Profit ($)
1	-8,085.04	6.79	-7,991.47	195.38	-5,392.51
2	-4,014.98	13.13	-3,834.03	291.34	-0.02
3	-3,705.09	27.92	-3,320.33	268.58	-3.79
4	-6,215.08	43.68	-5,613.12	445.09	-81.29
5	-5,952.16	60.47	-5,118.82	358.21	-1,015.67
6	-5,553.58	38.21	-5,027.00	398.71	-58.95
7	-4,878.77	43.66	-4,277.09	351.56	-33.92
8	-3,885.87	43.09	-3,292.05	280.06	-26.37
9	-7,356.23	28.32	-6,965.95	458.78	-1,033.78
10	-1,818.09	16.48	-1,590.98	131.66	-3.68
11	-4,712.76	17.54	-4,471.04	205.27	-1,883.93
12	-7,393.43	9.03	-7,268.99	418.15	-1,630.91
Total	-63,571.14	348.32	-58,770.94	3802.79	-11,164.89

4.5 Conclusions

In this work, a two-stage stochastic programming model for peak load shaving in Campus-integrated microgrid is proposed. The conditional GAN (C-GAN) is implemented to generate the scenarios of PV power generation and load to capture the uncertainties of these parameters. The only input for generating scenarios via GAN is the historical data, and there is no need for any other assumptions related to the distributions of historical data. Due to the computational complexity of stochastic programming with a large number of scenarios, K-medoids clustering-based approach is used for scenario reduction. The objectives of the two-stage stochastic model is to minimize the investment and operation costs while reducing/shaving the peak. The proposed method has been applied on a real-world case study of a university campus in Canada.

The proposed C-GAN performs better for generating PV power scenarios than load. However, future works have a space for using other deep learning techniques along with GAN to generate more accurate scenarios. The lack of data for generating more scenarios by GAN was a limitation of this study. Finding methods for generating scenarios that do not need large data sets is another future work. The effectiveness of using the PV-battery system in the two-stage stochastic model is shown in the three cases. The results show that using PV and battery can decrease the peak and also the costs considerably. However, PV and battery do not cover the total peak loads in some months, such as January. Therefore, there is a need to add more flexibility components to the building such as demand response management and vehicle-to-grid concept. Future works could consider electric vehicle and demand response strategies as another sources of flexibility to solve the problem of peak shaving.

CHAPTER 5 GENERAL DISCUSSION

This chapter presents a general discussion of the proposed framework and results. The main objective of this study was to propose a two-stage stochastic optimization for peak load shaving in a district buildings. The first stage decisions include the optimal sizing of MG components, i.e., installed PV power and battery capacity. The second stage defines the optimal power flows in MG in oerder to minimize the operation cost including peak load shaving.

The proposed stochastic optimization approach shows that it is necessary to model uncertainties properly. We selected the conditional GAN to generate monthly PV power and load scenarios by investigating the available scenario generation methods. For each month, 2500 scenarios for PV power and 2500 for load have been generated, representing the characteristics of PV power and load on days of the month. The auto-correlation coefficients of the generated and the real data in typical scenarios in all months were assessed to show the ability of C-GAN to generate scenarios. The results showed that C-GAN performed better on PV power than load.

The generated scenarios were included in the stochastic optimization problem for peak load shaving purpose. Since solving the stochastic problem for 356 days of 24 hours is very complex, the proposed method was implemented for each month. Due to the large number of scenarios, it is needed to decrease the scenario set into a smaller set while keeping keep the characteristics of the main set. In this regard, the scenario reduction technique has been applied. Hence, the PV power and load scenarios are decreased into five scenarios for each of them, and the entire scenarios is reduced to $5^2 = 25$ scenarios for each month.

Three cases, including MG without PV and battery, MG with PV and without battery, and the third case, MG with both PV and battery storage system, were considered for testing the proposed methodology to decrease costs. The results show that the costs were decreased significantly when the PV-battery is applied to MG operation.

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS

This chapter presents the summary of the contribution followed by a discussion on the limitations of the study and future research opportunities.

6.1 Summary of Works

In this study, first, a comprehensive review is done to define the gaps in MG sizing and operation, including the available optimization techniques. Due to the advantages of MG, there is a need for optimal sizing of its components. Over-sizing and under-sizing MGs are two main problems that affect the MG operation costs. Over-sizing makes additional investment costs for the users, while under-sizing leads to a large mismatch between the generated power and actual demand. Consequently, the importance of sizing and operation simultaneously is shown when MG consumers try to minimize both investment and operation costs. RES are clean energy resources that can provide power to end-users. RES are weather-related data affected by the seasonality effects. Moreover, there are uncertainties in the load demand due to the variability of users' demands. Hence, there is a need for optimization techniques to include those uncertainties. To capture the uncertainties, scenario generation techniques become essential. It is used to present the random nature of the parameters. In addition, a massive number of scenarios make the stochastic programming complex, and there is a need for techniques to decrease the total scenarios into a smaller set along with keeping the main characteristics of the scenario set. Peak load shaving strategies and handling the challenges mentioned earlier are also critical.

No study includes all of the challenges stated above. There is a gap in the field of MG for a study that considers sizing, operation, peak load shaving, scenario generation, and reduction simultaneously. In this work, a framework for peak load shaving in MGs using the PV power and the energy storage system has been proposed. Due to PV power generation and load uncertainties, two-stage stochastic optimization has been implemented. In the first stage, the optimal sizes of PV and battery have been defined. In the second stage, the optimal power flows of the system have been indicated. Conditional GAN (C-GAN) was proposed as a scenario generation technique. Due to a large number of scenarios, a classical scenario reduction method has been implemented to decrease the computation time of solving the stochastic problem.

The results of the scenario generation method were analyzed by auto-correlation coefficients between real historical and the generated scenarios. The proposed C-GAN performed better to generate RES scenarios than a load with the condition of the month. The proposed framework is tested on a real case study of a university campus in Montreal, including the integration of residential, commercial, and institutional buildings. The simulation results were assessed using three cases where no PV and battery were available, with PV power, and when the battery was added to the system. The PV-battery system decreased the costs as well as shave the peak significantly.

6.2 Limitations

The scenario generation via C-GAN is implemented in this study. In this regard, we applied the proposed method to PV power generation and load data. The results were better for PV power generation. It shows that the reference paper [23] is weak in the application of scenario generation on other parameters than RES.

Besides the advantages of implementing stochastic optimization and scenario generation using NN-based methods like C-GAN, the approach has some drawbacks. To implement C-GAN, it is not required to know the distribution of the historical data via predetermined formulations. However, NN-based scenario generation methods need extensive data set to learn the models properly and generate more accurate scenarios. The current data set was limited in our case study.

Moreover, stochastic optimization considers the variability of uncertain parameters in the decision-making process, and it leads to more reliable solutions, but stochastic optimization is computationally. To increase the computational efficiency, the operation of MG is conducted for typical scenarios in different months.

6.3 Future Research

Due to the weakness of the proposed scenario generation on loads, it is shown that there is a need to develop a methodology that can work for all types of uncertain parameters.

Moreover, making a framework that can work well on small data set to generate reliable scenarios is another future study.

Integrating components other than PV and battery into MG for peak shaving will help satisfy more loads locally. The technologies may include also electric vehicles. However, it is needed to have access to real EV charging station data that is limited too. Demand response programs also can be added to this study to assess the effect of different pricing mechanisms and incentive demand response in the current work.

The current case study includes the integration of five district building's load. In future work, for each building, a MG will be applied to manage each building's load locally.

REFERENCES

[1] A. Hirsch, Y. Parag et J. Guerrero, “Microgrids : A review of technologies, key drivers, and outstanding issues,” *Renewable and Sustainable Energy Reviews*, vol. 90, p. 402–411, 2018. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S136403211830128X

[2] M. A. Jirdehi, V. S. Tabar, S. Ghassemzadeh et S. Tohidi, “Different aspects of microgrid management : A comprehensive review,” *Journal of Energy Storage*, vol. 30, p. 101457, 2020. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S2352152X19305109

[3] N. Altin et S. E. Eyimaya, “A review of microgrid control strategies,” dans *2021 10th International Conference on Renewable Energy Research and Application (ICRERA)*, 2021, p. 412–417.

[4] H. Fontenot et B. Dong, “Modeling and control of building-integrated microgrids for optimal energy management – a review,” *Applied Energy*, vol. 254, p. 113689, 2019. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0306261919313765

[5] S. Choudhury, “Review of energy storage system technologies integration to microgrid : Types, control strategies, issues, and future prospects,” *Journal of Energy Storage*, vol. 48, p. 103966, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S2352152X22000147

[6] A. Ravichandran, S. Sirouspour, P. Malysz et A. Emadi, “A chance-constraints-based control strategy for microgrids with energy storage and integrated electric vehicles,” *IEEE TRANSACTIONS ON SMART GRID*, vol. 9, n°. 1, p. 346–359, 2018.

[7] H. J. Touma, M. Mansor, M. S. A. Rahman, V. Kumaran, H. B. Mokhlis, Y. J. Ying et M. A. Hannan, “Energy management system of microgrid : Control schemes, pricing techniques, and future horizons,” *Energy Research*, 2021.

[8] A. Zakaria, F. B. Ismail, M. H. Lipu et M. A. Hannan, “Uncertainty models for stochastic optimization in renewable energy applications,” *Renewable Energy*, vol. 145, p. 1543–1571, 2020.

[9] A. S. Farsangi, S. Hadayeghparast, M. Mehdinejad et H. Shayanfar, “A novel stochastic energy management of a microgrid with various types of distributed energy resources in presence of demand response programs,” *Energy*, vol. 160, p. 257–274, 2018.

[10] H. Li, Z. Ren, M. Fan, W. Li, Y. Xu, Y. Jiang et W. Xia, “A review of scenario analysis methods in planning and operation of modern power systems : Methodologies, applications, and challenges,” *Electric Power Systems Research*, vol. 205, p. 107722, 2022.

[11] M. Uddin, M. F. Romlie, M. F. Abdullah, S. Abd Halim, T. C. Kwang *et al.*, “A review on peak load shaving strategies,” *Renewable and Sustainable Energy Reviews*, vol. 82, p. 3323–3332, 2018.

[12] M. M. Rana, M. Atef, M. R. Sarkar, M. Uddin et G. Shafiullah, “A review on peak load shaving in microgrid—potential benefits, challenges, and future trend,” *Energies*, vol. 15, nº. 6, p. 2278, 2022.

[13] A. A. S. de la Nieta, I. Ilieva, M. Gibescu, B. Bremdal, S. Simonsen et E. Gramme, “Optimal midterm peak shaving cost in an electricity management system using behind customers’ smart meter configuration,” *Applied Energy*, vol. 283, p. 116282, 2021.

[14] Z. Zheng, X. Li, J. Pan et X. Luo, “multi-year two-stage stochastic programming model for optimal design and operation of residential photovoltaic-battery systems,” *Energy & Buildings*, 2021.

[15] J. Liang et W. Tang, “Wind power scenario generation for microgrid day-ahead scheduling using sequential generative adversarial networks,” dans *2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, 2019, p. 1–6.

[16] ——, “Sequence generative adversarial networks for wind power scenario generation,” *IEEE Journal on Selected Areas in Communications*, vol. 38, nº. 1, p. 110–118, 2020.

[17] W. Dong, X. Chen et Q. Yang, “Data-driven scenario generation of renewable energy production based on controllable generative adversarial networks with interpretability,” *Applied Energy*, vol. 308, p. 118387, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0306261921016251

[18] Y. Zhang, Q. Ai, F. Xiao, R. Hao et T. Lu, “Typical wind power scenario generation for multiple wind farms using conditional improved wasserstein generative adversarial network,” *International Journal of Electrical Power and Energy Systems*, vol. 114, p. 105388, 2020. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0142061519305010

[19] R. Yuan, B. Wang, Z. Mao et J. Watada, “Multi-objective wind power scenario forecasting based on pg-gan,” *Energy*, vol. 226, p. 120379, 2021. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0360544221006289

[20] J. Qiao, T. Pu et X. Wang, “Renewable scenario generation using controllable generative adversarial networks with transparent latent space,” *CSEE Journal of Power and Energy Systems*, vol. 7, nº. 1, p. 66–77, 2021.

[21] F. S. Gazijahani, S. N. Ravadanegh et JavadSalehi, “Stochastic multi-objective model for optimal energy ex-change optimization of networked microgrids with presenceof renewable generation under risk-based strategies,” *ISA Transactions*, nº. 73, p. 100–111, 2018.

[22] Y. Chen, P. Li et B. Zhang, “Bayesian renewables scenario generation via deep generative networks,” dans *2018 52nd Annual Conference on Information Sciences and Systems (CISS)*, 2018, p. 1–6.

[23] Y. Chen, Y. Wang, D. Kirschen et B. Zhang, “Model-free renewable scenario generation using generative adversarial networks,” *IEEE Transactions on Power Systems*, vol. 33, nº. 3, p. 3265–3275, 2018.

[24] Y. Wang, G. Hug, Z. Liu et N. Zhang, “Modeling load forecast uncertainty using generative adversarial networks,” *Electric Power Systems Research*, vol. 189, p. 106732, 2020.

[25] D. T. Ton et M. A. Smith, “The us department of energy’s microgrid initiative,” *The Electricity Journal*, vol. 25, nº. 8, p. 84–94, 2012.

[26] H. A. Rahman, M. S. Majid, A. Rezaee Jordehi, G. Chin Kim, M. Y. Hassan et S. O. Fadhl, “Operation and control strategies of integrated distributed energy resources : A review,” *Renewable and Sustainable Energy Reviews*, vol. 51, p. 1412–1420, 2015. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S1364032115007029

[27] B. Mukhopadhyay et D. Das, “Optimal multi-objective long-term sizing of distributed energy resources and hourly power scheduling in a grid-tied microgrid,” *Sustainable Energy, Grids and Networks*, vol. 30, p. 100632, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S2352467722000170

[28] S. Kumar, R. K. Saket, P. Sanjeevikumar et J. B. Holm-Nielsen, *A Comprehensive Review on Energy Management in Micro-Grid System.* John Wiley and Sons, Ltd, 2021, ch. 1, p. 1–24. [En ligne]. Disponible : https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119710905.ch1

[29] MobiMathew, M. S. Hossain, S. Saha, S. Mondal et M. E. Haque, “Sizing approaches for solar photovoltaic-based microgrids : A comprehensive review,” *IET Energy Systems Integration*, 2022.

[30] M. M. Rana, M. Uddin, M. R. Sarkar, G. Shafiullah, H. Mo et M. Atef, "A review on hybrid photovoltaic – battery energy storage system : Current status, challenges, and future directions," *Journal of Energy Storage*, vol. 51, p. 104597, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S2352152X22006132

[31] A. Sarhan, H. Hizam, N. Mariun et M. Ya'acob, "An improved numerical optimization algorithm for sizing and configuration of standalone photo-voltaic system components in yemen," *Renewable Energy*, vol. 134, p. 1434–1446, 2019.

[32] S.-G. Chen, "An efficient sizing method for a stand-alone pv system in terms of the observed block extremes," *Applied energy*, vol. 91, n°. 1, p. 375–384, 2012.

[33] D. Riza, S. Gilani, M. Aris *et al.*, "Standalone photovoltaic systems sizing optimization using design space approach : case study for residential lighting load," *Journal of Engineering Science and Technology*, vol. 10, n°. 7, p. 943–957, 2015.

[34] M. Bortolini, M. Gamberi et A. Graziani, "Technical and economic design of photovoltaic and battery energy storage system," *Energy Conversion and Management*, vol. 86, p. 81–92, 2014.

[35] R. Hosseinalizadeh, H. Shakouri, M. S. Amalnick et P. Taghipour, "Economic sizing of a hybrid (pv–wt–fc) renewable energy system (hres) for stand-alone usages by an optimization-simulation model : Case study of iran," *Renewable and Sustainable Energy Reviews*, vol. 54, p. 139–150, 2016.

[36] C. E. C. Nogueira, M. L. Vidotto, R. K. Niedzialkoski, S. N. M. de Souza, L. I. Chaves, T. Edwiges, D. B. dos Santos et I. Werncke, "Sizing and simulation of a photovoltaic-wind energy system using batteries, applied for a small rural property located in the south of brazil," *Renewable and Sustainable Energy Reviews*, vol. 29, p. 151–157, 2014.

[37] W. Ho, H. Hashim et J. Lim, "Integrated biomass and solar town concept for a smart eco-village in iskandar malaysia (im)," *Renewable Energy*, vol. 69, p. 190–201, 2014.

[38] M. Lee, D. Soto et V. Modi, "Cost versus reliability sizing strategy for isolated photovoltaic micro-grids in the developing world," *Renewable Energy*, vol. 69, p. 16–24, 2014.

[39] M. Kharrich, Y. Sayouti et M. Akherraz, "„microgrid sizing with environmental and economic optimization,"in 2018 renewable energies, power systems & green inclusive economy (reps-gie)," 2018.

[40] H. Borhanazad, S. Mekhilef, V. G. Ganapathy, M. Modiri-Delshad et A. Mirtaheri, "Optimization of micro-grid system using mopso," *Renewable energy*, vol. 71, p. 295–306, 2014.

[41] R. Atia et N. Yamada, “Sizing and analysis of renewable energy and battery systems in residential microgrids,” *IEEE Transactions on Smart Grid*, vol. 7, n°. 3, p. 1204–1213, 2016.

[42] M. Pham, T. Tran, S. Bacha, A. Hably et L. N. An, “Optimal sizing of battery energy storage system for an islaned microgrid,” dans *IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society*, 2018, p. 1899–1903.

[43] M. R. Jannesar, A. Sedighi, M. Savaghebi et J. M. Guerrero, “Optimal placement, sizing, and daily charge/discharge of battery energy storage in low voltage distribution network with high photovoltaic penetration,” *Applied Energy*, vol. 226, p. 957–966, 2018. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0306261918309061

[44] B. J. Donnellan, W. L. Soong et D. J. Vowles, “Critical capacity analysis for optimal sizing of pv and energy storage for a household,” dans *2018 IEEE Energy Conversion Congress and Exposition (ECCE)*, 2018, p. 5125–5132.

[45] G. Xu, C. Shang, S. Fan, X. Zhang et H. Cheng, “Sizing battery energy storage systems for industrial customers with photovoltaic power,” *Energy Procedia*, vol. 158, p. 4953–4958, 2019, innovative Solutions for Energy Transitions. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S1876610219307301

[46] J. Koskela, A. Rautiainen et P. Järventausta, “Using electrical energy storage in residential buildings – sizing of battery and photovoltaic panels based on electricity cost optimization,” *Applied Energy*, vol. 239, p. 1175–1189, 2019. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0306261919303113

[47] R. Khezri, A. Mahmoudi et M. H. Haque, “Optimal capacity of solar pv and battery storage for australian grid-connected households,” *IEEE Transactions on Industry Applications*, vol. 56, n°. 5, p. 5319–5329, 2020.

[48] M. Aghamohamadi, A. Mahmoudi et M. H. Haque, “Two-stage robust sizing and operation co-optimization for residential pv–battery systems considering the uncertainty of pv generation and load,” *IEEE Transactions on Industrial Informatics*, vol. 17, n°. 2, p. 1005–1017, 2020.

[49] A. G. Tsikalakis et N. D. Hatziargyriou, “Centralized control for optimizing microgrids operation,” dans *2011 IEEE power and energy society general meeting*. IEEE, 2011, p. 1–8.

[50] L. K. Panwar, S. R. Konda, A. Verma, B. K. Panigrahi et R. Kumar, “Operation window constrained strategic energy management of microgrid with electric vehicle and

distributed resources," *IET Generation, Transmission & Distribution*, vol. 11, n°. 3, p. 615–626, 2017.

[51] S. Sukumar, H. Mokhlis, S. Mekhilef, K. Naidu et M. Karimi, "Mix-mode energy management strategy and battery sizing for economic operation of grid-tied microgrid," *Energy*, vol. 118, p. 1322–1333, 2017. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0360544216316231

[52] M. H. Amrollahi et S. M. T. Bathaee, "Techno-economic optimization of hybrid photovoltaic/wind generation together with energy storage system in a stand-alone microgrid subjected to demand response," *Applied energy*, vol. 202, p. 66–77, 2017.

[53] N. Anglani, G. Oriti et M. Colombini, "Optimized energy management system to reduce fuel consumption in remote military microgrids," *IEEE Transactions on Industry Applications*, vol. 53, n°. 6, p. 5777–5785, 2017.

[54] C. Corchero, M. Cruz-Zambrano, F.-J. Heredia *et al.*, "Optimal energy management for a residential microgrid including a vehicle-to-grid system," *IEEE transactions on smart grid*, vol. 5, n°. 4, p. 2163–2172, 2014.

[55] V. Murty et A. Kumar, "Multi-objective energy management in microgrids with hybrid energy sources and battery energy storage systems," *Protection and Control of Modern Power Systems*, vol. 5, n°. 1, p. 1–20, 2020.

[56] P. P. Vergara, J. C. López, L. C. da Silva et M. J. Rider, "Security-constrained optimal energy management system for three-phase residential microgrids," *Electric Power Systems Research*, vol. 146, p. 371–382, 2017.

[57] D. E. Olivares, C. A. Cañizares et M. Kazerani, "A centralized energy management system for isolated microgrids," *IEEE Transactions on smart grid*, vol. 5, n°. 4, p. 1864–1875, 2014.

[58] S. Helal, R. Najee, M. O. Hanna, M. F. Shaaban, A. Osman et M. S. Hassan, "An energy management system for hybrid microgrids in remote communities," dans *2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE)*. IEEE, 2017, p. 1–4.

[59] H. Babazadeh, W. Gao, Z. Wu et Y. Li, "Optimal energy management of wind power generation system in islanded microgrid system," dans *2013 North American Power Symposium (NAPS)*. IEEE, 2013, p. 1–5.

[60] B. Heymann, J. F. Bonnans, P. Martinon, F. J. Silva, F. Lanas et G. Jiménez-Estévez, "Continuous optimal control approaches to microgrid energy management," *Energy Systems*, vol. 9, n°. 1, p. 59–77, 2018.

[61] S. R. Cominesi, M. Farina, L. Giulioni, B. Picasso, et R. Scattolini, “A two-layer stochastic model predictive control scheme for microgrids,” *IEEE TRANSACTIONS ON CONTROL SYSTEMS TECHNOLOGY*, vol. 26, n°. 1, p. 1–13, 2018.

[62] F. Luo, G. Ranzi, S. Wang et Z. Y. Dong, “Hierarchical energy management system for home microgrids,” *IEEE TRANSACTIONS ON SMART GRID*, 2019.

[63] P. Kou, D. Liang, L. Gao et F. Gao, “Stochastic coordination of plug-in electric vehicles and wind turbines in microgrid : A model predictive control approach,” *IEEE TRANSACTIONS ON SMART GRID*, vol. 7, n°. 3, p. 1537–1551, 2016.

[64] P. Kou, , D. Liang et L. Gao, “Stochastic energy scheduling in microgrids considering the uncertainties in both supply and demand,” *IEEE SYSTEMS JOURNAL*, vol. 12, n°. 3, p. 2589–2600, 2018.

[65] E. Grover-Silvaa, M. Helenob, S. Mashayekhb, G. Cardosob et G. K. Robin Girarda, “A stochastic optimal power flow for scheduling flexible resources in microgrids operation,” *Applied Energy*, n°. 229, p. 201–208, 2018.

[66] R. Aboli, M. Ramezani et H. Falaghi, “Joint optimization of day-ahead and uncertain near real-time operation of microgrids,” *Electrical Power and Energy Systems*, vol. 34-46, n°. 107, 2019.

[67] M. H. Shams, , M. Shahabi et M. E. Khodayar, “Stochastic day-ahead scheduling of multiple energy carrier microgrids with demand response,” *Energy*, n°. 155, p. 326–338, 2018.

[68] M. Sedighizadeh, M. Esmaili, A. Jamshidi et M.-H. Ghaderi, “Stochastic multi-objective economic-environmental energy and reserve scheduling of microgrids considering battery energy storage system,” *Electrical Power and Energy Systems*, n°. 106, p. 1–16, 2019.

[69] M.-C. Hu, S. Ying-Lu et Y.-H. Chen, “Stochastic programming and market equilibrium analysis of microgrids energy management systems,” *Energy*, n°. 113, p. 662–670, 2016.

[70] D. Wang, J. Qiu, L. Reedman, K. Meng et L. L. Lai, “Two-stage energy management for networked microgrids with high renewable penetration,” *Applied Energy*, n°. 226, p. 39–48, 2018.

[71] M. Aien, A. Hajebrahimi et M. Fotuhi-Firuzabad, “A comprehensive review on uncertainty modeling techniques in power system studies,” *Renewable and Sustainable Energy Reviews*, vol. 57, p. 1077–1089, 2016.

[72] W. Zhu, Y. Yu, M. Yang et Y. Zhao, “Review on probabilistic short-term power forecast,” dans *2021 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia)*, 2021, p. 880–884.

[73] C. Jiang, Y. Mao, Y. Chai, M. Yu et S. Tao, “Scenario generation for wind power using improved generative adversarial networks,” *IEEE Access*, vol. 6, p. 62 193–62 203, 2018.

[74] F. Wang, Z. Zhang, C. Liu, Y. Yu, S. Pang, N. Duić, M. Shafie-khah et J. P. Catalão, “Generative adversarial networks and convolutional neural networks based weather classification model for day ahead short-term photovoltaic power forecasting,” *Energy Conversion and Management*, vol. 181, p. 443–462, 2019. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0196890418313268

[75] Y. Chen, P. Li et B. Zhang, “Bayesian renewables scenario generation via deep generative networks,” dans *2018 52nd Annual Conference on Information Sciences and Systems (CISS)*, 2018, p. 1–6.

[76] Z. Li et C. A. Floudas, “Optimal scenario reduction framework based on distance of uncertainty distribution and output performance : Ii. sequential reduction,” *Computers & Chemical Engineering*, vol. 84, p. 599–610, 2016.

[77] N. Tomin, V. Shakirov, A. Kozlov, D. Sidorov, V. Kurbatsky, C. Rehtanz et E. E. Lora, “Design and optimal energy management of community microgrids with flexible renewable energy sources,” *Renewable Energy*, vol. 183, p. 903–921, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0960148121015937

[78] X. Sun, Y. Lin, Z. Zhu et J. Li, “Optimized design of a distributed photovoltaic system in a building with phase change materials,” *Applied Energy*, vol. 306, p. 118010, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0306261921013118

[79] A. Nourai, V. I. Kogan et C. M. Schafer, “Load leveling reduces t d line losses,” *IEEE Transactions on Power Delivery*, vol. 23, n°. 4, p. 2168–2173, 2008.

[80] M. Uddin, M. F. Romlie, M. F. Abdullah, S. A. Halim, A. H. A. Bakar et T. C. Kwang, “A review on peak load shaving strategies,” *Renewable and Sustainable Energy Reviews*, n°. 82, p. 3323–3332, 2018.

[81] R. H. Lasseter et P. Paigi, “Microgrid : a conceptual solution,” vol. 6. IEEE Power Electronics Specialists Conference, 2004.

[82] S. Spiecker et C. Weber, “The future of the european electricity system and the impact of fluctuating renewable energy – a scenario analysis,” *Energy Policy*, vol. 65, p. 185–197, 2014.

[83] Z. Yang, Y. Wang et K. Yang, “The stochastic short-term hydropower generation scheduling considering uncertainty in load output forecasts,” *Energy*, vol. 241, p. 122838, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0360544221030875

[84] S. M. Hakimi, A. Hasankhani, M. Shafie-khah, M. Lotfi et J. P. Catalão, "Optimal sizing of renewable energy systems in a microgrid considering electricity market interaction and reliability analysis," *Electric Power Systems Research*, vol. 203, p. 107678, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0378779621006593

[85] R. Xie, W. Wei, M. Shahidehpour, Q. Wu et S. Mei, "Sizing renewable generation and energy storage in stand-alone microgrids considering distributionally robust shortfall risk," *IEEE Transactions on Power Systems*, p. 1–1, 2022.

[86] M. Hannan, M. Faisal, P. Jern Ker, R. Begum, Z. Dong et C. Zhang, "Review of optimal methods and algorithms for sizing energy storage systems to achieve decarbonization in microgrid applications," *Renewable and Sustainable Energy Reviews*, vol. 131, p. 110022, 2020. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S1364032120303130

[87] M. MansourLakouraj, M. Shahabi, M. Shafie-khah et J. P. Catalão, "Optimal market-based operation of microgrid with the integration of wind turbines, energy storage system and demand response resources," *Energy*, vol. 239, p. 122156, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S036054422102404X

[88] Y. Li, K. Li, Z. Yang, Y. Yu, R. Xu et M. Yang, "Stochastic optimal scheduling of demand response-enabled microgrids with renewable generations : An analytical-heuristic approach," *Journal of Cleaner Production*, vol. 330, p. 129840, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0959652621040142

[89] C. Guo, X. Wang, Y. Zheng et F. Zhang, "Real-time optimal energy management of microgrid with uncertainties based on deep reinforcement learning," *Energy*, vol. 238, p. 121873, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0360544221021216

[90] B. Dey, S. Raj, S. Mahapatra et F. P. G. Márquez, "Optimal scheduling of distributed energy resources in microgrid systems based on electricity market pricing strategies by a novel hybrid optimization technique," *International Journal of Electrical Power and Energy Systems*, vol. 134, p. 107419, 2022. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S014206152100658X

[91] D. R. Prathapaneni et K. P. Detroja, "An integrated framework for optimal planning and operation schedule of microgrid under uncertainty," *Sustainable Energy, Grids and Networks*, vol. 19, p. 100232, 2019. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S2352467719301183

[92] P. A. Gooding, E. Makram et R. Hadidi, “Probability analysis of distributed generation for island scenarios utilizing carolinas data,” *Electric Power Systems Research*, vol. 107, p. 125–132, 2014.

[93] M. Aien, M. Rashidinejad et M. Fotuhi-Firuzabad, “On possibilistic and probabilistic uncertainty assessment of power flow problem : A review and a new approach,” *Renewable and Sustainable Energy Reviews*, vol. 37, p. 883–895, 2014.

[94] A. S. Farsangi, S. Hadayeghparast, M. Mehdinejad et H. Shayanfa, “A novel stochastic energy management of a microgrid with various types of distributed energy resources in presence of demand response programs,” *Energy*, vol. 160, p. 257–274, 2018.

[95] K. Zhang, J. Li, Z. He et W. Yan, “Microgrid energy dispatching for industrial zones with renewable generations and electric vehicles via stochastic optimization and learning,” *Physica A*, n°. 501, p. 356–369, 2018.

[96] G. C. Lazaroiu, V. Dumbrava, G. Balaban, M. Longo et D. Zaninelli, “Stochastic optimization of microgrids with renewable and storage energy systems,” dans *2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC)*, 2016, p. 1–5.

[97] S. R. Cominesi, M. Farina, L. Giulioni, B. Picasso, et R. Scattolini, “Two-layer predictive control of a micro-grid including stochastic energy sources,” *2015 American Control Conference*, 2015.

[98] D. R. Prathapaneni et K. P. Detroja, “An integrated framework for optimal planning and operation schedule of microgrid under uncertainty,” *Sustainable Energy, Grids and Networks*, 2019.

[99] I. M. Ibrahim, W. A. Omran et A. Y. Abdelaziz, “Optimal sizing of microgrid system using hybrid firefly and particle swarm optimization algorithm,” dans *2021 22nd International Middle East Power Systems Conference (MEPCON)*, 2021, p. 287–293.

[100] O. Talent et H. Du, “Optimal sizing and energy scheduling of photovoltaic-battery systems under different tariff structures,” *Renewable Energy*, vol. 129, p. 513–526, 2018. [En ligne]. Disponible : https://www.sciencedirect.com/science/article/pii/S0960148118306463

[101] M. Kharrich, Y. Sayouti et M. Akherraz, “Microgrid sizing with environmental and economic optimization,” dans *2018 Renewable Energies, Power Systems Green Inclusive Economy (REPS-GIE)*, 2018, p. 1–6.

[102] Y. Xiang, J. Liu et Y. Liu, “Robust energy management of microgrid with uncertain renewable generation and load,” *IEEE Transactions on Smart Grid*, vol. 7, n°. 2, p. 1034–1043, 2016.

[103] F. Yang, S. Yin, S. Zhou, D. Li, C. Fang et S. Lin, "Electric vehicle charging current scenario generation based on generative adversarial network combined with clustering algorithm," *Wiley Energy Research*, 2020.

[104] D. Dongol, T. Feldmann, M. Schmidt et E. Bollin, "A model predictive control based peak shaving application of battery for a household with photovoltaic system in a rural distribution grid," *Sustainable Energy, Grids and Networks*, n°. 16, p. 1–13, 2018.

[105] R. Karandeh, T. Lawanson et V. Cecchi, "Impact of operational decisions and size of battery energy storage systems on demand charge reduction," *IEEE Milan PowerTech*, 2019.

[106] J. Leadbetter et L. Swan, "Battery storage system for residential electricity peak demand shaving," *Energy and Buildings*, n°. 55, p. 685–692, 2012.

[107] B.-R. Ke, T.-T. Ku, Y.-L. Ke, C.-Y. Chung et H.-Z. Chen, "Sizing the battery energy storage system on a university campus with prediction of load and photovoltaic generation," *IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS*, vol. 52, n°. 2, p. 1136–1146, 2016.

[108] C. S. Ioakimidis, D. Thomas, P. Rycerski et K. N. Genikomsakis, "Peak shaving and valley filling of power consumption profile in nonresidential buildings using an electric vehicle parking lot," *Energy*, vol. 148, p. 148–158, 2018.

[109] A. A. S. de la Nieta, I. Ilieva, M. Gibescu, B. Bremdal, S. Simonsen et E. Gramme, "Optimal midterm peak shaving cost in an electricity management system using behind customers' smart meter configuration," *Applied Energy*, 2021.

[110] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley et Y. B. Sherjil Ozair, Aaron Courville, "Generative adversarial nets," *Neural Information Processing Systems*, p. 2672–2680, 2014.

[111] Y. Li, Q. Wang, J. Zhang, L. Hue et W. Ouyang, "The theoretical research of generative adversarial networks : an overview," *Neurocomputing*, 2021.

[112] M. Mirza et S. Osindero, "Conditional generative adversarial nets," *arXiv preprint arXiv :1411.1784*, 2014.

[113] Z. Wang, P. Jochem et W. Fichtner, "A scenario-based stochastic optimization model for charging scheduling of electric vehicles under uncertainties of vehicle availability and charging demand," *Journal of Cleaner Production*, vol. 254, 2020.

[114] H. Teichgraeber et A. R. Brandt, "Optimal design of an electricity-intensive industrial facility subject to electricity price uncertainty : Stochastic optimization and scenario reduction," *Chemical Engineering Research and Design*, vol. 163, p. 204–216, 2020.

[115] J. Hu et H. Li, “A new clustering approach for scenario reduction in multi-stochastic variable programming,” *IEEE Transactions on Power Systems*, vol. 34, n^o. 5, p. 3813–3825, 2019.

[116] A. Bhat, “K-medoids clustering using partitioning around medoids for performing face recognition,” *International Journal of Soft Computing, Mathematics and Control*, vol. 3, n^o. 3, p. 1–12, 2014.

[117] “Rate LG,” 2022, Accessed : 2022-06-16. [En ligne]. Disponible : https://www.hydroquebec.com/data/documents-donnees/pdf/electricity-rates.pdf#page=96

[118] A. Maleki et F. Pourfayaz, “Optimal sizing of autonomous hybrid photovoltaic/wind/battery power system with lpsp technology by using evolutionary algorithms,” *Solar Energy*, vol. 115, p. 471–483, 2015.

[119] L. Xu, X. Ruan, C. Mao, B. Zhang et Y. Luo, “An improved optimal sizing method for wind-solar-battery hybrid power system,” *IEEE Transactions on Sustainable Energy*, vol. 4, n^o. 3, p. 774–785, 2013.

[120] I. Dunning, J. Huchette et M. Lubin, “Jump : A modeling language for mathematical optimization,” *SIAM Review*, vol. 59, n^o. 2, p. 295–320, 2017.

[121] J. Hu et H. Li, “A transfer learning-based scenario generation method for stochastic optimal scheduling of microgrid with newly-built wind farm,” *Renewable Energy*, vol. 185, p. 1139–1151, 2022.