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OPTIMAL ALLOCATION OF DEMAND RESPONSE THROUGH AGGREGATORS CONSIDERING THE TRANSMISSION SYSTEM TOPOLOGY

VINICIUS NEVES MOTTA
Département de mathémathiques et de génie industriel

Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*
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Cette thèse intitulée :

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présentée par **Vinicius NEVES MOTTA**
en vue de l'obtention du diplôme de *Philosophiæ Doctor*
a été dûment acceptée par le jury d'examen constitué de :

Hanane DAGDOUGUI, présidente
Michel GENDREAU, membre et directeur de recherche
Miguel ANJOS, membre et codirecteur de recherche
Antoine LESAGE-LANDRY, membre
Kankar BHATTACHARYA, membre externe

DEDICATION

To my beloved wife Carmen, my mom and my brother,
who made all of this possible...

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RÉSUMÉ

La participation croissante des sources d'énergie renouvelables dans le réseau électrique entraîne de nouveaux défis opérationnels, tels que la fluctuation de la production des énergies renouvelables ainsi que la difficulté de prévoir adéquatement leur production. Il est donc nécessaire de trouver des moyens efficaces pour trouver des façons d'ajuster la demande, malgré sa nature distribuée dans le réseau. Les agrégateurs peuvent être utilisés pour gérer un ensemble de ces ressources dites de gestion de la demande de puissance (en anglais, "demand response"), facilitant ainsi leur utilisation par l'opérateur indépendant du système. Cependant, la conception des agrégateurs et la décision sur comment allouer leurs ressources sont des problèmes importants. Un des aspects qui nécessite plus d'attention est l'impact de la topologie du réseau électrique sur ces décisions.

Notre première contribution est un modèle d'optimisation à court terme pour l'allocation des ressources gestion de la demande de puissance (DR) ainsi que des ressources de production pour satisfaire la demande externe qui est offerte après que la décision de génération soit prise. Les ressources de DR ne pourront être utilisées qu'après la décision de la génération. Enfin, notre travail tient également compte de l'impact de la congestion du système de transmission lors de l'allocation des ressources DR. Des tests numériques avec les études de cas IEEE 96-RTS et ACTIVSG500 montrent que l'utilisation de la DR aide à gérer la congestion du système de transmission, permettant ainsi aux générateurs de satisfaire à une plus grande demande externe.

Dans notre deuxième contribution, nous considérons les incertitudes liées à la production d'énergies renouvelables et à l'offre de demande externe. En outre, nous ajoutons une autre couche de complexité au problème en considérant le problème d'engagement des unités de production. Cela conduit à un problème mixte stochastique semi-défini, qui est assez difficile à résoudre. Afin de résoudre ce problème, nous appliquons la décomposition de Benders généralisée (GBD), ce qui nous permet de surmonter la complexité du problème original. Comme l'algorithme GBD a souvent un taux de convergence lent, nous avons utilisé différentes méthodes d'accélération pour améliorer sa performance. Nous montrons également que toutes les méthodes employées contribuent de manière significative à la diminution du temps de résolution. En particulier, la méthode des coupes Pareto-optimales contribue le plus à l'amélioration des performances de l'algorithme GBD. Nous évaluons ces méthodes en résolvant plusieurs instances de notre problème avec la grille de test IEEE 96-RTS.

Comme les programmes de DR jouent un rôle plus important dans l'opération du réseau électrique, à la fois à court et à long terme, le problème de son allocation optimale devient primordial. Pour cette raison, notre contribution finale est une étude détaillée des travaux existants qui adoptent une approche intégrée pour planifier de manière optimale l'opération du réseau électrique et l'utilisation de la DR. Nous présentons les différentes approches pour résoudre ce problème ainsi que les recherches futures possibles sur ce sujet.

ABSTRACT

The increasing penetration of renewable energy sources in the power grid brings new operational challenges, such as the renewable energies generation fluctuation as well as the difficulty to adequately predict their generation. This brings up the need for effective means to provide demand response in spite of its distributed nature throughout the grid. Aggregators can be used to manage a set of such demand response resources, facilitating their usage by the independent system operator. However, both designing aggregators and deciding how to allocate their resources is an important problem. One of the aspects that needs more attention is the impact of the transmission system on these decisions.

Our first contribution is a short-term optimization model for allocating demand response (DR) resources as well as generation resources to supply external demand that is offered after the dispatch decision is made. The DR resources will only be available for use after the dispatch decision is made. Our work also considers the impact of congestion in the transmission system when allocating DR. Numerical tests with the IEEE 96-RTS and the ACTIVSG500 case studies show that DR usage helps to manage the transmission system congestion allowing for more external demand to be supplied by the generators.

In our second contribution, we consider the renewable energy generation and the external demand offer uncertainties. Besides that, we also add another layer of complexity to the problem by considering the unit commitment problem. This leads to a stochastic semidefinite mixed integer problem, which is fairly challenging to solve. In order to solve this problem, generalized Benders decomposition (GBD) is applied, allowing us to overcome the complexity of the original problem. Because the GBD algorithm often has a slow convergence rate, we have employed different acceleration methods to obtain improvements on its performance. We show that all of the employed methods contribute significantly to diminishing the time of solution when making a benchmark of them. In particular, the Pareto-Optimal cuts method contributes the most to improve the performance of the GBD algorithm. We benchmark those methods by solving several instances of our problem with the IEEE 96-RTS test grid.

As DR programs play a more significant role in the operation of the power grid, both in the short- and long-term horizon, the problem of the optimal allocation of DR resources becomes primordial. Because of that, our final contribution is a detailed survey of the existing works that take an integrated approach to optimally planning the operation of the power grid and the use of DR. We present the different approaches for solving this problem as well as possible future research on this topic.

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LIST OF SYMBOLS AND ABBREVIATIONS

DR	Demand Response
DG	Distributed Generation
ISO	Independent System Operator
DCOPF	DC Optimal Flow
ACOPF	Alternating Current Optimal Power Flow
DR	Demand Response Resources
OPF	Optimal Power Flow
UC	Unit Commitment
FACTS	Flexible Alternating Current Transmission System
SCM	Stochastic Congestion Management
VPP	Virtual Power Plant
EV	Electrical Vehicle
AC	Alternating Current
DC	Direct Current
SLP	Successive Linear Program
QC	Quadractic Convex
SOCP	Second-order Cone Programming
SDR	Semidefinite Relaxation
CHR	Chordal Relaxation
ED	Economic Dispatch
SCUC	Security-Constrained Unit Commitment
PTDF	Power Transfer Distribution Factor
MINLP	Mixed-Integer Linear Programming
MILP	Mixed-Integer Linear Programming
PSO	Particle Swarm Optimization
PSPSO	Partitioned Step Particle Swarm Optimization
RBNS	Relaxation-Based Neighbourhood Search
NLP	Non-Linear Programming
SDPR	Stochastic Dynamic Programming
NDP	Neuro-Dynamic Programming
SDDP	Stochastic Dual Dynamic Programming
ADMM	Alternating Direction Method of Multipliers
BD	Benders Decomposition

GBD	Generalized Benders decomposition
ARC	Adjustable Robust Counterpart
AARC	Affine Adjustable Robust Counterpart
DSO	Distribution System Operator
SUC	Stochastic Unit Commitment
LP	Linear Programming
MIR	Mixed-Integer Rounding
PO	Pareto Optimal
IBDR	Incentive-Based Demand Response
PBDR	Price-Based Demand Response
CVaR	Conditional Value-at-Risk
IGDT	Information Gap Decision Theory
RO	Robust Optimization
SRC	Static Robust Counterpart
C&CG	Column and Constraint Generation
LOLE	Loss of Load Expectation
DRO	Distributionally Robust Optimization

CHAPTER 1 INTRODUCTION

1.1 Context

Recently, there has been a significant technological evolution of the equipments available to use in the power grid as well as an expressive concern regarding energy generation environmental impacts. Therefore, there is an increasing participation of renewable energy in the energy mix, both through centralized and distributed generation [1], [2], and, also, the growing use of technology in the grid has incentizived the development of demand response (DR) programs, since it makes possible the use of customer assets. DR can be defined as the capacity of changing the consumption patterns of customers in order to mitigate demand peaks, this can be done through shifting the energy consumption or reducing it [3]. Renewable energy is increasingly used to meet the objective of minimizing the environmental impacts of electricity generation. DR programs have the objective of mitigating energy consumption peaks, delaying the need of expanding the generation capacity.

Because of that, new challenges for operating the power grid adequately appear, such as integrating both DR and distributed generation (DG) into the grid and managing adequately all of the DR resources in real-time. However, there are also many opportunities that are created, such as the possibility for costumers to take part into the electricity market and the emergence of companies dedicated to managing DR resources.

In the context of managing both DR and DG adequately and integrating them into the grid, an entity called aggregator was conceived. The main idea is that controlling individual residential DR or small DG sources is extremely challenging for the Independent System Operator (ISO) because of how they are geographically distributed on the power grid. Furthermore, most of the customers have little to no market power when negotiating their DR or DG resource [2]. Thus, there is a need for an interface between the ISO and the DR and DG resources in order to integrate these resources and give more market power to the residential DR service providers, which are the aggregators [2]. The former is necessary to facilitate the use of DR resources by the ISO when operating the grid. The latter will guarantee a better remuneration for the customers that take part into the DR market.

Consequently, there is also the challenge of designing aggregators adequately. In the literature, there are many works related to this aspect, as seen in [4–6]. Also, there have been many works in trying to integrate DR and DG into the power grid operation without aggregators, as seen in [7–11]. Futhermore, there have been a few works that deal with aggregators' bilateral contracts portfolio management, as seen in [12]. There are also works that try to integrate aggregators into the power grid operation, such as [13–16]. However, they consider a DC Optimal Power Flow (DCOPF) model, where the representation of the transmission system is significantly simplified and does not consider, for example, transmission losses, which can make the models give optimistic solutions.

Furthermore, there is also the issue of the uncertainty related to the renewable energy generation as well as to the energy demand, since we cannot predict them accurately, even in the short-term time horizon. As such, we also have to take uncertainties into consideration in our model, which forces us to consider either stochastic or robust optimization models.

To the best of our knowledge, there has been no works in integrating aggregators into the power grid operation considering a detailed representation of the network topology. We can see that, in these works, either a simplified representation of the transmission network is considered or the DR resources are not supplied by an aggregator. Besides that, most of the works considering either the renewable energy uncertainties or the energy demand uncertainties rarely consider a detailed representation of the transmission system.

As a consequence, we can see clearly that there is a need to develop a model that aims to integrate aggregators into the power grid operation taking into a consideration a detailed representation of the transmission network. This will, first, allow us to truly analyze the advantages of employing aggregators to supply DR resources. In addition, by considering all of the physical constraints of the transmission lines, we can analyze the importance of using DR to both manage the transmission system congestion and minimize the transmission losses.

1.2 Objectives

The general objective set in our thesis is to tackle the problem of integrating aggregators into the power grid operation considering a detailed representation of the transmission system. We will, in this thesis, aim to maximize the producers' energy exports considering both renewable energy and energy demand uncertainties after a dispatch decision is made. The main idea is developing a short-term horizon model, in which we will allocate the DR and DG resources of the aggregators and available generation adequately considering all of the aspects of the network topology.

Specifically, it will be modeled as a short-term economic dispatch problem with DR resources, which traditionally uses an Alternating Current Optimal Power Flow (ACOPF) transmission model to describe the grid's transmission, which is computationally costly to solve, we will consider a convex relaxation of the ACOPF transmission model to turn this problem into a tractable one. Also, we will consider that the generator can choose how much of the unexpected demand he will supply, thus making supplying this unexpected demand a decision, instead of a parameter.

Finally, because renewable energy generation and load cannot be predicted accurately, we will consider their uncertainty when developing our model. This will create a need for analyzing the performance of the available algorithms to solve stochastic optimization problems to guarantee finding the solution in a timely manner.

CHAPTER 2 LITERATURE REVIEW

This chapter will present the most relevant literature in regards to the scope of this thesis. First, we will present works that propose models to tackle the issue of the operation of the power grid and DR resources (DRR) in a coordinated fashion. Then, we will go over the different ways of modelling aggregators by presenting the pertinent papers. Finally, we will give an overview of the Optimal Power Flow (OPF) and Unit Commitment problems, as well as of the different ways to approach optimization under uncertainty problems, such as stochastic optimization and robust optimization.

2.1 Integrated power grid and DRR operation

There has been an effort to model the operation of the power grid integrating either DR, or DG, or both of them. In [7], the authors develop a model to integrate DR and unit commitment (UC) problems considering both the DR trading side, which aims to maximize their profits, and the Independent System Operator (ISO) side, which aims to minimize its operating costs. The authors model the DR service providers supply curves considering the costumers' willingness in participating in DR programs, costumers with more willingness mean lower prices for requesting DRR and more DRR available. With that the authors are able to include the DR cost in the objective function and the DR generation variables in the problem's constraints. Finally, when they analyze the results of the model for a case study considering different prices and levels of willingness, the authors conclude that an increasing DR price leads to an increase in operation cost and a smaller DR participation in the system operation.

In [8], the authors also develop an integrated DR and UC model, but their aim is to maximize the profits of the electricity utility taking into account the change of prices due to the costumers' DR and forecast error impacts in renewable energies generation. They consider the objective function as the sales revenue minus the operation cost. The demand forecast error is added to the objective function and to some of the constraints, they also add the photovoltaic and wind power generation errors in some of the constraints. When considering the forecast errors, they model the supply-load balance constraint as a chance constraint considering a normal distribution. The authors analyze the model's results for a small case study considering two different scenarios and they conclude that there is an increase in the operation cost as the forecast error increases.

In [9], the authors also propose an integrated DR and UC model and, in this case, the aim is to maximize the generators' profit. As in [8], the objective function is the difference between the revenues and the operating costs. The DR price is modelled considering the customers' willingness to participate in a DR program and the DR generation. With that, they define the constraints adding DR generation variables. In order to solve this problem, they use a meta-heuristic evolutionary optimization technique called Cat Swarm Optimization, which tries to emulate cats' hunting skills. The authors analyze the model with two case studies, one with DR and another one without. When analyzing the results, they find that there is a smaller operating cost and higher profit when using DR.

In [10], the authors also develop an integrated DR and UC model in order to be able to analyze the impact of DR in UC, dispatch, and electricity prices in a day-ahead electricity market. When modelling the problem, they aim to minimize the operating costs by minimizing production costs and maximizing the use of DR, where DR price is divided in demand bid blocks. They also add the DR constraints and its variables to the load-supply balance constraint. In order to analyze the model, they consider two case studies, one without network constraints and one with network constraints; in both they analyze the results with and without DR. In both case studies', they observe a smaller market price when using DR.

In [11], the authors develop an integrated DR and UC model with the objective of analyzing DR programs' economic and environmental impacts. When formulating the problem, the authors determine as the objective minimizing the operating costs, DR mobilization costs and emissions, which are represented in the objective function. For pricing the DR, they develop a responsive load economic model. Because they consider emissions and DR costs, they build constraints for determining the emissions generated through energy generation and add DR variables to the load-supply balance constraint. In order to analyze the model, they consider three small case studies for a small network. In the first case, there is no pollution, in the second, only the environmental pollution is considered and in the last one both DR programs and environmental pollution are considered. They were able to conclude that DR programs have economic and environmental benefits.

Finally, [13] develops a short-term stochastic security-constraint UC model that also considers DR programs. The problem is modeled as a two-stage stochastic problem, where the first-stage is the network constrained UC problem and second-stage checks the security constraints. The objective is to minimize operation and DR resources mobilization costs while guaranteeing a secure operation, which is reflected in the objective function. In the first stage, all of the UC problem constraints are defined with the inclusion of DR resources variables. In the second stage, only the constraints related to the security aspects of the UC problem are defined. The authors analyze the model with two case studies and find that the DR program model proposed in the paper is beneficial for the customers.

Besides the challenges to operate the grid, there are also possible benefits that can be obtained with its good operation, such as using DR and DG for congestion management. In [17], a congestion management method is developed based on the use of DR programs and flexible alternating current transmission system (FACTS) devices. The authors model DR considering incentives and penalty factors leading to more responsive control. First, a demand response bidding model is formulated to determine how much DR can be provided in each bus. Afterwards, a market clearing formulation is modeled, in which they solve, first, an optimization model to determine the market price and then they formulate an optimization problem to solve the congestion management problem. Finally, they present a case study to analyze the developed models comparing three different options: No DR and FACTS, DR and FACTS, and DR without FACTS. The authors conclude that a combination of DR and FACTS can reduce the total market cost.

In [18], the authors propose a stochastic congestion management (SCM) method using DR programs and considering the load uncertainty. In order to tackle this problem, the authors model the DR considering price elasticity of the demand and, thus, develop an economic model for the load. Afterwards, they model the probabilistic load as a normal distribution. Besides that, they use Monte-Carlo simulation to generate samples considering data distribution. Finally, they propose an optimization model in which the objective is to minimize congestion costs considering operation constraints, such as load-supply balance constraint and line flow limits. To analyze the model developed they solve a case study with 24 buses. They conclude that congestion costs and transmission losses grow as the load uncertainty grows.

In [19], a SCM method is developed considering DR programs, load shedding and generation uncertainty. This method also considers the trade-off between choosing DR programs and load shedding for congestion management. Initially, the authors propose an elastic load model based upon incentive and penalty. Afterwards, the power generation uncertainties are modeled with two different types of Monte Carlo simulation, the ordinary one and the lattice one. In the Monte Carlo simulations, they model the uncertainties using the probability of components outage. They also apply scenario reduction techniques to make the problem tractable for large scale systems. Finally, they develop an optimization model with the objective of minimizing the operating costs for the ISO, which is comprised of generation costs, load shedding payment and DR resources payment, under the system operation constraints. To analyze the model, the authors test it with a 24-bus power system and conclude that the

ISO employs more DR resources than load shedding. Also, they conclude that lattice Monte Carlo method gives more realistic scenarios than the ordinary one, considering that it gives a more accurate cost.

Finally, in [20], emergency and day-ahead DR programs are modeled and used to mitigate congestion in the transmission system while minimizing operating costs considering demand and power system uncertainties. First, the authors develop a load economic model for modeling customer response based on price elasticity. Afterwards, an optimization model is developed with the objective of maximizing producer profits being calculated as the consumer payment minus the producer surplus and minus the demand response cost. This value is maximized under the dispatch problem constraints with the addition of constraints related to DR. After determining the optimal dispatch by using this first model, it is necessary to manage the system's congestion, for which they develop a model that has the objective of minimizing the amount payed to the generators and for the DR service providers for alterating their generation output and guaranteeing minimal congestion. The authors analyze the model with a case study and they are able to conclude that congestion management using generation and demand re-dispach reduce significantly congestion costs.

2.2 Aggregators

Designing aggregators is a challenge that has started to be tackled recently. In fact, there are both technical and economical challenges in designing them.

Regarding the economical challenges, we have the work in [4], where the authors propose a business model for aggregators, in which the aggregators are responsible for managing the service quality for the consumers under their management. The idea is that the aggregator imposes a capacity limit or determine a capacity threshold that, if violated, it will incur penalties to the consumer. For that, first, they model economically DR in order to be able to determine the cost of implementing a curtailment policy. Then, they develop a general model of the aggregator's benefits from demand response that tries to maximize profit by choosing an adequate amount of DR resources to allocate under uncertainty.

With respect to the technical challenges, there are also several aggregator models. In [5], the authors propose to model the aggregator as a virtual power plant (VPP), which provides regulation services to the power grid and, at the same time, guarantees the power quality for the distribution network. First, they outline the distribution-network model that they will use, in which they approximate AC power-flow equations with linear equations. Afterwards, they propose a virtual power plant optimization model, which has the objective of minimizing production costs considering load-supply balance constraints and voltage regulation enforcement. Finally, they develop an algorithm that takes advantage of "primal-dual-gradients applied to regularized Lagrangian function". In order to test the model, they analyze the results of using it for two case studies; they conclude that the model is capable of adjusting aggregate DR very well.

In [6], the authors develop a method to help the VPPs (aggregators) schedule and aggregate DR and DG resources considering the necessity of minimizing operating costs and the resources remuneration. They develop a model in which the objective is to minimize the DG allocation cost, the DR resources services cost, these services being provided through incentive-base and price-based DR programs, and the suppliers costs. The VPP dispatch is under the load-supply balance constraint, DG and DR resources constraints, and also under participation constraints for both DG and DR. In order to analyze the model developed, they consider a case study in which they test it in a network with 937 buses and 20,310 consumers for different scenarios.

Furthermore, one also needs to consider the coordination between the aggregators and the ISO. In [21], the authors propose coordinating an electrical vehicle aggregator with the system operator developing an algorithm that integrates this aggregator with "simultaneous energy and reserve market clearing algorithms". In other to do that, they develop an optimization model that aims to minimize grid operating costs and energy procurement from eletrical vehicle (EV) costs. It is done subject to load-supply balance constraints, aggregator's constraints, which entails guaranteeing that EVs have sufficient energy stored for daily motion, and also spinning reserve constraints. For the purposes of analyzing it, the authors test the model for different scenarios in a test network. They are able to conclude that with this model it is possible to aggregate a large quantity of EVs without needing to invest in expanding the generation capacity. Finally, they find out that EVs resources will be only available to use if the aggregator offers them a competitive price.

Finally, there is also the issue of managing bilateral contracts by the aggregator. In [12], the authors propose an optimization model for managing bilateral contracts, both demand and resource contracts, to optimally deliver energy from the aggregator's clients to the grid. More specifically, they propose a two-frame model, one being a long-term model that captures all of the contracts, and the other a short-term model that guarantees that the aggregator supplies the demand adequately considering its uncertainty in a week's period. In both time horizons, the authors desire to minimize the mobilization cost of demand response resources. In the first one, this is done considering load supply balance constraints, i.e., guaranteeing that all demand contracts are supplied by the aggregator. In the second one, the authors also consider the stochasticity of the demand and the number of times that each resource can be requested over the week. To analyze the developed model, they perform 50 simulation runs for a contract portfolio and verify which resources are lacking to find an adequate resources allocation over time.

2.3 Optimal Power Flow

Because the model that we will develop in order to solve our problem will consider the transmission network topology, there is a need to use a transmission model to describe it, since this will be an optimal power flow (OPF) problem.

The OPF problem is a non-linear, non-convex optimization problem that may or may not consider integer variables. In order to solve it, different formulations have been developed. The original OPF problem is the alternating current (AC) OPF problem, which is non-linear, non-convex, a NP-hard problem. However, a formulation with DCOPF has also been developed, by not considering the imaginary part of the ACOPF problem and by considering the difference between the bus voltage angles negligible. The DCOPF formulation is a linear optimization problem [22].

In order to solve ACOPF problems, many solution methods have been developed, including both non-linear and quadratic programming methods. Some of the methods are the gradient methods, sequential linear programming, sequential quadratic programming, interior point methods, etc [22]. Another approach is applying a relaxation to the ACOPF model, which generally transforms the problem into a convex one, allowing us to find a solution in a reasonable amount of time.

In [23], the authors propose a successive linear program (SLP) approach to solve the ACOPF problem. In order to do so, they propose the IV-ACOPF formulation, which is equivalent to the original one. In order to solve the problem using SLP, the authors linearize the problem using piecewise linear interpolations, Taylor series approximations, relaxations and penalty factors. The authors test the algorithm for different case studies and show that the new method converges to the optimal solution.

In [24], the authors propose a strong semidefinite programming (SDP) relaxation for the ACOPF problem. Initially, the authors present the SDP and the quadratic convex (QC) relaxations for the ACOPF problem. In order to strengthen the SDP relaxation, the authors develop a model that is a SDP-QC relaxation of the problem, add valid inequalities and tighten the bounds of the problem. They were able to find out that the optimality gap is reduced to less than 1% when testing it with different case studies.

In [25], the authors propose a strong second-order cone programming (SOCP) relaxation for the ACOPF problem. They first define both the SOCP relaxation of the SDP relaxation and the classical SOCP relaxation. In this paper, they choose to strengthen the classical SOCP relaxation by adding a constraint to consider network cycles, and by adding inequalities to separate the SOCP problem from the SDP. They analyze the proposed relaxation by testing it with different case studies and they find that it comes extremely close to the SDP relaxation with respect to bounds and solutions, and that it is much faster than the SDP relaxation to obtain the optimal solution.

Finally, in [26], the authors propose a new conic relaxation for the ACOPF problem, which they call tight-and-cheap conic relaxation. Initially, the authors present the semidefinite relaxation (SDR), the chordal relaxation (CHR) and the SOCP relaxation. Afterwards, they present their relaxation, which is stronger than the SOCP one. Finally, they test the algorithm for different case studies and show that their relaxation is solved much faster than with both CHR and SDR ones.

2.3.1 Transmission Losses

In DCOPF models, however, the transmission network is considered lossless [27], i.e., it does not consider transmission losses. Thus, when solving an economic dispatch problem or an UC problem that considers DCOPF, the operation policy given by the model is optimistic.

Because of that, several works attempt to include a good representation of transmission losses in the model. The different approaches for that can be divided in two categories: quadratic approximation, and piecewise linear function approximation.

Regarding the quadratic approximation methodology, there is article [27]. In this work, the authors propose a method that approximates the ACOPF transmission loss function as a quadratic function for the DCOPF model. With this approximation, they propose that quadratically constrained quadratic program algorithm should be used to solve the economic dispatch with transmission losses problem. After that, the authors develop a model of economic dispatch considering this transmission loss approximation. To analyze the model, they test it for three case studies. When analyzing the results, the authors observe that the power mismatch between the proposed method and the ACOPF method is, generally, smaller than 1%, which shows that the method approximates really well the transmission losses.

Several papers consider a piecewise linear function approximation. In [28], the authors propose a new methodology for approximating transmission losses linearly on DCOPF models that are implemented using power transfer distribution factors. Initially, they propose two different methods of approximating transmission losses linearly: Marginal Line Losses and Standard Loss Derivation. After that, they develop a DCOPF model and they also derive the Local Marginal Prices by using its dual. This model is used for analyzing both approximation methods and they find that the Marginal Line Losses method approximates the best the transmission losses. However, the authors state that both methods only deliver good solutions if they start with a good base point. Thus, they propose a sequential linear programming method that is capable of updating the loss factors and avoids the need of starting at a good base point. When testing this new method, they find that it calculates transmission losses that are closer to the ones given by an ACOPF modelling.

In [29], the authors propose a dynamic piecewise linear model for DCOPF transmission losses. The main idea is that, instead of making a "static" piecewise linear approximation of the transmission losses quadratic function, one should build the piecewise linear approximation dynamically, avoiding an excessive number of constraints for approximating the transmission losses function. Because of that, the authors propose an iterative algorithm, in which, at each iteration, the optimal scheduling problem with its transmission losses approximation is solved and it is verified if the calculated transmission losses are a good approximation by comparing them with the "real" transmission losses. If it is, the algorithm skips to the feasibility step and guarantees that the proposed solution is feasible. Otherwise, it adds a new transmission losses constraint to the optimal schedule problem and it begins a new iteration of the algorithm. The authors test the model on a 118-bus system and they are able to conclude that both the operating costs and the time of solution increases. However, there is a great accuracy of the transmission losses approximation.

Finally, there are a couple of works in integrating either UC or economic dispatch with transmission losses. For example, in [30], the authors propose a security-constrained UC (SCUC) problem considering transmission losses and using power transfer distribution factor (PTDF). Similarly to the classic SCUC problem, the objective is to minimize production costs considering operating constraints. However, instead of using the standard DCOPF formulation, the authors propose a DC formulation using PTDF, in which is possible to use only one equation to guarantee that the power balance constraint is satisfied, instead having a nodal balance constraint for each node. In order to represent transmission losses, the authors propose a linearization of the quadratic function, building a pre-determined number of linear functions to approximate the quadratic transmission losses function. To analyze the model they test it for three different example networks. They are able to show that both formulations reach the same cost in all example networks, with the PTDF-DC flow formulation exhibiting better computational performance than the classical DC flow formulation.

In [31], the authors propose a short-term security constrained hydrothermal scheduling model that considers transmission losses. They propose a model in which the objective function minimizes the operating costs of the power grid under transmission network constraints, load-supply balance constraint, and water balance constraints. For approximating the transmission losses, they implement an iterative algorithm, in which the calculated transmission losses in the optimization model and the real transmission losses are compared in order to verify whether the model calculated losses adequately. When the difference between the calculated and real transmission losses is below an error tolerance, the algorithm stops, since it has found the real transmission losses. To analyze the model, the authors test it on a 118-bus network transmission system. They conclude that the transmission losses method used generates good approximations of the real one and that there is a slight increase in the operating cost as well as in the execution time.

2.4 Unit commitment

Although economic dispatch (ED) models are able to model in a reasonable way the energy production and distribution problems, it does not take into consideration most of the generating units characteristics. Generally, besides the maximum and minimum generation limits, generating units also have limits in ramping up and down their energy production as well as time constraints for their startup and shutdown. When these aspects of the problem are considered, we have the so called unit commitment models [32].

Both ACOPF and DCOPF models can be considered when modelling an UC problem. In [33], for example, the authors propose an UC-ACOPF model; because it is a mixed-integer nonlinear programming (MINLP) problem, they propose using an Outer Approximation method to decompose it in two problems, a Mixed-Integer Linear Programming (MILP) and a Non-Linear Programming (NLP) problems. In order to solve the NLP problem, the authors propose the use of the SLP algorithm. In [34], for example, an UC-DCOPF model is proposed in which the authors seek to solve the multi-area UC problem. Finally, in some cases, the transmission system is not considered in the UC model, such as in [35], where the focus is on a better representation of time-dependent startup costs, ramping limits, and mininum up and down times. It should be noted that because the UC-ACOPF problem is a MINLP problem, it tends to be very hard to solve. Consequently, UC-DCOPF models with a linearized objective function are favoured, since they correspond to a MILP problem.

However, it should be noted that even UC-DCOPF models can be hard to solve. Thus, in some cases an heuristic is used to solve them, such as in [36, 37]. In [36], the authors propose an UC model that takes into consideration the energy reserve provided by diesel generators in order to manage the renewable energies' uncertainties. To solve the proposed model, they use a variation of the particle swarm optimization (PSO) heuristic called partitioned step PSO (PSPSO). In [37], a relaxation-based neighbourhood search (RBNS) and improved relaxation inducement are proposed with the objective of improving the solution time of large-scale UC problems, since large-scale MILP problems are often computationally intensive to solve.

Finally, considering the security of the transmission system when determining unit commitment and economic dispatch is also a very important issue. Thus, SCUC models were proposed with the objective of guaranteeing that the solution given by the models also guaranteed a secure operation of the power grid. There are many SCUC that were developed such as [38].

2.5 Optimization under uncertainty

If we do not consider any possible data uncertainty, our proposed problem can be either a MILP (DCOPF) problem or a NLP (ACOPF) problem which are not very hard to solve. However, there are many sources of uncertainty, such as the demand uncertainty and the generation uncertainty. Specifically, the renewable generation uncertainty comes from the wind and photovoltaic generations. Both of these uncertainties have a noticeable impact in planning both the dispatch and the selection of which demand response resources to use for supplying the unexpected demand.

When we consider these possible uncertainties, the problem becomes significantly harder to solver when modelling it as either a MILP problem or a NLP problem, since the problem size could grow exponentially in order to represent these uncertainties. Thus, we are interested in possible ways of modelling this problem such that it is feasible to be solved. In the literature, there are two main optimization domains that are specifically directed towards solving problems with data uncertainty, these are stochastic optimization and robust optimization. In our problem, it would be interesting to use one of these techniques.

2.5.1 Stochastic Optimization

When solving a MILP stochastic optimization problem, we have different algorithm options for solving it. These options include Stochastic Dynamic Programming (SDPR) [39], Neuro-Dynamic Programming (NDP) [40], and Stochastic Dual Dynamic Programming (SDDP) [41], since a part of the stochastic programming problems can be modelled as dynamic programming problems considering that they are either two-stage or multi-stage decision problems.

In our project, we will not consider using SDPR to solve our problem, if modelled as a stochastic MILP problem. Such decision was taken because the number of problems to be solved by SDPR grows very rapid as we consider more time periods, more scenarios, and more nodes in our problem. This rapid growth in problem numbers is known as the dimensionality's curse. Although improved versions of the SDPR algorithm have been developed, such as the convex hull SDPR [42], this issue is still present in such improved versions.

Therefore, we will consider the use of either SDDP or NDP in this project if we model the problem as a stochastic MILP problem.

The main idea of the SDDP, according to [41], is to iteratively build the problem's feasibility region. In a two-stage problem, this is done by obtaining the dual of the second stage problem in which, if we could obtain all of the basic solutions, we could build the feasibility region. Because it is too costly to obtain all of them, we obtain a subset of them iteratively by adding the second stage dual's solution as a restriction in the first stage problem. The more basic solutions considered, the closer the algorithm gets to the solution. In other words, it converges to the optimal solution.

However there are still issues with the number of problems to be solved, which can be avoided using scenario reduction techniques [43]. We are able to prove that solving the problem for a subset of scenarios will still give us a solution that is either close to the optimal one or optimal. For example, in [43], the authors are able to achieve a 50% reduction in the number of scenarios and still have about 90% of accuracy in the problem solution. Also, in [44], the authors develop a method to generate smarter scenario trees, avoiding very large trees.

In addition to that, there are several techniques that can improve the algorithm's performance, such as cut selection [45], [46] and progressively considering a greater number of scenarios [46]. Finally, its convergence to the optimal value is already proven and tested [47], [48]. It also is possible to implement a risk-averse SDDP, avoiding optimistic policies [48], [49].

After that, we have the NDP algorithm, which is based on the idea of using both DP and neural networks concepts together [40]. The main idea is to approximate the future cost using a vector of parameters, which can be obtained by using reinforcement learning techniques. Thus, there are different NDP methods, such as iteratively adjusting the parameter vector using the notion of temporal difference, or the rollout method, in which one approximates the optimal solution by calculating the cost of a *base policy*, which can be obtained analytically or by simulation [40].

Finally, in [50], the authors propose a risk-averse dynamic programming algorithm with quantile-based risk measures. First, they define what is a dynamic risk measure stating that it is a sequence of conditional risk measures such that it is possible to calculate the risk at any stage of the problem. Afterwards, they define the algorithm, in which the main idea is implementing a time-dependent version of approximate value iteration; in the first step, it approximates the quantile based risk measures and, afterwards, it uses these approximations and the data observed to generate a more refined approximation of the optimal value for the objective function.

On the other hand, when solving a stochastic NLP problem, SDDP and NDP algorithms are not applicable, since they were developed for stochastic linear programming problems. Thus, it is necessary to consider different algorithms to solve this type of problem. In general, to solve this problem, we either use a decomposition technique or use a chance-constraint approach.

In [51], the authors propose a two-stage stochastic program formulation for the economic dispatch considering the ACOPF model. In order to solve this problem, they use the Alternating Direction Method of Multipliers (ADMM) to decompose the problem. This method is based on decomposing the Lagrangian reformulation of the original problem, such that it finds both the solution for the first-and-second-stage problems and updates the values of the dual variables of the first-stage problem. The algorithm does this iteratively until the solution for both stages converge. The authors analyzed the algorithm's performance for different case studies and they have found that the algorithm is able to converge reasonably fast even for large grids.

In [52], the authors propose a multi-stage stochastic problem formulation for the AC optimal power flow problem. They propose using an approximate chance-constraint formulation to solve this problem. Specifically, they develop an iterative method for approximating the chance-constraints of the current and the voltage, in which the AC optimal power flow problem is solved first and, afterwards, the uncertainty margins of the voltage and of the current are calculated. The difference between the uncertainty margins found in the last two iterations is calculated, if its value is lower than the value chosen as the stopping criteria, the algorithm stops executing and returns the solution. Otherwise, another iteration is executed.

In [53], the authors propose a multi-stage stochastic problem formulation for the AC optimal power flow problem. They propose using a convex chance-constraint formulation to solve this problem. First they define a semidefinite relaxation of the original problem and afterwards they propose a piecewise affine policy considering a Gaussian distribution to approximate the semidefinite chance constraints. Finally, they test this formulation in a case study and show that this formulation is accurate, has a small number of constraint violations and ensures a tight near-global optimality.

Finally, Benders decomposition (BD) is another decomposition technique used to solve stochastic programming problems. Alhough BD was initially conceived to solve MILP problems, a more generalized version of BD, that is also applicable to convex NLP problems, was proposed by [54]. Generalized BD (GBD) has been widely applied in all kinds of stochastic NLP problems with success, including OPF and UC problems, such as in [55–57]. However, GBD convergence rate is not always satisfactory, which can lead to performance issues. This has lead to the development of enhancement methods for the GBD algorithm, such as the Benders based branch-and-cut algorithm [58], the Pareto-optimal cuts [59] and the mixed-integer rounding cuts [60].

2.5.2 Robust Optimization

Differently from the stochastic optimization techniques, the robust optimization techniques do not require knowledge about the data distribution and only requires the data itself. More specifically, *uncertainty sets* are used to model the uncertainty, and they require that any solution found for the problem to be feasible for any value in the set. In some cases, this can be a huge advantage, since it is not always possible to determine adequately the data distribution. Besides that, there is another difference between them, which is the fact that robust optimization has as an objective delivering the solution for the worst case scenario, instead of delivering the expected cost, as done by stochastic optimization [61].

When choosing how to solve a robust optimization problem, we have several modelling options. The simplest one is the Static Robust Counterpart, in which we obtain a dual of the restriction that contains the uncertainty and solve the problem [61]. However, this technique may generate overly conservative solutions for certain kinds of problems, such as ours. For dynamic programming problems like the one proposed in this project, there are some techniques that are more adequate, such as the Adjustable Robust Counterpart (ARC) [62], and the Affine Adjustable Robust Counterpart (AARC) [62–64]. All of them deliver less conservative solutions and they have the advantage of each stage being able to consider the past stages uncertainty [62]. Another possibility is using Distributionally Robust Optimization for modelling our problem, this technique is applicable when we know the distribution of the uncertain parameter values, but the distribution's parameters are uncertain [65].

CHAPTER 3 THESIS ORGANIZATION

In this thesis, the contributions that are presented are aimed at both tackling the problem presented in the Chapter 1 and exploring in detail what are the possible gaps in the research of this kind of problem. We, first, present a deterministic model that considers neither the uncertainties nor the unit commitment problem. Afterwards, we present a model that considers both the uncertainties and the unit commitment problem and we also explore the possible approaches to improve the performance of the algorithm used to solve the proposed model. Finally, we explore in detail the literature in regards to the integration of DR into the power grid operation in order to be able to point the gaps in the research, leading to possible improvements to the model or the consideration of new aspects of the problem for future works.

In the first contribution (Chapter 4), we propose a short-term optimization model in which we want to optimally allocate DR resources as well as generation to supply external demand considering the transmission system topology after the dispatch decision is made. DR is only available for use after the dispatch is defined. Its main use is to supply external demand and it can also be used to mitigate transmission congestion in order to allow generators to offer more energy for a lower cost. It should be emphasized, however, that the generator has no obligation of supplying all of the external demand and can choose how much of this demand he wants to supply. Thus, the external demand here is not a parameter, but a variable. Finally, because representing the transmission system with an ACOPF leads to a problem that is very hard to solve, we use a relaxation of the ACOPF model in our optimization model.

However, the model proposed in the first contribution does not consider the UC problem and it does not consider the renewable generation and demand uncertainties. Because of that, in the second contribution (Chapter 5), we propose a two-stage stochastic UC model where the decisions that have to be made before the realization of the uncertainties are the unit commitment and the DR use, and, after their realization, the economic dispatch and the external demand that will be supplied will be decided. In order to solve this model, we propose the use of the GDB. However, because of its slow rate of convergence , we employ acceleration methods, such as Pareto-optimal cuts, the Benders-based branch-and-cut, and mixed integer rounding cuts, to improve its performance. With the objective of analyzing which of the enhancement methods truly contribute to the improvement of GDB's performance, we do a benchmark where we compare their contributions to GBD's performance.

In the third, and last, contribution (Chapter 6), we make a thorough review of the existing works that integrate DR into either power grid operation or power grid expansion planning. Our objective is to be able to understand what has been done and what are the research gaps that are present. First, we explore the power grid operation models, analyzing what is the objective of DR in them as well as what kind of problems they solve (e.g.: renewable energy integration). We also survey the solution methods applied to solve the problem of power grid operation uncertainty. Then, we do the same with regards to the power grid expansion planning models, but in this case, we also consider whether the models are generation or transmission system expansion planning models.

In Chapter 7, we present our general discussion, where we discuss about the results that we found, what are their meaning and their importance, and we also talk about the limitations of the proposed models. Finally, in Chapter 8, we make our concluding remarks and talk about some of the possible future works.

CHAPTER 4 ARTICLE 1: OPTIMAL ALLOCATION OF DEMAND RESPONSE CONSIDERING TRANSMISSION SYSTEM CONGESTION

Paper initially submitted to the International Journal of Electrical Power and Energy Systems. It is currently submitted to Computational Management Science.

Co-authors: Miguel F. Anjos, Michel Gendreau

Abstract

The increasing penetration of renewable energy sources in the electricity grid brings new operational challenges. This brings up the need for effective means to provide demand response in spite of its distributed nature throughout the grid. Aggregators can be created to manage a set of such demand response resources, but deciding how to allocate an aggregator's resources is an important problem. One of the aspects that needs more attention is the impact of the transmission system on these decisions. In this paper, we propose a short-term optimization model for allocating demand response (DR) resources as well as generation resources to supply external demand that is offered after the schedule decision is made. In our model, the DR resources will only be available for use after the schedule decision is made. Finally, our work will also consider the impact of congestion in the transmission system when allocating DR.

Keywords: Demand Response, Optimal Power Flow, Aggregator, Semidefinite Programming, Smart Grid

Nomenclature

Parameters

- D_m^t, Q_m^t - Active and reactive power demand, respectively.
- W_m^t, FV_m^t - Active wind and solar power generation, respectively.
- QW_m^t, QFV_m^t - Reactive wind and solar power generation, respectively.
- B_{mn} - Susceptance in the branch connecting bus n to bus m.
- Y_{mn} - Admittance in the branch connecting bus n to bus m.

- B'_m, G'_m - Shunt susceptance and shunt conductance on the bus m, respectively
- Tn_{mn} - Turns ratio in the branch connecting bus n to bus m.
- f_{DR} - Percentage of the reduced demand that will be shifted to other periods of time.
- r_{et} - Revenue obtained for exporting demand at node e in time step t.
- c^D_{dt} - Cost for using demand response resources at node d in time step t.
- a^{Th}_j, b^{Th}_j - Coefficients of the generation cost function for thermal plant j in time step t.
- $\underline{T^t_{jm}}, \overline{T^t_{jm}}$ - Lower and upper bounds for active thermal power generation
- $\underline{QT^t_{jm}}, \overline{QT^t_{jm}}$ - Lower and upper bounds for reactive thermal power generation
- $\underline{Vm^t_m}, \overline{Vm^t_m}$ - Lower and upper bounds for voltage magnitude at bus m.
- $\overline{ED^t_e}$ - Upper bound for the demand exports that can be supplied by the generators at bus e
- $\overline{DR^t_d}$ - Upper bound for demand response in bus m.
- $\overline{S^t_{mn}}$ - Upper bound for the branch connecting bus n to bus m transmission capacity.
- Th_m - Set of thermal plants connected to the bus m.
- Ω_m - Set of transmission lines connected to bus m.
- Φ - Set of nodes that have an external demand offer.
- Ψ - Set of nodes that can supply demand response.

Variables

- T^t_{jm}, QT^t_{jm} - Active and reactive thermal power generation.
- ED^t_e - Demand exports that will be supplied by the generators at bus e.
- DR^t_d - Demand response in bus m.
- ΔD^t_m - Demand shift in bus m.
- ΔQ^t_m - Reactive demand power adjustment at bus m.
- I^p_{emnt}, I^q_{emnt} - Active and reactive power injection in the “to” point of the branch nm.

- I^p_{fmnt}, I^q_{fmnt} - Active and reactive power injection in the “from” point of the branch nm.
- Vm^t_m - Voltage magnitude at bus m.

4.1 Introduction

Recently, there has been a significant technological evolution of the equipments available to use in the power grid as well as an expressive concern regarding energy generation environmental impacts. Therefore, there is an increasing participation of renewable energies in the energy mix, both through centralized and distributed generation [1], [2]. The growing use of new technologies has incentived the development of demand response (DR) programs that make it possible to use residential demand to mitigate the variability in renewable generation, and to delay the need for system capacity expansion [3]. These developments lead to new operational challenges, including the management of DR as well as distributed generation (DG) resources, and to new opportunities for companies dedicated to this purpose.

In the context of integrating both DR and DG adequately into the grid, an entity called aggregator was conceived. The main idea is that interacting with individual residential DR or small DG sources is extremely challenging for the Independent System Operator (ISO), and that most of the customers have little to no market power when bidding their DR or DG resource individually [2]. Thus, there is a need for aggregators as intermediaries between the ISO and the distributed resources to efficiently allocate these resources and ensure the viability of DR service providers [2].

This leads to the challenge of designing aggregators adequately. There is an extensive literature on this, as seen in [4–6]. There has also been research on the integration of distributed resources without aggregators [7–11]. In [7], the authors develop a model that aims to both maximize the profits of DR providers and to minimize the operating costs of the ISO. A model to maximize the profits of the electricity utility considering both the change of prices due to DR and the renewable energy generation and demand forecast errors, was developed in [8]. Similarly, in [9], the authors develop a model that aims to maximize generator profits considering both DR and the unit commitment (UC) problem. The DR price depends on the willingness of the consumer to join a DR program. In [10], an integrated DR and UC model is developed with the goal of minimizing operating costs and maximizing DR use. It considers a DR model in which the DR resource can be bought by placing bids with each bid having a certain quantity of demand allocated to it. The authors of [11] develop a model to minimize the operating costs, DR use costs, and emissions which integrates both UC and DR. There has been research on managing an aggregator’s bilateral contracts portfolio [12].

Some authors have proposed models for an integrated operation of aggregators and the grid, such as [14–16, 21, 66–68]. In [21], the authors propose a day-ahead economic dispatch model that aims to have a coordinated operation of the system between the ISO and the aggregators of electrical vehicles (EVs). The idea is to minimize both the generators operating costs and the aggregated EV demand mobilization costs, considering the effect of the EVs on the load-supply balance, and guaranteeing that the EVs will have the energy required for their daily needs.

In [66], a hierarchical DR bidding framework is developed in which the DR aggregators procure DR from individual costumers and offer it to the ISO. The authors integrate the model developed for the DR with a DC optimal power flow (DCOPF) model such that the ISO can operate the grid centrally by choosing which DR aggregators offers it will accept so as to minimize operational costs.

In [67], a day-ahead AC optimal power flow (ACOPF) model that considers the offer of DR resources through aggregators is proposed. In this model, the aggregators submit DR bids to the ISO so that it can decide how to operate the grid at minimum cost by taking into consideration both DR and generation. The DR bidding function is modeled as a piecewise linear cost function, where each load curtailment segment has a specific price.

In [14], the authors propose a model that integrates DR aggregators in the grid operation aiming to minimize operating costs for the ISO and maximize profits for the aggregators in the day-ahead market. Furthermore, they consider the interactions between the aggregators and individual customers, as well as wind energy generation with its uncertainty. Thus, they model the problem as a stochastic bi-level programming problem in which they use the KKT conditions of the lower level program to transform it into a single-level problem. Subsequently in [68], they propose a model that also considers real-time grid operation for taking advantage of possible customers to offer DR in this time frame. For that end, they propose a two-stage stochastic programming problem in which the first stage is the day-ahead planning, and the second stage is the real-time planning.

In [15], the authors propose a day-ahead grid operation model for optimizing the allocation of DR and DG by the distribution system operator (DSO) considering the generation made available by the ISO. In the proposed model, the aggregators submit their generation, consumption and DR usage schedule to the DSO. Then the DSO and the generators companies send their generation schedule to the ISO. The ISO decides their dispatch taking into consideration the bids submitted by both the DSO and the generators, and, with the knowledge of the ISO's decisions, the DSO dispatches the DR resources and the wind plants in accordance with the aggregators' planning.

Although [66], [14–16, 68] have proposed models that integrate the operation of the grid and of the aggregators in a coordinated fashion, they use a DCOPF model. However, a DCOPF model does not represent the transmission system adequately, since it does not consider, for example, transmission losses, which can lead to optimistic dispatch decisions. Another option is using an ACOPF model, which adequately represents the transmission system, such as in [67]. The issue is that it is too costly to solve such problems because of their non-convexity.

We are interested here in the impact of the transmission system on the integration of aggregators in the grid operation. For this purpose we consider the need to meet external demand, representing changes in demand that appear after determining the operational schedule. An example of external demand would be when the system operator of one power grid requests energy from a different power grid. This demand can be met by either available generation or by allocating DR resources from the aggregators. In this work, it is the aggregators' responsibility in choosing which DR business model they will implement, we are only interested on the financial impact of using DR. Our contribution is an optimization model that maximizes the profits from meeting the unexpected demands. Specifically, we consider a short-term scheduling problem with DR resources and integrating the transmission system using an AC power flow model in which we consider a regulated electricity market. The integration of features such as the transmission system topology and the location of the generators, the DR resources, and the demand contracts allows the model to provide more accurate information. We also consider that a generator can choose how much of the external demand it will supply, thus making supplying this demand a decision variable (instead of a parameter).

Although there are uncertainties related to the wind and photovoltaic generation, and the energy prices, the additional complexity of considering them can lead to an intractable problem for larger grids. Nonetheless, a deterministic model is a critical step towards a possible future stochastic model.

In summary, our main contributions are:

- The consideration of external demand on day-ahead operation. Such demand is not known ahead of time, it is offered only after the schedule decision made, and can be opportunistically supplied by the generators by either generating more energy or using DR resources. Furthermore, the generators can choose how much of this demand will be supplied. A typical example would be the possibility that some energy markets have of exporting their energy production to other power grids.

- The use of AC power flow leads to a non-convex optimization model that has been shown to be NP-hard [69] and generally incurs a significant computational cost to solve; thus we cannot guarantee that we will find the global optimal solution. We propose the use of an ACOPF relaxation, turning the problem into a tractable problem and giving us a solution closer to the global optimum. This solution will be, in turn, used as the starting solution for the original problem, transforming it into a tractable problem. The proximity of the solution given by the relaxation can be seen by analyzing its optimality gap.

This paper is organized in the following way. In Section 4.2, we present our approach with the full non-convex ACOPF system model. In Section 4.3, we present the relaxation used as part of our method to solve the model proposed in section 4.2. In Section 4.4, we report the computational results for two case studies. Section 4.5 summarizes the outcomes of our work.

4.2 Optimization Model

In this section we present the proposed optimization model for optimal allocation of DR resources. We consider hourly decision-making in a short-term horizon such as one day or one week.

- Objective function:

$$\max \sum_{t=1}^{T} \left[\sum_{e\in\Phi} r_{et} ED_e^t - \sum_{d\in\Psi} c_{dt}^D DR_d^t - \sum_{m=1}^{N} \sum_{j\in Th_m} a_j^{Th} \left(\left({T_{jm}^t}^2 - \underline{T_{jm}^t}^2 \right) - b_j^{Th} \left(T_{jm}^t - \underline{T_{jm}^t} \right) \right) \right] \tag{4.1}$$

In the objective function, (4.1), our aim is to minimize the cost of the extra generation and DR that may be necessary to meet the external demand while maximizing the revenue generated by supplying the external demand.

- Active power balance constraint:

$$\begin{aligned} &\sum_{j\in Th_m} T_{jm}^t + \sum_{\{m,n\}\in\Omega} I_{fmnt}^p + \sum_{\{n,m\}\in\Omega} I_{enmt}^p - G'_m Vm_m^2 + DR_m^t - \Delta D_m^t = \\ &ED_m^t + D_m^t - W_m^t - FV_m^t \quad \forall m \in N, \forall t \in T \end{aligned} \tag{4.2}$$

- Reactive power balance constraint:

$$\sum_{j \in Th_m} QT_{jm}^t + \sum_{\{m,n\} \in \Omega} I_{fmnt}^q + \sum_{\{n,m\} \in \Omega} I_{enmt}^q + B_m' Vm_m^2 + \Delta Q_m^t = Q_m^t - \\ QW_m^t - QFV_m^t \quad \forall m \in N, \forall t \in T \tag{4.3}$$

In (4.2), we observe the addition of ED_m^t on the demand side of the constraint. Unlike D_m^t, ED_m^t is a variable, meaning that the generator can decide how much of the external demand to supply. This decision is directly connected to how profitable it is to supply this extra demand. There is also the addition of DR_m^t and ΔD_m^t to represent the DR and the shift of the demand due to DR. Otherwise, (4.2) is a standard power balance constraint, guaranteeing that the generation summed to the eventual energy transmitted or received through transmission lines is equal to the demand.

In (4.2), DR_m^t represents the demand response. It should be noted however, that DR is composed of both demand reduction and demand shift actions. To compensate the demand shift that occurs because of DR, we have the ΔD_m^t variable, that guarantees that any demand that is shifted will be supplied in another period of time.

The reactive power balance constraint, (4.3), has the additional term ΔQ_m^t that adjusts reactive power demand according to the decision to supply a certain amount of the external demand.

- Transmission constraints:

$$I_{fmnt}^p + jI_{fmnt}^q = \\ -\frac{Vm_m^t}{Tn_{mn}}\left[\left(j\frac{B_{mn}}{2} + Y_{mn}\right)\frac{Vm_m^t}{Tn_{mn}} - Y_{mn}Vm_n^t\right] \\ \forall \{m,n\}, \in \Omega, \forall t \in T \tag{4.4}$$

$$I_{emnt}^p + jI_{emnt}^q = \\ -\frac{Vm_n^t}{Tn_{mn}}\left[\left(j\frac{B_{mn}}{2} + Y_{mn}\right)Vm_n^t - Y_{mn}\frac{Vm_m^t}{Tn_{mn}}\right] \\ \forall \{m,n\}, \in \Omega, \forall t \in T \tag{4.5}$$

$$(I_{mnt}^p)^2 + (I_{mnt}^q)^2 \leq \overline{S_{mn}^t}^2 \qquad \forall \{m,n\}, \in \Omega, \forall t \in T \tag{4.6}$$

$$\underline{Vm_m^t} \leq Vm_m^t \leq \overline{Vm_m^t} \quad \forall m \in N, \forall t \in T \tag{4.7}$$

The transmission constraints (4.4)-(4.7) are the rectangular ACOPF formulation using complex numbers.

- Thermal plants bounds:

$$\underline{T^t_{jm}} \leq T^t_{jm} \leq \overline{T^t_{jm}} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{4.8}$$

$$\underline{QT^t_{jm}} \leq QT^t_{jm} \leq \overline{QT^t_{jm}} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{4.9}$$

- Demand Constraints:

$$0 \leq DR^t_d \leq \overline{DR^t_d} \quad \forall d \in \Psi, \forall t \in T \tag{4.10}$$

$$-\overline{\Delta Q^t_m} \leq \Delta Q^t_m \leq \overline{\Delta Q^t_m} \forall m \in N, \forall t \in T \tag{4.11}$$

$$0 \leq ED^t_e \leq \overline{ED^t_e} \quad \forall e \in \Phi, \forall t \in T \tag{4.12}$$

The bounds on generation, transmission, demand response and extra demand are enforced in (4.8)-(4.12).

- Demand Shift Constraints:

$$\sum_{t=24(wd-1)+1}^{24wd} (f_{DR} DR^t_d - \Delta D^t_d) = 0 \quad \forall d \in \Psi, \forall wd \tag{4.13}$$

The demand shift constraint is defined in (4.13); it guarantees that any demand that is shifted will be supplied in another time step. It should also be noted that we cannot decompose the problem in hourly problems precisely because of this constraint, that spans over 24 hours.

Finally, one can observe that we have defined an ACOPF problem with additional variables DR^t_m for provided DR, ED^t_m for external demand, ΔQ^t_m for reactive power demand adjustment, and ΔD^t_m for demand shift caused by the use of DR.

4.3 Methodology

The optimization problem presented in Section 4.2 is non-convex because of constraints (4.4), (4.5) and (4.6). The key difficulty are the terms of the form $Vm^t_m Vm^t_n$. The non-convexity makes it challenging to solve the problem to global optimality in a reasonable amount of time.

For this reason, we use a semidefinite relaxation (SDR) of this problem. SDR relaxations are convex optimization problems for which there are efficient algorithms to compute a global optimal solution. We then use the solution of the relaxation as the starting solution for a nonlinear optimization solver to solve the formulation in Section 4.2.

Specifically, we use the Tight and Cheap Relaxation (TCR) introduced in [26], which can be solved in practice in reasonable time. Thus, we define $VM^t = Vm^t(Vm^t)^H$ and reformulate the transmission constraints, (4.4), (4.5) and (4.7), in the following way:

$$\begin{aligned} I^p_{fmnt} + jI^q_{fmnt} &= -\frac{1}{|Tn_{mn}|^2}\left(-j\frac{B_{mn}}{2} + Y^*_{mn}\right) VM^t_{mm} \\ &- \frac{Y^*_{mn}}{Tn_{mn}} VM^t_{mn} \quad \forall m, \forall n, \forall t \end{aligned} \tag{4.14}$$

$$\begin{aligned} I^p_{emnt} + jI^q_{emnt} &= -\frac{Y^*_{mn}}{Tn^*_{mn}} VM^t_{nm} + \\ &\left(-j\frac{B_{mn}}{2} + Y_{mn}\right) VM^t_{nn} \quad \forall k, \forall m, \forall t \end{aligned} \tag{4.15}$$

$$\underline{Vm^t_m}^2 \leq VM^t_{mm} \leq \overline{Vm^t_m}^2 \quad \forall m, \forall t \tag{4.16}$$

This transformation eliminates the nonlinear elements of the constraints at the cost of introducing the new nonlinear constraint $VM^t = Vm^t(Vm^t)^H$.

One option is to relax it as a positive semidefinite constraint $VM^t \succeq 0$. This is the standard SDR, as first proposed in [70]. However, this relaxation is known to be computationally too costly to solve for power grids with hundreds or thousands of buses. For this reason, we use the relaxation TCR proposed in [26] that further relaxes the constraint $VM^t \succeq 0$ as follows:

$$VM^t_{11} \leq (\underline{Vm^t_1} + \overline{Vm^t_1}) Re(Vm^t_1) - \underline{Vm^t_1}\,\overline{Vm^t_1} \tag{4.17}$$

$$Im(Vm^t_1) = 0 \tag{4.18}$$

$$\begin{bmatrix} 1 & (Vm^t_m)^* & (Vm^t_n)^* \\ Vm^t_m & VM^t_{mm} & VM^t_{mn} \\ Vm^t_n & (VM^t_{mn})^* & VM^t_{nn} \end{bmatrix} \succeq 0 \quad \forall m, \forall n, \forall t \tag{4.19}$$

The resulting optimization problem can be solved in reasonable time even for large-scale grids.

In summary, our problem is solved in two steps, since the scheduling is decided well in advance and the unexpected demand is only informed shortly before the execution of the planned schedule. As such, we need to first determine the schedule, and, afterwards, we will determine how to supply this unexpected demand.

In the first step, we solve the scheduling problem, since we will decide how much extra demand will be supplied after the grid's operation is determined. We will label this step's models as ACOPF and as TCR-ACOPF. The former is composed by (4.1)-(4.10),(4.12) and the latter is composed by (4.1)-(4.3), (4.9), (4.10), (4.12), (4.15)-(4.20). In both cases, the variables ED_m^t, DR_m^t and ΔD_m^t are not considered.

In the second step, we solve our proposed model by using the generation values given by the solution of the first step as the lower bounds for the generation. We also define the extra demand that will be available to be supplied and the DR resources available to be used. We will label this step's models as Proposed Model, which is composed by (4.1)-(4.13), and as TCR-Proposed Model, which is composed by (4.1)-(4.3),(4.8)-(4.19).

We summarize the solution algorithm in the following way:

- First Step - Scheduling
  - Solve the TCR-ACOPF problem.
  - Use the optimal solution of TCR-ACOPF as the initial solution for the ACOPF problem and solve it.
- Second Step - Extra demand supply and DR use
  - Use the generation values of the first step's solution as the generation lower bounds to the TCR-Proposed Model problem and solve it.
  - Use the optimal solution of TCR-Proposed Model as the initial solution for the Proposed Model problem and solve it.

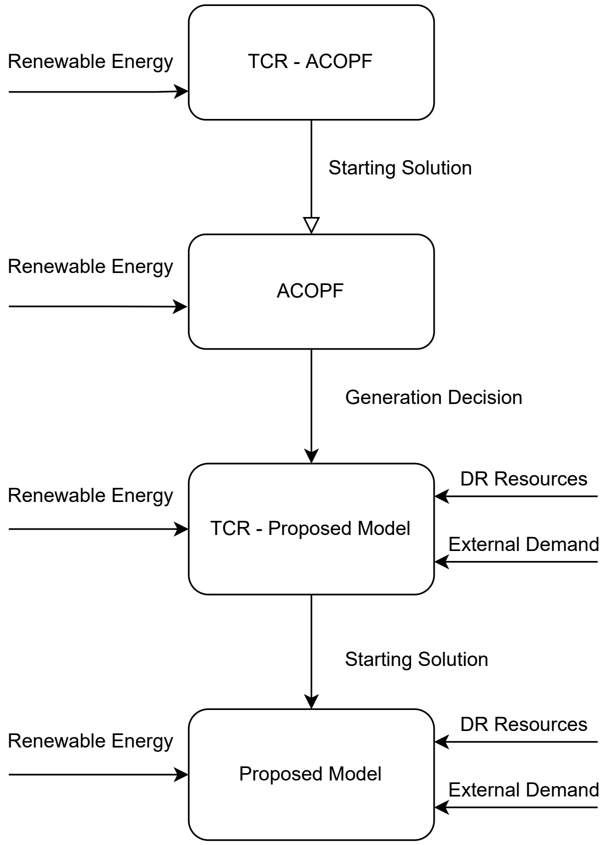

Figure 4.1 Problem execution flowchart.

4.4 Results

In this section, we report results for two case studies to demonstrate the capabilities of our proposed approach. The first case study uses the IEEE 96 RTS from [71], and the second uses the ACTIVSG500 system from the MATPOWER dataset [72].

The computations were carried out in MATLAB using CVX 2.1 [73], [74] and the solver MOSEK 8.1.0.60 to solve TCR, and using YALMIP [75] and the solver SNOPT 7.2.8 [76], [77] to solve the ACOPF formulation of the problem.

4.4.1 IEEE 96 RTS

For this case we have a 73 bus-system that can be divided into 3 zones with the same number of buses, except for the last zone, which has one more. We consider a one-week time horizon with 168 hourly time steps. We took the data for this case study from [71] but made small changes to the generators' installed capacity, node demands, load profile, and operating costs.

Furthermore, the load profile data for the period was taken from [78] taking into consideration the number of nodes in our case study.

We also made some changes to the demand and load profile of some nodes. Specifically, in our study nodes 317, 318 and 321 have 160 MW, 403 MW and 220 MW as their demand, respectively. Concerning the load profile, there was a value subtracted from all nodes for some time steps, see Table 4.1.

Table 4.1 Load profile reduction per time step

Time(h)	Load Profile Reduction
19	0.19
36	0.17
64	0.1
65	0.1
82	0.18
104	0.12
130	0.23
163	0.05

Regarding the generators, we increased the installed capacity by 16% for all nodes except those shown in Table 4.2. In this table, we have the generation data for the plants that have had their installed capacities modified. We also note that at some of the nodes we added wind or solar energy generation, and the generation capacity and type of plant added on each of these nodes can be found in Table 4.3.

Table 4.2 Generators installed capacity

Generator	Capacity(MW)
121	464
123-1	179.8
123-2	179.8
123-3	406
218	580
221	580
223-1	643.8
318	139.2
321	255.2

Besides that, in Fig. 4.2, we can see the demand curve for this case study. Also, DR can be activated in all nodes with active demand greater than 0 in zones 1 and 2, and the nodes 314, 318 and 321, being limited to a maximum of 10% of the demand with a cost of $25.55 per

Table 4.3 Generation capacity for wind and solar plants.

Node	Capacity Installed (MW)	Energy Source
103	15	Solar
105	10	Wind
108	20	Solar
118	15	Wind
206	20	Wind
209	10	Wind
211	15	Solar
219	20	Wind

MWh. Finally, nodes 106, 112, 119, 120, 319, and 320 will offer the possibility of supplying extra demand up to a maximum of 18% of the demand. Node 317 offers this possibility as well, but up to a maximum of 200 MW. All of them offer a revenue of $85.55 per MWh.

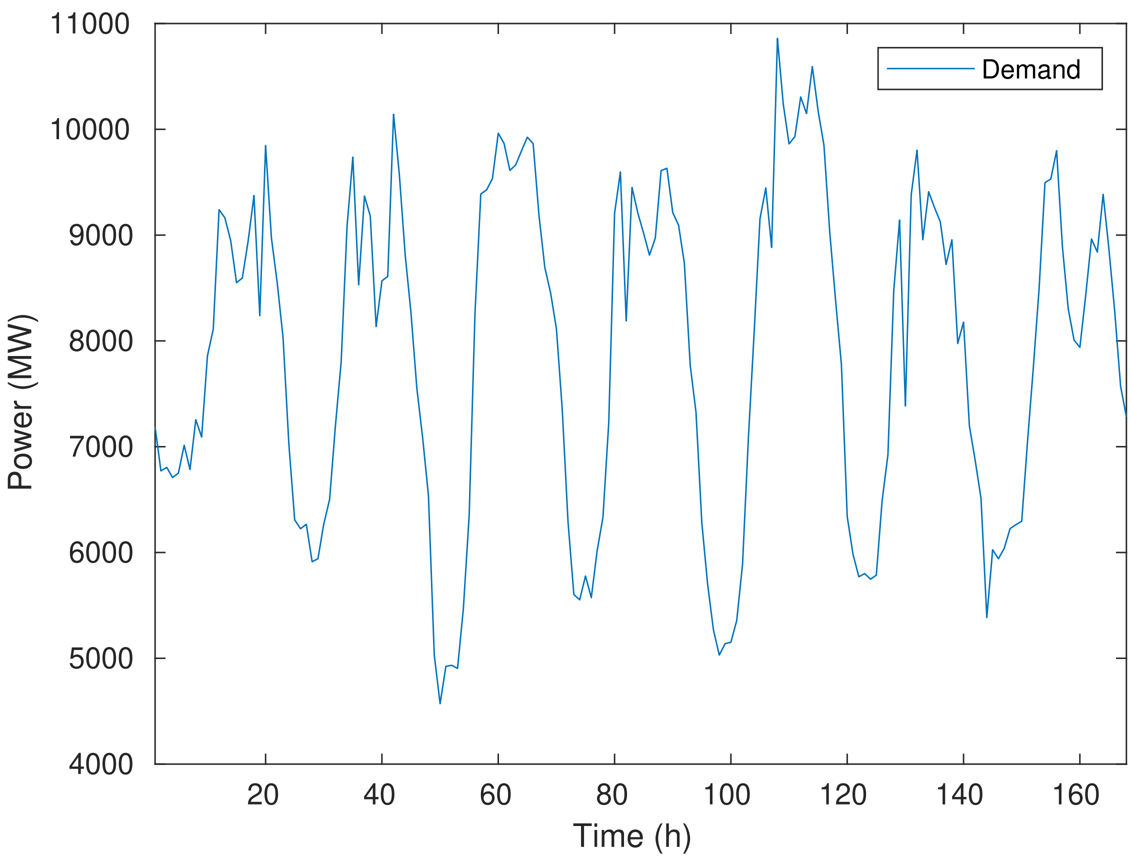

Figure 4.2 Case study total demand over time.

First, we compare the performance of solving the original problem with the performance of our proposed solution method. For the former, it took 36 hours and two minutes, and, for the latter, it took 24 hours and 36 minutes, representing a 31.71% improvement on the execution time.We also observe an optimization gap of 4.13% when comparing the solution given by the TCR-Model to the original model.

Afterwards, we analyze the results for DR resources use and the extra generation in this instance of the problem, which can be seen in Fig. 4.3. It is possible to see that both thermal generation and DR resources were used to supply the extra demand available in a profitable way. However, we also see that the DR resources were not the least expensive resource in all cases because there is plenty of DR resources that were not used to supply the exports demand. In other words, sometimes it was either more profitable to supply this demand with thermal generation or to not supply it at all. This can be explained, in part, by the fact that when using DR resources, we shift the load that the consumers choose not to consume. In other words, in other time periods, there is an increase of the demand to be supplied, meaning that we need to generate more energy in these time periods, which can be seen in Fig. 4.3. As a consequence, the cost of supplying energy with DR is the cost of using DR plus the cost of the generation for the demand that has been shifted.

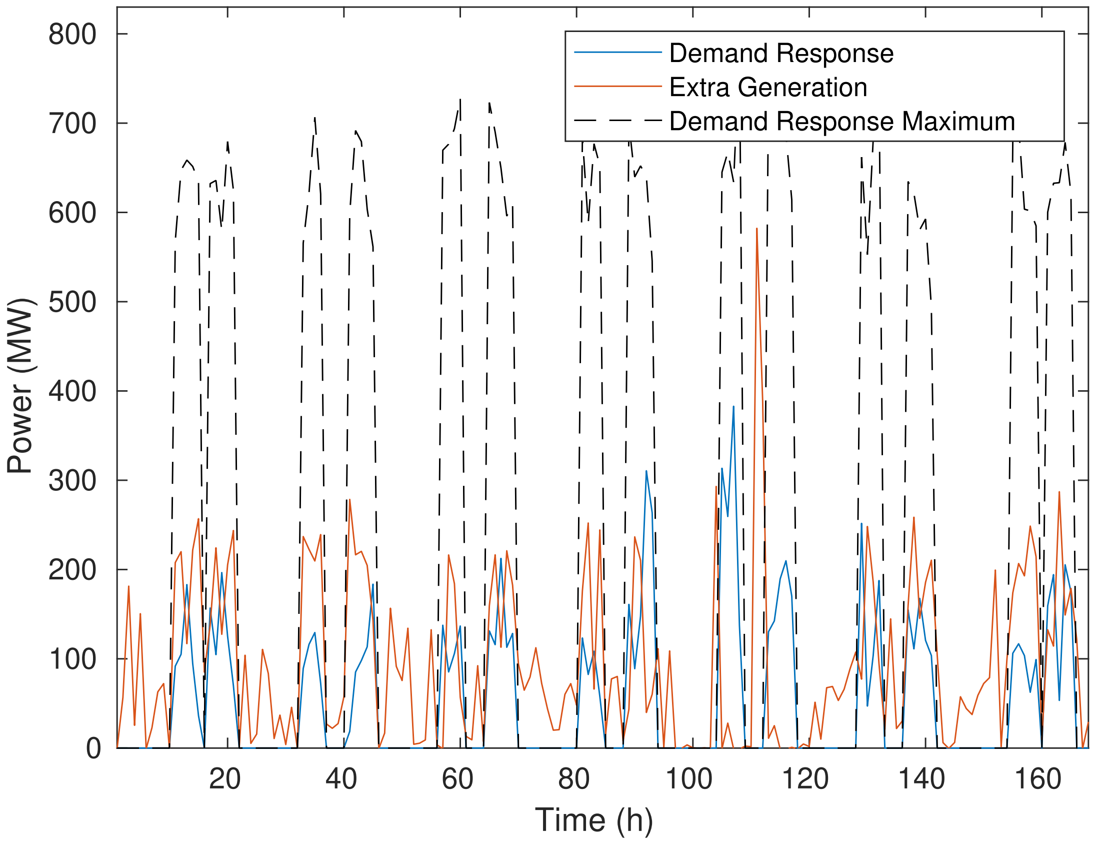

Figure 4.3 Extra generation and DR resources use over time.

When we observe the results for the extra demand, we notice that at some time steps the generators decide not to supply all of the possible extra demand. Analyzing the results for node 317 specifically in Fig. 4.6, we can establish that it is mostly because of not supplying all of the demand at this node. This is probably because all of the resources available in zone 3 are being used, including DR, and because the congestion in the transmission line 223-318 means that no DR resources from the other 2 zones can be used to supply this demand. Also, either there is no generator with capacity of generating more energy to completely supply the demand of this node or it is too expensive to do so, thus not being profitable.

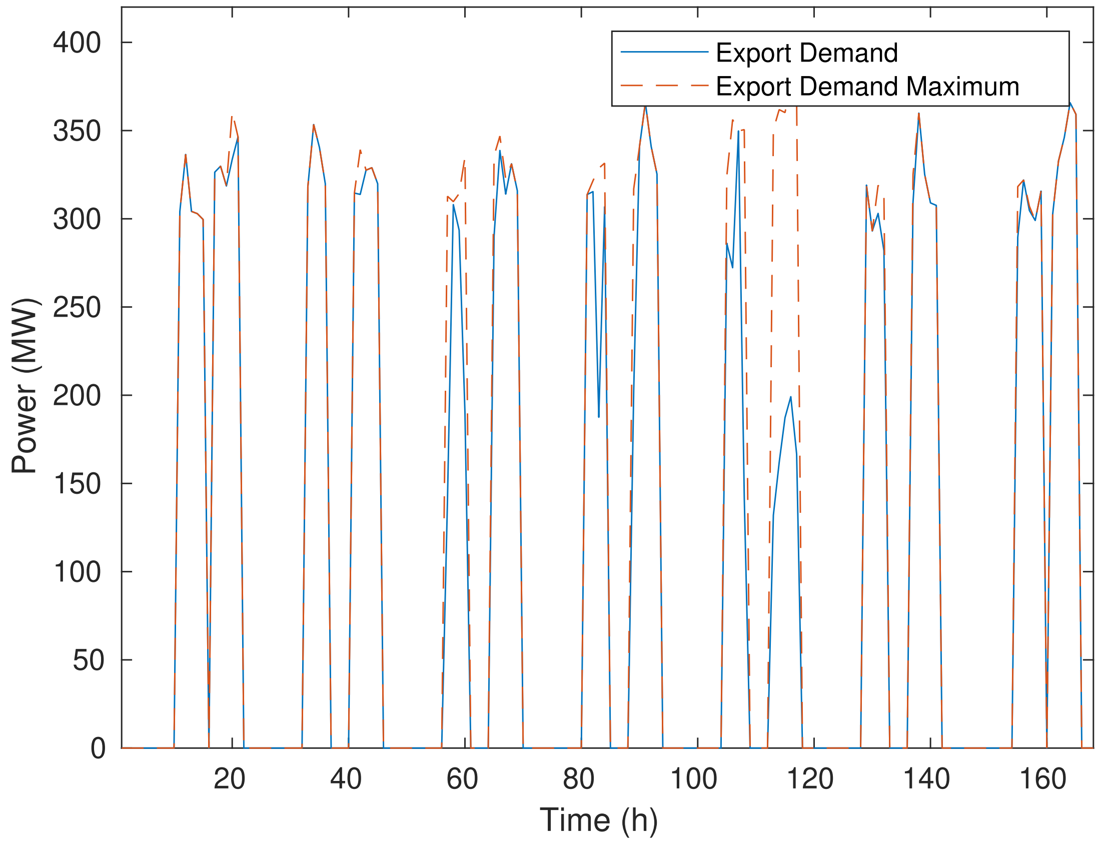

Figure 4.4 Extra demand supplied over time.

We also analyze the usage of DR at nodes 314, 318 and 321 and the supplying of extra demand for nodes 317, 319, 320, since the transmission line between nodes 223 and 318 is used close to its maximum capacity in peak demand times. We can see in Fig. 4.5 that there is a strong use of DR resources at nodes 314 and 318, which is coherent with the supplying of extra demand at nodes 317, 319 and 320, observable in Fig. 4.6. This corroborates what we see in Fig. 4.4, namely that DR is the only way that allows us to supply most of the extra demand available at these nodes, because the only transmission line that connects these nodes to the other zones is congested and there is limited extra generation capacity in zone 3. The only alternative to using DR would be to leave a significant portion of the extra demand unsupplied.

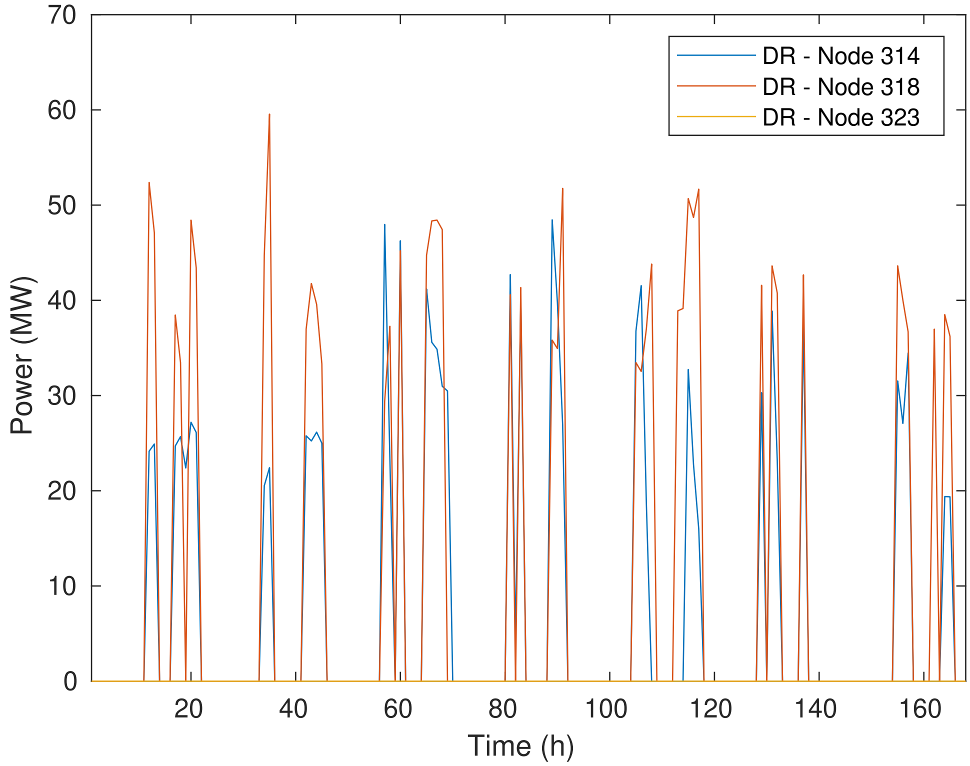

Figure 4.5 DR resources used at nodes 314, 318 and 323 over time.

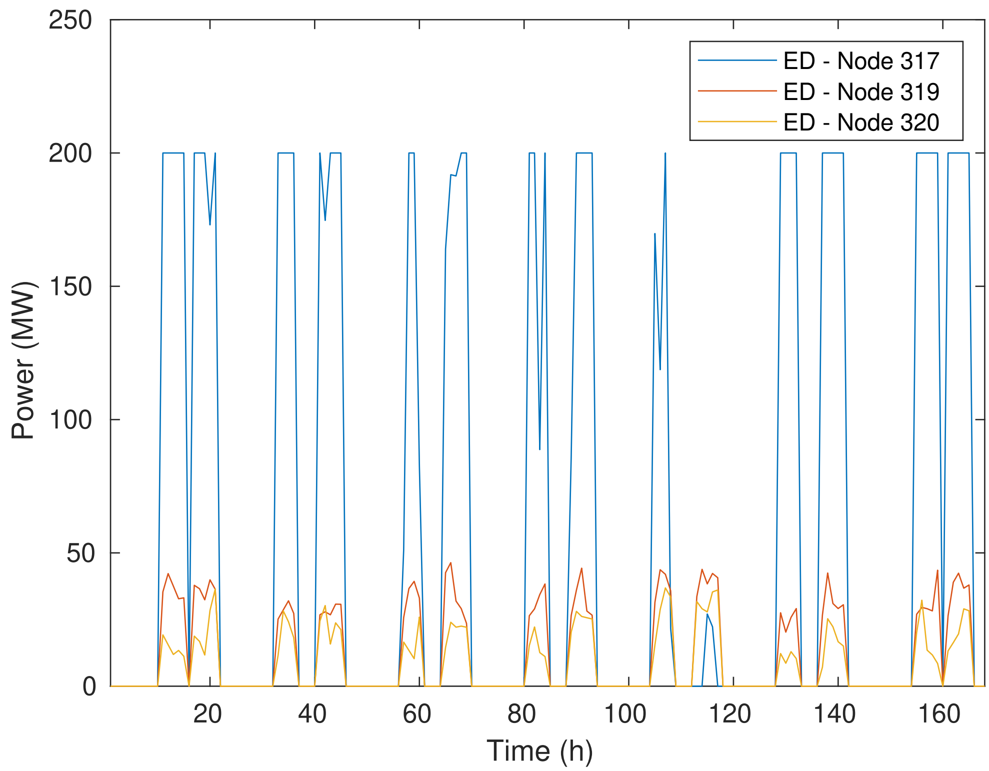

Figure 4.6 Extra demand supplied at nodes 317, 319 and 320 over time.

Finally, it is possible to infer that the extra generation we see in Fig. 4.3 is a consequence of the fact that it is cheaper to supply demand at nodes 106, 112, 119 and 120 with the available generation capacity than by using DR resources. This means that, in this case study, DR resources have the best cost-benefit when there is transmission line congestion that impedes energy being supplied by generators. When there is little or no congestion, generating more energy may have a better cost-benefit than using DR.

4.4.2 ACTIVSG500

In this case study, we have a 500 bus-system, and we consider a day-ahead time horizon divided in 24 hourly time steps. We took the data for this case study from [72] but made small changes to the generators' installed capacity, node demands, load profile, and operating costs in order to properly test our model. Furthermore, the load profile data for the period was taken from [79] taking into consideration the number of nodes in our case study. We also made some changes to the demand and load profile of some nodes, as shown in Table 4.4 and Fig. 4.7. In addition to that, we have lowered the demand by 5% for all of the previously unchanged nodes.

Regarding generation, at some of the nodes we added wind (WP) or solar energy generation (SP), the generation capacity and type of plant added at each of these nodes can be seen in Table 4.5. It should be also noted that the linear coefficients of the generation costs were multiplied by ten and that for plants with no operating cost, we added a \$50 per MWh operating cost. Finally, we raised the installed capacity of all generators by 17%.

We also changed the transportation limits for some of the transmission lines, which can be seen in Table 4.6. In addition to that, we have removed lines 181-97, 460-340, 221-447 and 214-403 for this case study.

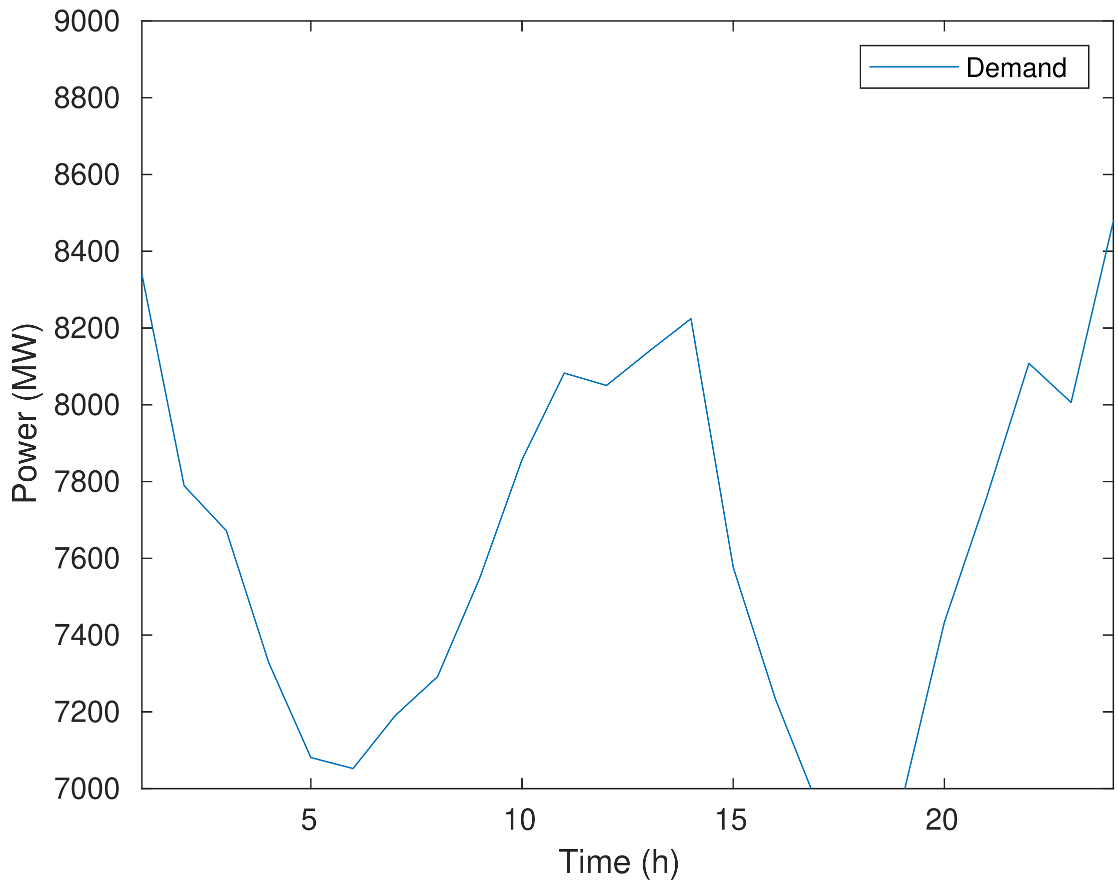

Figure 4.7 Case study total demand over time.

Besides that, DR can be activated at every node with active demand greater than 0 that has no external demand offer, being limited to a maximum of 10% of the demand with a cost of \$54 per MWh. Finally, nodes 34, 75, 94, 341, 182, 448, 404, 22, 311, 100, 38, 252, 266,

Table 4.4 Modified nodes demand.

Node	181	310	341	447	403	21	74	93	33
Demand (MW)	20	30	30	40	40	80	10	15	40

Table 4.5 Generation capacity for wind and solar plants

Node	4	59	130	142	148	213	282
Capacity(MW)	20	20	20	20	10	20	20
Source	WP	WP	WP	SP	SP	SP	SP

370, 381, 492 and 485 will offer the possibility of supplying extra demand up to a maximum of 18% of the demand offering a revenue of $180 per MWh. At the same time, some other nodes offer a fixed demand export possibility, which can be seen in Table 4.7.

First, we compare the performance of our solution method with the performance of solving the original problem. For the former, it took 10 hours and 59 minutes, and for the latter we weren't able to find a feasible solution. We also observe an optimization gap of 28.05% when comparing the solution given by the TCR-Model to the original model.

Afterwards, we analyze the results for DR resources use and the extra generation in this instance of the problem, which can be seen in Fig. 4.8. We see that both thermal generation and DR resources were used to supply the extra demand available in a profitable way. However, although there is much more DR available than extra generation, the external demand is supplied by both sources of energy. In other words, for the nodes that are not connected to congested transmission lines, the use of the remaining generation capacity available can be more advantageous to supply the external demand.

Table 4.6 Transmission lines maximum transportation capacity.

Transmission Line	Capacity (MW)
181-487	122.5
310-281	119
279-340	63.5
295-447	40
358-97	114.5
349-403	69.5
21-112	21
21-196	276.5
74-189	5.5
240-74	19
269-93	38.5
336-93	61
83-33	21.5
112-33	94.5

Table 4.7 External demand offer per node.

Node	34	75	94	341	182	448	404	22	311
Demand (MW)	4.5	1.1	1.65	3.5	2.5	4.5	4.5	9	3.5

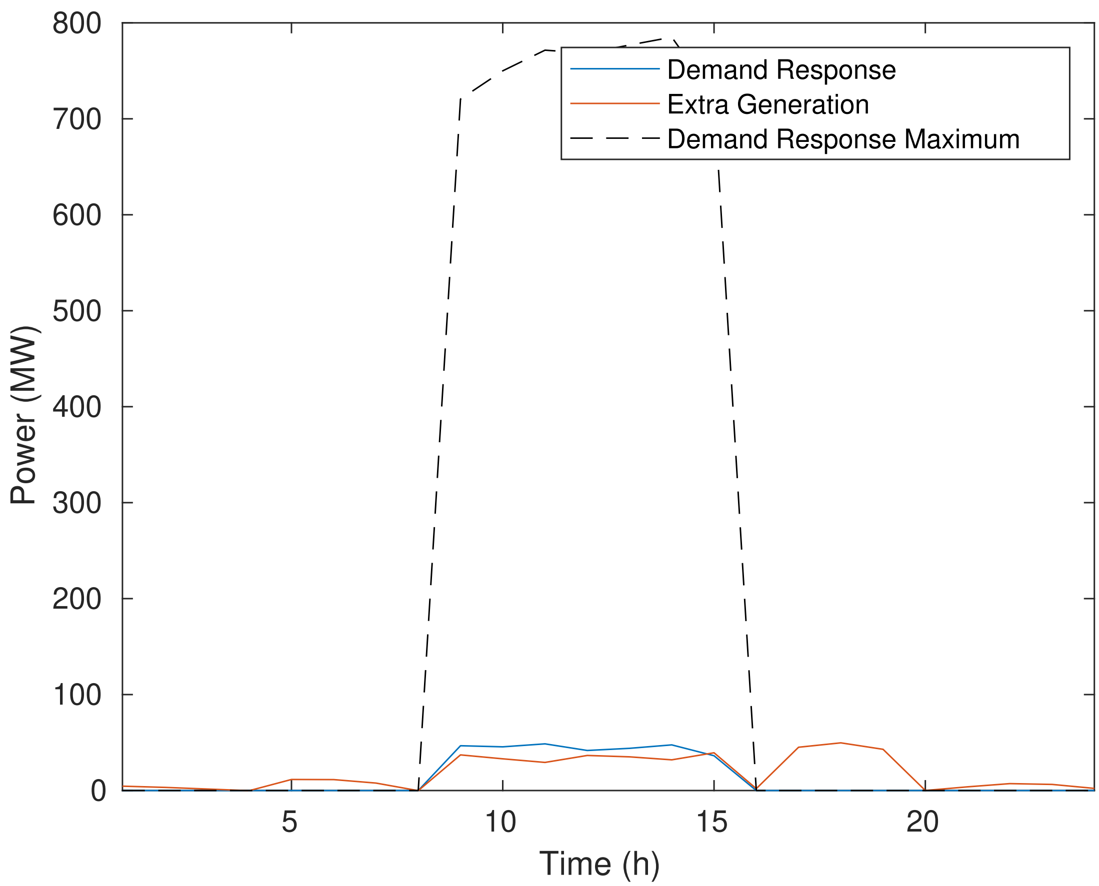

Figure 4.8 Extra generation and DR resources use over time.

Finally, analyzing the results for the external demand, we can observe that it was not profitable to supply it completely. Considering that there were still DR resources available to supply this demand, it is possible that there is either some transmission line congestion that cannot be further mitigated or that it is too expensive to use DR and supply the consequent shifted demand.

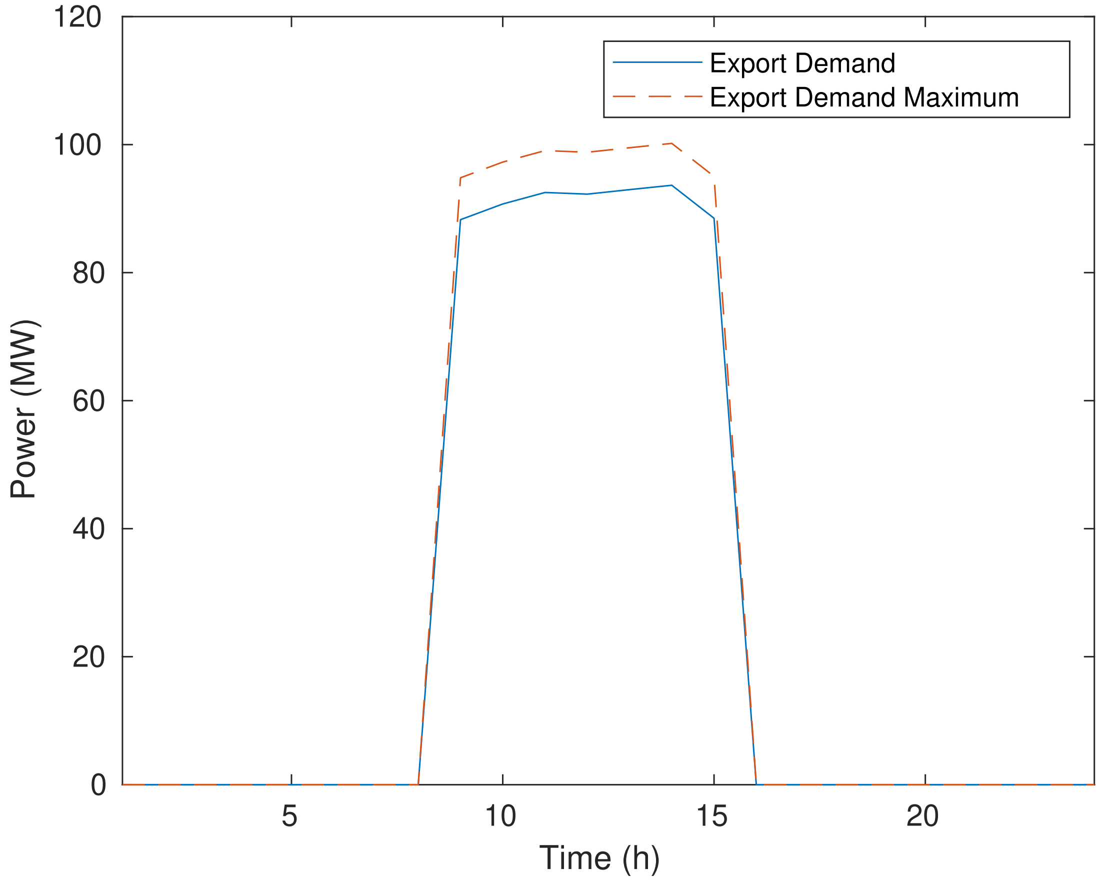

Figure 4.9 Extra demand supplied over time.

4.5 Conclusion

In this paper, we proposed a model that maximizes the profit of supplying external demand using an ACOPF model with DR resources available through aggregators. We used the semidefinite relaxation TCR to obtain a reliable starting point to solve our problem as well as making it tractable and solvable in a reasonable amount of time. Our results shows that we were able to have an improvement on the execution time of 31.71% for the first case study and, in the second study, our approach allowed us to find the optimal solution of our problem. We can also see that the optimization gap is 4.13% for the first case study and 28.05% for the second study, which shows that the relaxation give us a very good starting solution for our problem. Also, we showed that, by letting the generators decide how much of the external demand should be supplied, in some cases supplying all of this demand is either not profitable or not possible at all due to prices and transmission constraints. We also observed that DR acts, in some cases, as a transmission congestion manager by mitigating it and allowing more demand to be met.

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CHAPTER 5 ARTICLE 2: IMPROVED GENERALIZED BENDERS DECOMPOSITION FOR STOCHASTIC UNIT COMMITMENT MODELS WITH DEMAND RESPONSE

Initially submitted to the European Journal of Operations Research. It has been resubmitted to the Computers and Operations Research.

Co-authors: Miguel F. Anjos, Michel Gendreau

Abstract

The increasing penetration of renewable electricity generation as well as the implementation of demand response programs has led to new challenges in the operation of the power grid. The output of renewable sources fluctuates, and this adds uncertainties to the problem. The distributed nature of the demand response resources is an additional operational challenge that is normally addressed by the creation of aggregators that manage these resources. The impacts of the power transmission system must also be taken into account. We propose a short-term unit commitment model to allocate DR resources considering the variability of renewable sources and the needs of the grid. We formulate this as a mixed nonlinear integer optimization problem that is challenging to solve, which motivates, first, the application of a semidefinite relaxation to the problem, and, second, the use of Generalized Benders Decomposition (GBD) to tackle it. It is well known that the GBD algorithm can suffer from slow convergence to an optimal solution, therefore we use a Benders-based Branch-and-Cut with various enhancement methods to improve its performance. In order to choose which enhancement methods should be used, we analyze their impact on the performance of the GBD algorithm using the IEEE RTS-96 network. We conclude that while all of the enhancement methods considered improve the convergence rate and solution time for our model, the Pareto-Optimal cuts are the most significant improvement, both in terms of convergence rate and computational time.

Keywords: OR in Energy, Demand Response, Stochastic Optimization, Unit Commitment, Optimal Power Flow, Benders Decomposition

5.1 Introduction

The operation of electric power grids is becoming more challenging with the growing penetration of renewable electricity sources such as wind and solar generation, as well as the implementation of demand response (DR) programs. The fundamental challenges are that renewable generation fluctuates by its very nature, and that DR resources that can provide flexible support are normally small in scale and distributed geographically, which makes their management more complex.

The operation of DR resources requires specific instructions for each individual residential or commercial source of DR. This challenge has led to the creation of entities called aggregators. An aggregator is tasked with the management of a set of DR resources so as to supply their flexibility to the Independent System Operator (ISO). They effectively act as intermediaries between the DR service providers and the ISO [2]. However, designing aggregators adequately is also a challenging task, and there are several works that propose aggregator models, such as [4–6]. There is also the need to coordinate the operation of the power grid in the presence of aggregators.

Furthermore, because renewable energy generation is variable, there will always be a degree of uncertainty when predicting it. The models used for finding the optimal commitment and dispatch of generating units as well as the optimal use of DR resources need to consider the uncertain aspects of renewable generation. This leads to a unit commitment (UC) problem that is an optimization problem under uncertainty that integrates the operation of the power grid with the dispatch of DR resources (through the aggregators).

Usually, the UC problem considers which generating units are available, which ones should be committed, and how much energy they should produce to meet the demand. It is also possible to consider transmission system security when making the aforementioned decisions, which leads to the security-constrained unit commitment (SCUC) problem. Both problems are modelled as either mixed-integer linear or mixed-integer nonlinear optimization problems under uncertainty.

For modelling this type of problem, there are two main approaches, stochastic optimization and robust optimization. There are several works using the former, such as in [80–99]. There are also different alternatives in regards to modelling the transmission system, such as not considering it or considering either a DC Optimal Power Flow (DCOPF) or an Alternating Current Optimal Power Flow (ACOPF) model.

There are some models that do not consider the transmission system, such as [85, 88, 96]. In [88], a fuzzy chance-constrained stochastic UC model is proposed to minimize the generation and start-up costs. It considers the wind power and DR capacity as uncertainties.

In [85], the authors propose a two-stage UC model that aims to minimize generation, DR use, solar energy generation curtailment and battery use costs under solar energy generation uncertainty. The decisions taken before the uncertainty realization are the UC and determining the incentive charge for DR. In [96], they propose a bi-level stochastic SCUC model which aims to minimize generator and DR use costs under wind power uncertainty. The upper-level of the problem determines the operation of the power grid. The lower level problem determines the Incentive-based DR successful bidders.

However, the fact that no transmission system model is taken into consideration may give us solutions that are too optimistic. Therefore, in several projects it was decided to consider a DCOPF model, as seen in [82, 83, 86, 89–95, 98].

In [89], they propose a dynamic multistage stochastic UC (SUC) model in which the demand is uncertain with the aim to minimize generators operating costs. Similarly, [82] developed a model that considers wind and solar energy uncertainties instead.

In [93], the authors propose a two-stage SUC model aiming to minimize generation and DR operating costs taking into consideration wind generation as an uncertain parameter. Similarly, [98] aims to minimize generation operating costs. The decision taken before the uncertainty realization is the commitment of slow generation units. Finally, we also have models that aim at guaranteeing a secure operation of the transmission system, such as [86], which proposes a chance-constrained stochastic SCUC model.

In [91], a two-stage chance-constrained UC model is proposed with the aim of minimizing generators operating costs wind power and demand uncertainties. The UC and initial generators dispatch are decided before the uncertainty realization. In [90], the authors propose a model that also considers the demand response and wind spillage costs. In the first stage, they consider, additionally, the required up/down spinning reserve. Finally, [95] propose a stochastic SCUC model to minimize generator operating costs that uses compressed air energy storage to manage the uncertainty.

In [83], a two-stage SCUC model is proposed. This model considers the wind generation and the equipment outages as uncertainties and it aims to minimize the generation and reserve operating costs. In [94], they propose a two-stage SUC model considering transmission line and generators outages and demand uncertainties with the objective of minimizing generation and DR use costs. The DR reserve capacity and UC are decided before the uncertainty realization. In [92], it is proposed a two-stage SUC model in which the wind generation, demand and the outage of generating units and transmission lines are considered uncertain. The objective is to minimize generation, DR, reserves and wind spillage operating costs.

Nonetheless, a DCOPF model does not consider certain aspects of the transmission system, such as transmission losses. This may lead to optimistic solutions and thus some works consider a more detailed representation of the transmission system using an ACOPF model, such as in [87, 97, 99]

In [97], they propose a two-stage stochastic SCUC model that aims to minimize generators operating costs and takes into consideration wind power uncertainty. In [99], the authors propose a two-stage stochastic SCUC model with the objective of minimizing generation, DR use and load loss costs under wind power uncertainty. In the first stage, the UC problem is first solved without considering a transmission system, afterwards its solution feasibility is verified for both DCOPF and ACOPF transmission systems. Finally, in the second stage the wind power scenarios are considered and it is solved using the first-stage solution as a starting solution. In [87], the authors build up on the previous work and consider additionally DR uncertainties with the aim of minimizing generators and DR operating costs and maximizing the operator's revenues. However, it should be noted that they use a linearization of the ACOPF model to solve the second-stage problem, thus not solving it exactly.

Finally, there are also works on robust optimization models for the UC problem under uncertainty, as seen in [100–102], with some of them considering the SCUC problem.

[100] propose a multi-objective hybrid stochastic and robust UC model with the objective of both minimizing generation and emission costs, and risks under demand, transmission lines and generation outages uncertainties. In [101], the authors propose a two-stage distributionally robust optimization UC model that aims to minimize generators operating costs under wind power uncertainty. In [102], a robust UC model is proposed with the aim of minimizing generators and DR use costs taking into consideration wind power and solar power uncertainties.

Table 5.1 summarizes the different contributions made by each of the papers mentioned in this literature review. We can observe that most of the works do not consider a detailed representation of the transmission system as well as the impact of DR.

As it can be seen, none of the aforementioned works consider the DR as a decision to be taken before any uncertain parameter is realized. Also, most of them do not consider a detailed representation of the transmission system but instead ignore it or use a DCOPF representation. Models that consider a full representation of the transmission system with an ACOPF model will be nonconvex nonlinear optimization problems that are generally extremely hard to solve, with limited or no guarantee of finding a global optimal solution. There is a need for a model that provides a solution with greater accuracy than the existing models and that can be solved in a reasonable amount of time.

Furthermore, there is also a need to consider the limitations of the methods to solve nonlinear stochastic optimization problems, which is not explored by the works presented in our literature review. We are particularly interested in the Generalized Benders Decomposition (GBD) algorithm, which allows us to solve convex nonlinear stochastic optimization problems by decomposing them into smaller problems and finding the solution in an iterative fashion. However, it is known that the GBD can possibly have convergence and performance issues. Because the model proposed in this paper is a day-ahead operation planning problem, it needs to be possible to solve it in a 24-hour time frame. This has prompted us to explore methods for accelerating the GBD.

In this paper, we develop a stochastic UC model with the objective of maximizing the profit from supplying energy to meet unexpected demands. Specifically, the unexpected demand is a demand for energy that may appear after determining the operation schedule for the grid, which means that we are interested in using the resources available to supply this unexpected demand. An example of unexpected demand would be when the system operator of one power grid requests energy from a different power grid. In this problem, we consider the renewable generation and the unexpected demand availability as sources of uncertainty, and both the DR use and the UC will be considered as the decisions taken before the realization of the uncertainties. Therefore, our idea is to develop a short-term horizon model, in which we allocate the DR resources and available generation optimally under uncertainty considering all of the aspects of the transmission system topology with the objective of maximizing the generators' profits.

Specifically, it is modeled as a short-term scheduling problem with DR resources, which traditionally uses an AC power flow transmission model to describe the grid's transmission. However, considering an AC power flow leads to a nonconvex optimization model, which is computationally costly to solve, since it is a NP-hard problem [69]. Therefore, we consider a convex relaxation of the AC transmission model to turn this problem into a tractable one and this allows us to use the GBD algorithm. In other words, we solve large-scale problems in a reasonable amount of time, opening the path to use this model for large-scale networks.

The main contributions of this paper are the following:

- We apply a relaxation of the standard stochastic UC-ACOPF problem, which is a nonlinear stochastic optimization problem, that allows us to have a tractable model. Thus we are able to solve the UC-ACOPF problem taking into consideration wind and solar energy generation, as well as the demand availability uncertainties in a reasonable amount of computational time.

- We use various enhancement methods to improve the performance of GBD for solving our problem. To the best of our knowledge, there have been no such investigations of the use of GBD acceleration methods for the solution of UC-ACOPF models. In this paper, we show the possible time gains from using such methods.

Table 5.1 List of contributions of reviewed papers.

Reference	DCOPF	ACOPF	Stochastic Optimization	Robust Optimization	Uncertainty	Demand Response
[82]	X		X		WP	
[88]			X		WP, DR	1st, 2nd and 3rd stages
[89]	X		X		Demand	
[90]	X		X		WP, Demand	
[91]	X		X		WP, Demand	
[92]	X		X		WP, Outages, Demand	2nd stage
[93]	X		X		WP	2nd stage
[94]	X		X		Outages, Demand	2nd stage
[98]	X		X		WP	
[85]			X		WP	1st and 2nd stages
[83]	X		X		WP, Outages	
[86]	X		X		WP	
[87]		X	X		WP, PV, DR	2nd stage
[95]	X		X		WP, Demand	2nd stage
[80]	X		X		Outages	1st and 2nd stages
[96]			X		WP	2nd stage
[97]		X	X		WP	
[99]		X	X		WP	
[100]			X	X	Outages, Demand	
[101]	X			X	WP	
[102]	X			X	WP, PV, DR	3rd stage

This paper is organized in the following way. In Section 5.2, we present our proposed model for solving the stochastic UC-ACOPF problem. In Section 5.3, we present the solution methodology, the GBD and its acceleration methods. Finally, in Section 5.4, we present the computational experiments in which we analyze the performance of the different acceleration methods. Section 5.5 summarizes the findings of our work.

5.2 Model

We consider a stochastic UC model that maximizes the revenue of exporting demand while minimizing the cost of supplying it with extra generation or with DR resources. In our model, we consider that the wind and solar energy generation are uncertain parameters as well as the export demand. Our formulation of the deterministic model is as follows:

- Objective function:

$$\min \sum_{t=1}^{T} \Bigg(- \sum_{e \in \Phi} r_{et} ED_e^t + \sum_{d \in \Psi} c_{dt}^D DR_d^t + \sum_{m=1}^{N} \\ \Big(\sum_{j \in Th_m} y_{jm}^t c_{jm}^U + a_j^{Th} \big(\big(T_{jm}^t\big)^2 - \big(\underline{T_{jm}^t}\big)^2 \big) + b_j^{Th} \big(T_{jm}^t - \underline{T_{jm}^t}\big)\Big)\Big) \Bigg) \tag{5.1}$$

Here, T_{jm}^t is the active power generation, $\underline{T_{jm}^t}$ being its lower bound, DR_m^t is the provided DR, and ED_m^t is the external demand. There are also the coefficients of the generation cost function, $a_j^{Th}, b_j^{Th}, c_{jm}^U$ as well as the cost of using DR, c_{dt}, and the revenue for supplying external demand, r_{et}. We also have the set of nodes that have external demand offers Φ, the set of nodes that have DR resources, Ψ, the set of buses, N, and the set of thermal plants connected to the bus m, Th_m. Finally, we have the number of time steps of the problem, T.

The objective function (5.1) considers the cost of the extra generation and DR that may be necessary to meet the external demand, as well as the revenue generated by supplying this external demand.

- Active power balance constraint:

$$\sum_{j \in Th_m} T_{jm}^t + \sum_{\{m,n\} \in \Omega} I_{fmnt}^p + \sum_{\{n,m\} \in \Omega} I_{enmt}^p - G'_m Vm_m^2 \\ + DR_m^t - \Delta D_m^t = ED_m^t + D_m^t - W_m^t - FV_m^t \quad \forall m \in N, \forall t \in T \tag{5.2}$$

- Reactive power balance constraint:

$$\begin{aligned}&\sum_{j\in Th_m} QT^t_{jm} + \sum_{\{m,n\}\in\Omega} I^q_{fmnt} + \sum_{\{n,m\}\in\Omega} I^q_{enmt} + B'_m Vm^2_m \\ &+ \Delta Q^t_m = Q^t_m - QW^t_m - QFV^t_m \qquad \forall m \in N, \forall t \in T\end{aligned} \tag{5.3}$$

where QT^t_{jm} is the reactive power generation; the active and reactive power injections in the "to" point of the branch are, respectively, I^p_{emnt}, I^q_{emnt}, and in the "from" point of the branch are I^p_{fmnt}, I^q_{fmnt}, respectively. ΔQ^t_m is the reactive power demand adjustment, and ΔD^t_m is the demand shift caused by the use of DR. Vm^t_m is the voltage magnitude at a bus, B'_m, G'_m are the shunt susceptance and the shunt conductance, respectively, and D^t_m, Q^t_m are the active and reactive power demands. Finally, we have W^t_m, QW^t_m for the active and reactive wind energy generation, FV^t_m, QFV^t_m for the active and reactive photovoltaic generation. We also have the set of transmission lines, Ω.

In (5.2), we observe the addition of ED^t_m on the demand side of the constraint. Unlike D^t_m, ED^t_m is a variable, meaning that the generator can decide how much of the external demand to supply. This decision is directly connected to how profitable it is to supply this extra demand. Otherwise (5.2) is a standard power balance constraint, guaranteeing that the generation summed to the eventual energy transmitted or received through transmission lines is equal to the demand.

In (5.2), DR^t_m represents the demand response. It should be noted however, that DR is composed of both demand reduction and demand shift actions. To compensate the demand shift that occurs because of DR, we have the ΔD^t_m variable, that guarantees that any demand that is shifted will be supplied in another period of time.

The reactive power balance constraint (5.3) has the additional term ΔQ^t_m that adjusts reactive power demand according to the decision to supply a certain amount of the external demand.

- Transmission constraints:

$$
\begin{aligned}
& I^{p}_{fmnt} + iI^{q}_{fmnt} = \\
& -\frac{Vm^{t}_{m}}{Tn_{mn}} \left[\left(i\frac{B_{mn}}{2} + Y_{mn} \right) \frac{Vm^{t}_{m}}{Tn_{mn}} - Y_{mn} Vm^{t}_{n} \right] \\
& \quad \forall \{m, n\}, \in \Omega, \forall t \in T
\end{aligned} \tag{5.4}
$$

$$
\begin{aligned}
& I^{p}_{emnt} + iI^{q}_{emnt} = \\
& -\frac{Vm^{t}_{n}}{Tn_{mn}} \left[\left(i\frac{B_{mn}}{2} + Y_{mn} \right) Vm^{t}_{n} - Y_{mn} \frac{Vm^{t}_{m}}{Tn_{mn}} \right] \\
& \quad \forall \{m, n\}, \in \Omega, \forall t \in T
\end{aligned} \tag{5.5}
$$

$$\underline{Vm^{t}_{m}} \leq Vm^{t}_{m} \leq \overline{Vm^{t}_{m}} \quad \forall m \in N, \forall t \in T \tag{5.6}$$

$$(I^{p}_{mnt})^2 + (I^{q}_{mnt})^2 \leq \overline{S^{t}_{mn}}^{2} \quad \forall \{m, n\}, \in \Omega, \forall t \in T \tag{5.7}$$

where the transmission line susceptance, admittance and their turns ratio are B_{mn}, Y_{mn} and Tn_{mn}, respectively. $\overline{S^{t}_{mn}}^{2}$ is the maximum transmission capacity for a transmission line and $\overline{Vm^{t}_{m}}, \underline{Vm^{t}_{m}}$ are the maximum and minimum voltage possible in bus m.

The transmission constraints (5.4)-(5.7) are the rectangular ACOPF formulation using complex numbers.

- Thermal plants bounds:

$$\underline{T^{t}_{jm}} x^{t}_{jm} \leq T^{t}_{jm} \leq \overline{T^{t}_{jm}} x^{t}_{jm} \quad \forall m \in N, \forall j \in Th_{m}, \forall t \in T \tag{5.8}$$

$$\underline{QT^{t}_{jm}} x^{t}_{jm} \leq QT^{t}_{jm} \leq \overline{QT^{t}_{jm}} x^{t}_{jm} \quad \forall m \in N, \forall j \in Th_{m}, \forall t \in T \tag{5.9}$$

- Demand Constraints:

$$0 \leq DR^{t}_{d} \leq \overline{DR^{t}_{d}} \quad \forall d \in \Psi, \forall t \in T \tag{5.10}$$

$$-\overline{\Delta Q^{t}_{m}} \leq \Delta Q^{t}_{m} \leq \overline{\Delta Q^{t}_{m}} \quad \forall m \in N, \forall t \in T \tag{5.11}$$

$$0 \leq ED^{t}_{e} \leq \overline{ED^{t}_{e}} \quad \forall e \in \Phi, \forall t \in T \tag{5.12}$$

where $\underline{T^{t}_{jm}}$ is the minimum active power generation, $\underline{QT^{t}_{jm}}, \overline{QT^{t}_{jm}}$ are the maximum and minimum reactive power generation, $\overline{DR^{t}_{d}}$ is the upper bound for DR resource allocation, $\overline{\Delta Q^{t}_{m}}$ is the maximum reactive power demand adjustment, and $\overline{ED^{t}_{e}}$ is the unexpected demand offer. Finally, x^{t}_{jm} is the generating unit on/off state variable.

The bounds on generation, transmission, demand response and extra demand are enforced in (5.8)-(5.12). It should be noted, however, that the generation bounds are dependent on whether the unit has been committed or not.

- Start-up and Shutdown Constraints:

$$x_{jm}^{t-1} - x_{jm}^{t} + y_{jm}^{t} - z_{jm}^{t} = 0 \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{5.13}$$

$$x_{jm}^{t}, y_{jm}^{t}, z_{jm}^{t} \in \{0,1\} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{5.14}$$

- Ramping Constraints:

$$T_{jm}^{t} - T_{jm}^{t-1} \leq R_{jm}^{U} x_{jm}^{t-1} + S_{jm}^{U} y_{jm}^{t} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{5.15}$$

$$T_{jm}^{t-1} - T_{jm}^{t} \leq R_{jm}^{D} x_{jm}^{t} + S_{jm}^{D} z_{jm}^{t} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{5.16}$$

- Demand Shift Constraints:

$$\sum_{t=24(wd-1)+1}^{24wd} (f_{DR} DR_d^t - \Delta D_d^t) = 0 \quad \forall d \in \Psi, \forall wd \tag{5.17}$$

y_{jm}^t and z_{jm}^t are the start-up and shutdown variables. R_{jm}^U, R_{jm}^D are the maximum ramp-up and ramp-down rate of a generating unit, respectively. S_{jm}^U, S_{jm}^D are the start-up and shutdown rates. f_{DR} is the proportion of the demand reduced that is due to demand shift. Finally, wd represents a week day.

In (5.13)-(5.16), start-up, shutdown, as well as the generation ramping constraints are defined. Finally, in (5.16) the demand shift constraint is defined. It guarantees that the total demand of the system remains unchanged independently of the amount of DR used. It also should be observed that in our work we have decided to consider only the incentive-based DR, where the ISO pays the user to either shift or reduce their demand.

As it can be seen, the proposed model is a nonconvex mixed-integer optimization problem. The fact that the model is nonconvex makes finding an optimal solution very time consuming and there is no way to guarantee that it will find the global optimum. In order to overcome these issues, we consider the use of semidefinite relaxations. Specifically we choose to use the Tight-and-Cheap relaxation (TCR) [26] that allows us to find a solution close to the optimal in a reasonable amount of time. In [26], it has been show that the optimization gap between the solution given by TCR and the original formulation of the scheduling problem is relatively small.

5.2.1 TCR Relaxation

First, we reformulate the problem by defining $VM^t = Vm^t(Vm^t)^H$. With that we can reformulate the transmission constraints and eliminate their non-convexity. The modified constraints can be seen below:

$$\begin{aligned} & I^p_{fmnt} + iI^q_{fmnt} = -\frac{1}{|Tn_{mn}|^2}\left(-i\frac{B_{mn}}{2} + Y^*_{mn}\right)VM^t_{mm} \\ & -\frac{Y^*_{mn}}{Tn_{mn}}VM^t_{mn} \qquad \forall\{m,n\}, \in \Omega, \forall t \in T \end{aligned} \tag{5.18}$$

$$\begin{aligned} & I^p_{emnt} + iI^q_{emnt} = -\frac{Y^*_{mn}}{Tn^*_{mn}}VM^t_{nm} + \\ & \left(-i\frac{B_{mn}}{2} + Y_{mn}\right)VM^t_{nn} \qquad \forall\{m,n\}, \in \Omega, \forall t \in T \end{aligned} \tag{5.19}$$

$$\underline{Vm^t_m}^2 \le VM^t_{mm} \le \overline{Vm^t_m}^2 \quad \forall m \in N, \forall t \in T \tag{5.20}$$

However, the problem is still nonconvex (and nonlinear) so we replace the constraint $VM^t = Vm^t(Vm^t)^H$ by the following constraints:

$$\begin{bmatrix} VM^t_{11} & VM^t_{1m} & VM^t_{1n} \\ (VM^t_{1m})^* & VM^t_{mm} & VM^t_{mn} \\ (VM^t_{1n})^* & (VM^t_{mn})^* & VM^t_{nn} \end{bmatrix} \succeq 0 \quad \forall\{m,n\}, \in \Omega, \forall t \in T \tag{5.21}$$

thus defining a convex relaxation of the original problem. With a convex problem, it is possible to guarantee the convergence of the solution algorithm towards a global optimal solution.

5.2.2 Stochastic Model

In order to solve this problem, we consider it as a two-stage stochastic optimization problem.

In the first stage, decisions are made about UC and the use of DR resources. The first-stage optimization problem can be seen below:

- Objective function:

$$\max \sum_{t=1}^{T}\sum_{m=1}^{N} -c^D_{mt}DR^t_m - \Big(\sum_{j \in Th_m} y^t_{jm}c^U_{jm}\Big) \tag{5.22}$$

- Demand Shift Constraints:

$$\sum_{t=24(wd-1)+1}^{24wd} (f_{DR} DR_d^t - \Delta D_d^t) = 0 \quad \forall d \in \Psi, \forall wd \tag{5.23}$$

- Start-up and Shutdown Constraints:

$$x_{jm}^{t-1} - x_{jm}^t + y_{jm}^t - z_{jm}^t = 0 \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{5.24}$$

$$x_{jm}^t, y_{jm}^t, z_{jm}^t \in \{0,1\} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{5.25}$$

As it can be seen, the dispatch as well as the offer of external demand are not considered on the first-stage.

In the second stage, the final dispatch and the external demand to be supplied are determined, and an ACOPF transmission system model is used to determine the dispatch. Finally, in the second stage we consider the realizations of wind and solar energy generation as well as the realization of the external demand offered.

$$\max \sum_{t=1}^{T} \left(\sum_{e \in \Phi} r_{et} ED_{es}^t - \sum_{m=1}^{N} (\sum_{j \in Th_m} a_j^{Th} (\left(T_{jms}^t\right)^2) + b_j^{Th} (T_{jms}^t))) \right) \tag{5.26}$$

Subject to,

(5.2)-(5.3), (5.8)-(5.16), (5.18)-(5.21)

where $s \in S$, S being the set of scenarios considered in the problem.

In this problem, the UC and DR variables are considered as parameters and the values of the parameters are obtained from the solution of the first-stage. In the case of DR resources, that happens because we do not consider the uncertainty of the DR and we also consider that all of the DR resources purchased through the aggregators have to be guaranteed in the second stage. As a consequence, all of the constraints related to DR resources and unit commitment are not considered.

5.3 Generalized Benders Decomposition

In order to solve this mixed-integer nonlinear stochastic optimization problem, we use the Generalized Benders Decomposition (GBD), which is a generalization of the Benders Decomposition method for convex nonlinear problems [54] that can be also applied to stochastic problems. In general, it allows us to solve a problem in the form of:

$$\begin{aligned} \max \quad & dx + cy \\ s.t. \quad & Ax + Cy - b \geq 0 \\ & x \in X, y \in Y \end{aligned} \tag{5.27}$$

In this problem, y is a vector of complicating variables, meaning that if we had a fixed value for y, the problem would be much easier to solve. Dividing this problem in two stages, we define the master problem:

$$\begin{aligned} \max \quad & y_0 \\ s.t. \quad & y_0 \leq L^*(y, u^j) \\ & L_*(y, \lambda^j) \geq 0 \\ & y \in Y \end{aligned} \tag{5.28}$$

where

$$L^*(y, u) = \max_{x \in X} \{dx + cy + u^t \left(Ax + Cy - b\right)\} \tag{5.29}$$

$$L_*(y, \lambda) = \max_{x \in X} \{\lambda^t \left(Ax + Cy - b\right)\} \tag{5.30}$$

$y_0 \leq L^*(y, u^j)$ is the optimality cut, $L_*(y, \lambda^j) \geq 0$ is the feasibility cut, and j is the number of iterations of the GBD algorithm.

Afterwards, we can define the subproblem as:

$$\begin{aligned} \max \quad & dx + cy_{j-1} \\ s.t. \quad & Ax + Cy_{j-1} - b \geq 0 \\ & x \in X \end{aligned} \tag{5.31}$$

In order to find the optimal solution the following algorithm was devised:

1. Solve the problem (5.31) with an user supplied initial solution $\hat{y}$, retrieve the optimal multiplier vector u_0 and create $L^*(y, u_0)$. Store the objective function of (5.31) as the lower bound (LBD).

2. Solve the master problem, (5.28), adding either $y_0 \leq L^*(y, u_j - 1)$ or $L_*(y, \lambda^j - 1) \geq 0$ as a constraint to it, and find the optimal solution $\hat{y}^0$. If $\hat{y}^0 - LBD \leq \epsilon$, stop the algorithm, the optimal solution has been found. Otherwise, proceed to the next step.

3. Solve the revised subproblem using the master problem solution.

   (a) If the objective function has a finite value and is greater than LBD, update LBD. If $\hat{y}^0 - LBD \leq \epsilon$, the optimal solution has been found, stop the algorithm. Otherwise, retrieve the optimal multiplier vector u_j and create $L^*(y, u_j)$. Go to step 2.

   (b) If the problem is infeasible, determine a λ^j, calculate $L_*(y, \lambda^j)$ and go to step 2.

Unfortunately, the GBDalgorithm has performance issues due to the master problem being an integer problem. When solving its linear relaxation there is also the same issue [59]. In order to be able to attain an acceptable performance for our algorithm, it will be necessary to use different enhancement techniques, which are aimed at either choosing good cuts, providing a stronger formulation for our problem or avoiding solving the integer master problem several times. These techniques are presented in the coming subsections.

It should be noted that the impact of the aforementioned methods can only be measured experimentally.

5.3.1 DCOPF Inequalities

In our model, the first-stage problem's constraints provide little information to find the optimal solution. As a consequence, it may take an enormous amount of time for the GBD algorithm to converge and find the optimal solution. The addition of new constraints that give us more information about our problem and, consequently, improve its lower bound, becomes necessary.

We can improve our first-stage problem by adding the constraints for determining the scheduling with a DCOPF model. With this addition, there will be more information for determining the unit commitments in the first-stage. The following constraints are added to our model:

- Power balance constraint:

$$\sum_{j \in Th_m} T^t_{jm} - \sum_{\{n,m\} \in \Omega} I^p_{nmt} + DR^t_m - \Delta D^t_m = D^t_m \quad \forall m \in N, \forall t \in T \tag{5.32}$$

- Transmission constraints:

$$I^p_{mnt} = B_{mn}(\theta^t_n - \theta^t_m) \quad \forall\{m,n\}, \in \Omega, \forall t \in T \tag{5.33}$$

$$-\overline{P^t_{mn}} \leq (I^p_{mnt}) \leq \overline{P^t_{mn}} \quad \forall\{m,n\}, \in \Omega, \forall t \in T \tag{5.34}$$

- Thermal plants bounds:

$$\underline{T^t_{jm}} x^t_{jm} \leq \widehat{T^t_{jm}} \leq \overline{T^t_{jm}} x^t_{jm} \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{5.35}$$

$$\tag{5.36}$$

- Demand Constraints:

$$0 \leq DR^t_d \leq \overline{DR^t_d} \quad \forall e \in \Phi, \forall t \in T \tag{5.37}$$

When adding these constraints, we consider the scheduling costs, as well, and we change the objective function accordingly, as can be seen below:

$$min \sum_{t=1}^{T} \left(\sum_{d \in \Psi} c^D_{dt} DR^t_d + \sum_{m=1}^{N} (\sum_{j \in Th_m} y^t_{jm} c^U_{jm} + a^{Th}_j \left(T^t_{jm} \right)^2 + b^{Th}_j T^t_{jm}) \right) \tag{5.38}$$

However, we now have a mixed-integer nonlinear optimization problem, which is computationally costly. If we can replace the current objective function with a linear one, the problem becomes considerably easier to solve because it becomes a mixed-integer optimization problem (MILP). Thus, we linearize the objective function by representing as a piecewise linear function as seen in [35, 103–106].

In our first-stage problem we have, for the generation cost, the following function:

$$f(T_i, x_i) = aT_i^2 + bT_i + cx_i \tag{5.39}$$

We choose $k+1$ points in the interval $[\underline{T_i}, \overline{T_i}]$, $T_i^0, T_i^1, \ldots, T_i^k$, and propose a piecewise linear function in which its linear functions are interpolations of the chosen points two by two, giving us an upper approximation. We also create k new variables named δ^i_{ls} that represent each segment of the piecewise linear function. With that, we can create the constraints and modify the objective function:

- Constraints:

$$T_i = \sum_{ls=1}^{k} \delta_{ls}^i + \underline{T_i} x_i \quad \forall i \tag{5.40}$$

$$0 \leq \delta_{ls}^i \leq T_i^{ls} - T_i^{ls-1} \quad \forall i, \forall ls \tag{5.41}$$

- We define the linear cost for each segment as:

$$F_{ls}^i = \frac{f(T_i^{ls}) - f(T_i^{ls-1})}{T_i^{ls} - T_i^{ls-1}} \tag{5.42}$$

- Objective function:

$$\sum_{i=1}^{N} (f(\underline{T_i}) x_i + \sum_{ls=1}^{k} F_{ls}^i \delta_{ls}^i \tag{5.43}$$

In this way, the quadratic objective function is linearized and our first stage problem becomes a MILP, which we can solve in a reasonable amount of time.

5.3.2 Benders Based Branch-and-Cut

Solving a stochastic MILP can be very computationally costly, principally when there are many integer variables in the problem. Its linear programming (LP) relaxation, however, is significantly faster to solve, and, according to [107], all of the optimality and feasibility cuts generated when solving the LP version of our problem are valid for our original problem.

Based on that, the Benders Based Branch-and-Cut algorithm was proposed, in which we first solve the stochastic optimization problem at the root node to optimality. Afterwards, we build the branch-and-cut tree and add new cuts to the pool whenever we reach a node that gives us an integer solution. According to [107], all cuts generated by solving the sub-problems, no matter what is the given first-stage problem, are global cuts. If the node becomes infeasible or does not give us an integer solution after the addition of new cuts, it is pruned from the tree. The branch-and-cut tree is explored until we find an optimal solution [58]. We use this algorithm to improve the performance of GBD.

5.3.3 Mixed-Integer Rounding Cuts

When using the Benders Based Branch-and-Cut approach, we initially solve the root node problem, which is a LP relaxation. However, the cuts that are generated by this relaxed problem do not take into consideration that some of our variables are integer, which can lead to a weak LP relaxation. Because of that, we want to generate constraints that will add integrality restrictions to our problem, which we call Mixed-Integer Rounding(MIR) cuts [60].

In each iteration of the GBD we generate a benders cut, $y_0 \geq a - \sum_{i=1}^{N} b_i y_i$, being $y_0 \geq a^{it} - \sum_i^N b_i^{it} y_i^{it}$ the last generated benders cut. Also, let us define $f_0 = \beta(a - a^{it}) - \lfloor \beta(a - a^{it}) \rfloor$ and $f_i = \beta(b_i - b_i^{it}) - \lfloor \beta(b_i - b_i^{it}) \rfloor$, where β is a parameter that respects the condition $0 < \beta \leq 1$. With that we can build the following cut:

$$y_0 \geq d_0 - \sum_{i=1}^{N} d_i y_i$$

Where:

$$d_0 = a^{it} + \frac{f_0 \lceil \beta(a - a^{it}) \rceil}{\beta}$$

$$d_i = \frac{\min\{f_0 \lceil \beta(b_i - b_i^{it}) \rceil, f_i + f_0 \lfloor \beta(b_i - b_i^{it}) \rfloor\}}{\beta} + b_i^{it}$$

Because this cut is generated by combining the last generated cut with another existing cut, we have to choose which of the potential cuts is the best suited for the problem. Therefore, we verify which of the generated cuts is the most violated by the solution given in the last iteration and we choose it as the MIR cut. Our criterion for making this choice is the scaled violation defined as:

$$\frac{\max\{d_0 - \sum_{i=1}^{N} d_i y_i^{it} - y_0, 0\}}{\| (1, d) \|_2}$$

where $d = (d_0, ..., d_N)$. Finally, we choose the cut that give us the maximal scaled violation.

It should be noted that in [60], the proposed family of cuts is shown to be valid inequalities, and, as such, they will always contribute to the convergence of GBD.

5.3.4 Pareto Optimal Cuts

In [59], the authors propose a method for finding the best possible cut at each iteration of the GBD algorithm. We state that a cut $f(x, y) + u_1^t g(x, y)$ dominates another cut $f(x, y) + u_2^t g(x, y)$ when $f(x, y) + u_1^t g(x, y) \geq f(x, y) + u_2^t g(x, y)$, and we define it as a nondominated cut or Pareto optimal (PO) cut when no other cut dominates it. When a cut dominates another cut, we say that it is a stronger cut and that it contributes more to the convergence of the GBD algorithm.

Let us define a core point y_0 as a point such that it is in the relative interior of the convex hull of the master problem solution space. In order to find such a cut, we need to find a core point of the master problem, which will be used to solve a modified version of the dual of the sub-problem. First, we define the sub-problem:

$$\begin{aligned} \min \quad & dx \\ s.t. \quad & Ax = b - Cy \\ & x \in X \end{aligned} \tag{5.44}$$

Here, we define $\hat{y}$ as the optimal solution of the master problem and $v(\hat{y})$ as the value of the objective function of the subproblem when considering $\hat{y}$. Then, we can solve the following optimization problem to find the PO cut:

$$\begin{aligned} \max \quad & u(b - Cy^0) \\ s.t. \quad & uA \leq d \\ & u(b - C\hat{y}) = v(\hat{y}) \\ & x \in X \end{aligned} \tag{5.45}$$

However, finding y^0 and solving the proposed optimization problem is often difficult. Because of that, [108] propose an enhancement to the method proposed in [59]. Instead of solving the problem initially proposed, we solve the problem with the constraint $u(b - C\hat{y}) = v(\hat{y})$ removed. In [108], the authors prove that this new problem also generates a PO cut. Furthermore, to avoid the cost of finding a core point each time we want to find a PO cut, we find an initial core point y^0 and use the equation $\bar{y} = \frac{y_0 + \hat{y}}{2}$ to update the core point in each iteration [108].

5.4 Computational Results

5.4.1 Test Network

In order to analyze the performance of the enhancement techniques that we have chosen to improve the convergence speed of GBD, we apply our proposed method to the IEEE RTS-96 test network.

The IEEE RTS-96 is a 73 bus-system that can be divided into 3 zones with the same number of buses, except for the last zone, which has one more. We consider a one-week time horizon with 168 hourly time steps. We took the data for this case study from [71] but made small changes to the generators' installed capacity, node demands, load profile, and operating costs.

Furthermore, the load profile data for the period was taken from [78] taking into consideration the number of nodes in our case study.

We also made some changes to the demand and load profile of some nodes. Specifically, in our study nodes 317, 318 and 321 have 160 MW, 403 MW and 220 MW as their demand, respectively. Concerning the load profile, a value of 0.06 was subtracted from all nodes for the hours 13 and 14.

Regarding the generators, we increased the installed capacity by 21% for all nodes except those shown in Table 5.2. In this table, we have the generation data for the plants that have had their installed capacities modified. We also note that at some of the nodes we added wind or solar energy generation, and the generation capacity and type of plant added on each of these nodes can be found in Table 5.3.

Table 5.2 Generators installed capacity

Generator	Capacity(MW)
121	464
123-1	179.8
123-2	179.8
123-3	406
218	580
221	580
223-1	643.8
318	139.2
321	255.2

Table 5.3 Generation capacity for wind and solar plants.

Node	Capacity Installed (MW)	Energy Source
103	150	Solar
105	50	Wind
108	150	Solar
206	100	Wind
209	150	Wind
211	250	Solar
219	300	Wind
221	50	Solar
223	600	Wind
316	120	Wind

Besides that, DR can be activated in all nodes with active demand greater than 0 in zones 1 and 2, and in the nodes 314, 318 and 321, being limited to a maximum of 10% of the demand with a cost of $25.55 per MWh. Finally, nodes 106, 112, 119, 120, 319, and 320 will offer the possibility of supplying extra demand up to a maximum of 18% of the demand. Node 317 offers this possibility as well, but up to a maximum of 200 MW. All of them offer a revenue of $85.55 per MWh.

5.4.2 Algorithms Performance Comparison

The proposed model was implemented using Julia 1.2.0 and we have used CPLEX 12.10.0.0 to solve our problems, adding the optimality and feasibility cuts in the Benders based Branch-and-cut tree through the use of callbacks. We used a PC with an Intel Core i7-9750H CPU 2.60 GHz and 16 GB of RAM memory to solve all of the problem's instances.

For our analysis, we solved our model using this test network considering 5 and 20 scenarios, so that we can see how our performance is impacted by the size of the problem. That will also give us the opportunity to analyze the impact of the different enhancements methods in the Benders based Branch-and-cut performance in regards to the size of the problem.

We set the maximum number of iterations on the root node to 500 and we imposed a time execution limit of 24 hours. Thus, if the algorithm is able to find an integer solution with an integrality gap of less than 1.00% in less than 24 hours, its execution is stopped. Finally, we add MIR cuts only at the root node. The MIR cuts are added after every three iterations, since our tests have shown that adding them more frequently does not help in finding an integer solution faster and it also slows down the convergence of the algorithm.

The computational results from our experiments are summarized in Tables 5.4 and 5.5. They were obtained by solving several instances of the problem for the two cases of 5 and 20 scenarios. In each of these tables, we have the information about the best, worst and average time of execution to find the optimal solution. In addition, we also have the number of iterations at the root node, Benders decomposition gap and integrality gap, which are the columns it, S-Gap and I-Gap, respectively, for the instance with the smallest execution time.

Table 5.4 Results for the 5 scenarios instances, with a limit of 500 iterations in the root node.

PO	MIR	DC	Avg. time (s)	Min. time (s)	Max time (s)	S-Gap	I-Gap	It
✓	✓	✓	16307	5714	41648	0.97%	0.96%	32
✗	✓	✓	54177	36999	86400	0.99%	1.00%	57
✓	✗	✓	42177	16393	77408	0.97%	0.99%	30
✓	✓	✗	42993	12993	76092	0.93%	0.94%	91

Analyzing the results, we can conclude that all of the proposed acceleration methods for

Table 5.5 Results for the 20 scenarios instances, with a limit of 500 iterations in the root node.

PO	MIR	DC	Avg. time (s)	Min. time (s)	Max time (s)	S-Gap	I-Gap	It
✓	✓	✓	39835	6353	86400	0.70%	0.84%	28
✗	✓	✓	74863	28719	86400	0.82%	2.13%	68
✓	✗	✓	61208	27476	86400	0.86%	1.00%	30
✓	✓	✗	59506	15419	86400	0.58%	0.96%	59

the Benders decomposition contribute positively to improve its performance. Considering the average time of execution for the instances with 5 and 20 scenarios, we can see that the PO cuts is the method that has the most impact on GBD's performance. Also, we can see that it has a significant impact on the convergence of the root node problem. We observe the same thing when analyzing the impact of the DCOPF constraints: there was a bigger impact in the solution time of the root node problem, which translates in less iterations, and little change on the time spent exploring the B&C tree. Finally, we note that the MIR has significant impact in the time spent exploring the B&C tree, as well as a negligible impact on the time to find a solution for the root node.

Besides that, although all of the acceleration methods have a significant impact on the execution time, the addition of the DCOPF constraints has the biggest impact. Also, when solving the various instances, we were able to conclude that the improvement in the execution time by using MIR cuts is highly dependent on the value of β. It is necessary to test various values of β to possibly find one such that it improves the performance of the GBD algorithm. However, it should be noted that even if the chosen β does not improve performance, the quality of the solution found is not affected, it will merely take more time to find the optimal solution.

When analyzing the impact of the number of scenarios on the solution time, we can see that when we use all of the available acceleration methods, the impact of considering more scenarios on the performance is minimized. When any of the acceleration methods is not considered, there is a significantly larger impact on the performance, which is also dependent on which method is not used. Also, we can observe that both the PO cuts and the DCOPF constraints have a more significant impact on the time of solution of the root node problem, due to their impact on the number of iterations. Finally, we also see that the PO cuts also have a larger impact in the performance of the Benders based branch-and-cut algorithm.

Finally, computational experiments with a version of the code without PO, MIR and DCOPF on a subset of instances show that these improvements, in fact, reduce solution times for both 5-scenarios and 20-scenarios instances. More specifically, it reduces the solution time, on average, by 74.15%, from $24,841$s to $6,421$s, for the instances with 5 scenarios and by 74.84%, from $60,324$s to $15,175$s, for the instances with 20 scenarios. Other experiments that involve using only a subset of the proposed enhancement methods did not yield results that were as clear: sometimes CPU times are improved, sometimes they deteriorate.

5.5 Conclusion

In this paper, we proposed a model that maximizes the profit of supplying external demand using an ACOPF model with DR under uncertainty. We have also proposed the use of several different methods to improve the performance of the GBD algorithm in order to solve our problem in a reasonable amount of time. We were able to observe that the proposed acceleration methods were successfully able to improve GBD's performance significantly. That allowed us to solve instance with more scenarios and it also enables us to solve instances with larger power grids.

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CHAPTER 6 ARTICLE 3: SURVEY OF OPTIMIZATION MODELS FOR INTEGRATED POWER SYSTEM PLANNING WITH DEMAND RESPONSE

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Co-authors: Miguel F. Anjos, Michel Gendreau

Abstract

With the implementation of demand response (DR) programs and its increasing penetration in the power grid, various new challenges to the grid's operation have emerged. As a consequence, optimizing the operation of the grid and the allocation of DR resources, in the short-term, medium-term and long-term, has become a fundamental problem. This survey presents a review of the models that take an integrated approach to the operation of the power grid and the use of DR resources, including the power grid's expansion planning problem. We conclude with highlights for possible future research directions.

Keywords: OR in energy, power system operation, power system expansion, demand response, unit commitment, optimal power flow

6.1 Introduction

With the advent of smart grids and the growing adoption of renewable energy, the operation of power grids has become more challenging. More specifically, smart grids have enabled and incentivized the development of DR programs that employ residential demand to help operate the power grid. For example, DR aids on mitigating the generation fluctuations of renewable energy. Therefore, an integrated approach for operating the power system taking into account DR has become necessary. In this survey, we approach the integration of DR with the optimal power flow (OPF), the unit commitment (UC) and the expansion planning problems.

OPF models were conceived to solve the problem of generating and distributing energy optimally considering the transmission system restrictions [109]. These models can consider all kinds of energy sources on the generation side. Furthermore, the transmission system model can be either more detailed by considering an Alternating Current Optimal Power Flow (ACOPF) model or simplified by considering a DC Optimal Power Flow (DCOPF) model.

UC models have the same general objective as OPF models, however, they further complexify the problem at hand, because they consider the implications of committing specific generating units, accounting for the costs incurred when starting up these plants as well as physical constraints when ramping up or down production [110].

Finally, we have expansion planning models, which are conceived to tackle the operation of the power grids over a long-term time horizon. Differently from the short-term or medium-term models, the long-term models need to take into consideration the fact that energy demand grows over time and that the current installed capacity eventually will become incapable of supplying this demand adequately. Thus, there is a need to build new power plants and expand the transmission system to guarantee enough energy supply over a long period of time, and with the least amount of investment [111–113].

Demand response (DR) can be defined as the ability to change the consumers energy consumption patterns so that one can alleviate energy demand peaks [3]. In order to implement DR in the power grid there are several options, which will be briefly explained in the next section.

As a result of the fact that DR resources are so sparsely distributed throughout the power grid, operating them and the power grid at the same time in a coordinated fashion is very challenging. To overcome this difficulty, the concept of aggregator was developed. An aggregator is an entity that is responsible for the management of DR resources [2], which facilitates the integrated operation of the grid and the DR resources. Nonetheless, this problem is still very challenging.

Although there are a few reviews that approach some of the problems that interest us, such as [114–117], none of them discuss both operations and expansion planning problems considering DR. In [114], even though they discuss the DR-OPF integration, they neither present models nor examine the DR-UC integration. In [115], they review the techniques to handle uncertainty in smart grids, but they do not discuss DR-UC or DR-OPF problems. In [116], although the authors consider OPF problems in general, they only briefly discuss the inclusion of DR in OPF models. Finally, [117] discusses very briefly the impacts of DR in operational problems. As a consequence, there is a need for a survey that explores in detail the operational models, OPF and UC, and the expansion planning models that consider DR.

Because of that, we review the different approaches used to model and solve the problem of planning the operation of the power grid and of DR resources in a coordinated fashion. This survey explores both the deterministic power grid operation models and the power grid operation under uncertainty models, covering both the operation and expansion planning models. We are interested in identifying the optimization techniques used as well as modelling approaches to tackle these problems. We are also interested in highlighting the existing research gaps, both in terms of modelling and optimization techniques.

This survey is organized in four sections. Section 6.2 introduces the key concepts for this survey, such as OPF, DR and UC. In section 6.3, we explore the operation planning models, and, in section 6.4, the expansion planning models. Finally, in section 6.5, we present our concluding remarks.

6.2 Definitions

6.2.1 Optimal Power Flow

The OPF model aims for the optimal operation of the power grid considering the transmission constraints and the minimization of the generation costs.

Generally, a power grid is composed of buses, $m \in N$, which have power plants connected to them, $j \in Th_m$, as well as transmission lines, $\{m, n\} \in \Omega$. The OPF model is a mathematical representation of this grid.

When formulating an OPF model, there are several variables of interest. The first ones are the active and reactive power generation, that are represented by T_{jm}, QT_{jm}, respectively. There is also the voltage magnitude at a bus, Vm_m, the active and reactive power injections in the "to" point of the branch m, I^p_{emn}, I^q_{emn}, as well as in the "from" point of the branch m, I^p_{fmn}, I^q_{fmn}. Besides that, there are several parameters that have to be taken into consideration. In each bus there are the active and reactive power demands, D_m, Q_m, the shunt susceptance and the shunt conductance, B'_m, G'_m. In regards to the transmission lines, there is their susceptance , B_{mn}, their admittance , Y_{mn}, and their turns ratio, Tn_{mn}. There are also the coefficients of the generation cost function for the thermal plants, $a^{Th}_{jm}, b^{Th}_{jm}, c_{jm}$. Finally, there are also the upper and lower bounds for all variables and for the transmission. $\underline{T^t_{jm}}, \overline{T^t_{jm}}$ are the maximum and minimum active power generation, $\underline{QT^t_{jm}}, \overline{QT^t_{jm}}$ are the maximum and minimum reactive power generation. $\overline{S^t_{mn}}^2$ is the maximum transmission capacity for a transmission line and $\overline{Vm^t_m}, \underline{Vm^t_m}$ are the maximum and minimum voltage possible in bus m.

The OPF model general formulation is as follows:

- The objective function is defined as:

$$min \sum_{m=1}^{N} \sum_{j \in Th_m} \left(a_{jm}^{Th} T_{jm}^2 + b_{jm}^{Th} T_{jm} + c_{jm} \right) \tag{6.1}$$

- Active power balance constraint:

$$\sum_{j \in Th_m} T_{jm} + \sum_{\{m,n\} \in \Omega} I_{fmn}^p + \sum_{\{n,m\} \in \Omega} I_{enm}^p - G_m' Vm_m^2 = D_m \; \forall m \in N \tag{6.2}$$

- Reactive power balance constraint:

$$\sum_{j \in Th_m} QT_{jm} + \sum_{\{m,n\} \in \Omega} I_{fmn}^q + \sum_{\{n,m\} \in \Omega} I_{enm}^q + B_m' Vm_m^2 = Q_m \quad \forall m \in N \tag{6.3}$$

- Transmission constraints:

$$\begin{aligned} & I_{fmn}^p + i I_{fmn}^q = \\ & -\frac{Vm_m}{Tn_{mn}} \left[\left(i\frac{B_{mn}}{2} + Y_{mn} \right) \frac{Vm_m}{Tn_{mn}} - Y_{mn} Vm_n \right] \quad \forall \{m,n\} \in \Omega \end{aligned} \tag{6.4}$$

$$\begin{aligned} & I_{emn}^p + i I_{emn}^q = \\ & -\frac{Vm_n}{Tn_{mn}} \left[\left(i\frac{B_{mn}}{2} + Y_{mn} \right) Vm_n - Y_{mn} \frac{Vm_m}{Tn_{mn}} \right] \quad \forall \{m,n\} \in \Omega \end{aligned} \tag{6.5}$$

$$\underline{Vm_m} \leq Vm_m \leq \overline{Vm_m} \quad \forall m \in N \tag{6.6}$$

$$(I_{mn}^p)^2 + (I_{mn}^q)^2 \leq \overline{S_{mn}}^2 \qquad \forall \{m,n\} \in \Omega \tag{6.7}$$

- Generation plants bounds:

$$\underline{T_{jm}} \leq T_{jm} \leq \overline{T_{jm}} \quad \forall m \in N, \forall j \in Th_m \tag{6.8}$$

$$\underline{QT_{jm}} \leq QT_{jm} \leq \overline{QT_{jm}} \quad \forall m \in N, \forall j \in Th_m \tag{6.9}$$

The objective function aims to minimize the generation cost for supplying the energy demand. As for the constraints, there are the power balance constraints, (6.2)-(6.3), the transmission constraints, (6.4)-(6.7), that, in this case, represents an ACOPF transmission system model. Finally, there are the generation plants generation bounds, (6.8)-(6.9). Because of restrictions (6.4),(6.5) and (6.7), this model is a non-convex non-linear optimization problem, and even checking its feasiblity is strongly NP-hard [118].

Because of the very high computational cost to solve the ACOPF model, the use of the

DCOPF model is often proposed. To obtain the DCOPF model, one removes (6.3)-(6.7) and (6.9), and the power balance constraint is also updated accordingly. A new variable is also added, θ_n^t, which represents the voltage angle at a given bus. The following constraints are also added to the problem:

$$I_{mn}^p = B_{mn}(\theta_n - \theta_m) \quad \forall\{m,n\} \in \Omega \tag{6.10}$$
$$-\overline{S_{mn}} \leq (I_{mn}^p) \leq \overline{S_{mn}} \quad \forall\{m,n\} \in \Omega \tag{6.11}$$

An excellent introduction to the OPF problem is given by [119].

6.2.2 Unit Commitment

The UC models have an objective similar to the OPF models, but they consider the physical constraints of the generating units. Thus, one needs to consider some additional variables, which are the start-up, shutdown and on/off state variables, $y_{jm}^t, z_{jm}^t, x_{jm}^t$. There are also some additional parameters, which are the maximum ramp-up and ramp-down rate of a generating unit, R_{jm}^U, R_{jm}^D, and the start-up and shutdown rates. S_{jm}^U, S_{jm}^D. We also add the following constraints to the original OPF model:

$$x_{jm}^{t-1} - x_{jm}^t + y_{jm}^t - z_{jm}^t = 0 \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{6.12}$$
$$T_{jm}^t - T_{jm}^{t-1} \leq R_{jm}^U x_{jm}^{t-1} + S_{jm}^U y_{jm}^t \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{6.13}$$
$$T_{jm}^{t-1} - T_{jm}^t \leq R_{jm}^D x_{jm}^t + S_{jm}^D z_{jm}^t \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{6.14}$$
$$\sum_{k=t-T_j^U+1, k\geq 1}^{t} y_{jm}^k \leq x_{jm}^t \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{6.15}$$
$$\sum_{k=t-T_j^D+1, k\geq 1}^{t} z_{jm}^k + x_{jm}^t \leq 1 \quad \forall m \in N, \forall j \in Th_m, \forall t \in T \tag{6.16}$$

First, the constraint that guarantees that one cannot turn on and turn off a generating unit at the same time instant is defined in (6.12). The constraints (6.13)-(6.14) are the generation ramping constraints, and, finally, there are the uptime and downtime constraints, (6.15)-(6.16). The generation bounds constraints also need to be modified, guaranteeing that they are non-zero only when the generation unit is on. Improved versions of some of these inequalities that lead to a tighter description of the feasible operating schedules for generators were proposed in [120].

More detailed presentations on UC problems can be found in [121] and [32].

6.2.3 Demand Response

Demand response can be defined as the capacity of managing demand and supply that allows energy consumers to change their consumption pattern according to the system operator's needs. They can do that by either shifting or reducing their consumption. The system operator gives consumers incentives to convince them to change their consumption habits. [122].

To implement DR in the power grid, several DR programs were developed. We can divide them into two main categories, incentive-based DR (IBDR) programs and price-based DR (PBDR) programs.

IBDR programs pay the users to either reduce or shift their energy consumption. The idea is to directly incentivize users to change their energy consumption pattern during the day [122]. Examples of IBDR programs are Direct Load Control and Emergency Demand Reduction.

PBDR programs devise an electricity pricing scheme such that it incentivizes users to change their consumption pattern. The idea is that they will avoid consuming energy when the price is higher by consuming more energy when the price is lower. Therefore, the electricity price works as a motivator for users to change their consumption patterns [122]. Examples of PBDR programs are time-of-use pricing and real-time pricing.

However, coordinating the operation of the power grid and of the DR resources is usually very challenging, since DR resources are supplied by many small providers. Thus, to overcome this problem, an entity called *aggregator* was defined to act as a middleman between the system operator and the DR resources [2]. Although they facilitate the communication between the system operators and the DR resources, designing aggregators is challenging and there are several options for doing so, such as designing virtual power plants.

We refer the reader to [122] for a better understanding of DR and DR programs, and to [2] for a recent survey on aggregators.

6.3 Operation Planning

When considering DR in the operation of the power grid, there are several different objectives that can be considered by the models. In the short and medium term time horizon, the DR resources can help diminish the energy demand at peak times or mitigate the effects of the intermittent energy generation by renewable energy, among other things. Because of that, in this section, operation planning models that take into consideration DR will be explored.

However, one also has to take into consideration that many of the parameters considered in this type of problem depend on data that cannot be predicted accurately, which means that one has to consider uncertainty. Nonetheless, it is often not considered for two main reasons, the problems become too complex and, consequently, too hard to solve, or there is a lack of data to adequately consider that uncertainty. Thus, in this section, we discuss both stochastic and deterministic models, and, then, we explore the algorithms and techniques used to approach the optimization under uncertainty problems.

When considering DR in the power grid operation, most models will consider what kind of DR program is implemented, affecting the choices of how to consider DR in the model. Besides that, because of the challenges to coordinate DR resources, some of the proposed models consider that DR is offered through aggregators, which also impacts modelling choices. We see models in which DR is offered through an IBDR program (e.g., [123, 124]), in others it is offered through a PBDR program (e.g., [125, 126]). In some situations, both types of programs are considered in the models (e.g., [127]), and, finally, in some models the DR program through which DR is offered is not taken into consideration (e.g., [128, 129]).

Besides that when modelling the problem to be solved, one can choose whether the transmission system will be considered or not. If it is taken into account, as discussed in Section 6.2, the model for the transmission system model must be chosen; this can be either the DCOPF or the ACOPF model.

Typically in the literature, either a transmission system model is not considered or a DCOPF model is used. In the case of DCOPF models, it should be noted, however, that, because it does not consider transmission losses, some authors add constraints to calculate them to more accurately model the transmission system, such as in [130]. However, there are models that consider an ACOPF transmission system, such as in [67, 126, 131–137].

Most approaches consider a DCOPF transmission system model because ACOPF is a often computationally very challenging. By not using an ACOPF representation, it is possible to consider more detailed representations of other aspects of the problem. It also enables solving the problem for large-scale power grids. However, this simplification may generate optimistic solutions, which is not desirable.

6.3.1 DR purpose in the power grid

Most authors are interested in being able to integrate DR and power grid operation adequately, such as in [10, 66, 126, 131, 134, 135, 138–149]. In [138], that also includes using DR as another source of energy for reserve capacity. Also, in some cases, the problem of optimal location and sizing of DR resources is considered, such as in [143].

DR can also be a huge asset in dealing with the intermittent energy generation of renewable energy. In these models, DR will help mitigate this issue by shifting loads, such as in [8,67,124, 125,127,150–152]. In [153], the main concern is protecting the security of frequency dynamics, which becomes primordial with the increasing penetration of wind power generation units, thus, DR and plug-in electric vehicles are used for this purpose. In [125], differently from other models, the authors propose that industrial, commercial and residential DR should be considered separately. In fact, commercial and residential DR resources are modelled as being supplied by an aggregator, which is not the case for the industrial DR resources. In [8], it should be noted that, although the authors do not model the problem as a stochastic optimization, they still take into account the forecast error. Finally, some approaches also aim to minimize environmental impacts, such as the greenhouse gas emissions, as we can see in [154, 155].

There are also models that focus on the power grid operation security. In [156], a security-constrained unit commitment (SCUC) problem is modelled and DR is used to guarantee supply security. In [128], the authors use DR to supply reserve capacity to guarantee a more secure operation of the grid when there are thermal units outages. In [157], DR is used to manage transmission lines outages. Additionally, voltage stability is another very important issue for a secure operation of the power grid as well, and, in some cases, DR can be used to help in guaranteeing voltage stability and avoiding voltage collapses, such as in [132, 158]. In [158], specifically, DR is only activated when there are critical events, which, in this case, are possible voltage collapse scenarios. In [159], the authors propose a methodology for evaluating the reliability value of DR in power grids, creating the concept of capacity credit with that goal. Finally, DR can also be considered for helping to control the frequency of power grids, which also helps in guaranteeing a secure operation of the grid, as seen in [123, 153]. In [123], DR is both used for demand shift and frequency control in the grid.

Besides that, there are some approaches that use DR to manage congestion in the transmission system. In [17], the authors consider both DR and flexible alternating current transmission system (FACTS) devices to manage congestion in the transmission system. In [136], not only it is proposed using DR for congestion management, but also it is used to avoid locational marginal price spikes. In [160], a transmission line congestion probability measure is used to guarantee that the transmission system congestion will be less than a certain probability level. In [19], the authors also take into consideration possible transmission lines and generating units outages when using DR for congestion management.

In some cases, when considering PBDR programs, price responsiveness is represented in terms of demand side bids, such as in [145].

DR is also used to help mitigate electricity price volatility. More specifically, in [161], DR is used to mitigate nodal price volatility, and, similarly, in [162], DR is used to smooth the local marginal price.

Considering how the customers will respond to DR and how to make it more attractive to them is an important aspect too, which is explored in [151]. The authors of [151] propose to measure the customers' comfort, in addition to setting an attractive price, when deciding how to request DR resources from them.

On the other hand, in [137], the authors are interested in analyzing the impacts of DR on the power grid operation, such as system losses, voltage profiles and service reliability. Similarly, in [130], the authors focus on evaluating whether taking DR into the consideration is the most beneficial alternative or not, and they also analyze how the net load baseline inflation impacts the DR and, consequently, the operation of the grid.

Furthermore, DR can also be used to reduce nodal price volatility and enhance the reliability of the power system, which can be seen in [126]. DR resources are used in moments of contingencies, such as when there are transmission system limits violations.

There is also the possibility determining the operation of the DR resources and the power grid in a coordinated fashion without the need of a centralized calculation. In other words, solving the problem in a distributed fashion, which one can see in [147], where the authors use the Alternating direction method of multipliers (ADMM) for this purpose.

In some cases, the cost of implementing the infrastructure necessary for DR is also taken into consideration as well as the optimal location for DR resources, as can be seen in [163, 164].

Finally, there are some approaches where the DR is considered in a more detailed fashion, not only having upper and lower bounds, but also having ramping rate limits and constraints for the time of use of DR resources, such as in [129, 130, 139, 141, 146, 150, 152]. In [141], because the authors propose an UC model, the DR also has an on/off state variable. In [152], however, DR resources are modeled similarly to an energy storage system, with state of charge, power charged and discharged decisions.

Although most of the models consider the DR as a variable, there are some approaches that favour directly calculating a new demand considering the DR usage, such as in [133, 136, 144, 145, 147, 151, 165, 166]. Specifically in [165, 166], it is calculated based on the incentive valued offered by the operator to the customers. In [133], a system of rewards and penalties is used, instead. Customers will adjust their demands according to the rewards and penalties offered to them by the operator.

6.3.2 Aggregators

Because the DR resources are often spread thin throughout the power grid and most of the consumers can only offer a very small amount of energy through DR, many models consider aggregators instead of each customer's DR.

In much of the literature in which aggregators are considered, a model for an aggregator is not included, as one can see in [17, 66, 67, 125, 136, 138, 167]. As such, the impact of aggregators is the smaller number of variables and the tractability of the problem.

Models of the aggregator are sometimes taken into consideration. In [123], the aggregator offers the DR resources through a virtual power plant (VPP), and, consequently, DR becomes akin to a generation plant. In [134], the aggregation is done through finding an equivalent price elasticity at a system level, and, as a consequence, the authors were able to implement price-based DR through aggregators.

Finally, in [140, 168], models for aggregators are developed. In [168], the authors propose a model where the objective is to maximize the aggregators profit for using DR both for energy supply and reserve capacity. Although [140] present a model with a similar objective, they aggregate DR contracts, instead of energy, and they also consider different types of DR separately. In [169], a DR market model is developed for the aggregator to operate on, which is applied only at the distribution system level. The decisions of DR resources use at the distribution level are then used at the transmission system level. In [68], the aggregators offer DR resources through DR contracts; there are both day-ahead DR and real-time DR contracts.

6.3.3 Operation Planning under uncertainty

As mentioned earlier, when planning the operation of the power grid, there are several parameters that cannot be predicted accurately, such as demand, solar and wind energy generation, etc. Therefore, there is a need to consider their uncertainty, transforming the original problem into an optimization under uncertainty problem. There are three main different approaches available to solve it, stochastic optimization, robust optimization and chance-constrained optimization.

Stochastic optimization problems are any problem that considers uncertainty in some of its parameters. More specifically, in this survey, this means problems that represent uncertainty through a set of different scenarios. For a more detailed introduction to stochastic optimization, see [170].

In robust optimization, uncertainty is modeled through *uncertainty sets*. When using *uncertainty sets*, the solution of the problem has to be feasible for any value within the set. As a consequence, the solutions that are found solving robust programming problems tend to be very conservative. Finally, while we need to know the uncertain data distribution when solving a stochastic optimization problem, this is not the case here. A more detailed explanation of robust optimization can be found in [171].

Chance-constrained optimization problems approach the uncertainty in the problem differently. Instead of considering the expected value or the worst case scenario, one considers the probability of the constraints that are impacted by uncertain parameters to be respected. The article of [172] remains an excellent reference about chance-constrained optimization.

Stochastic Optimization

When solving a stochastic problem, regardless of modelling the problem as a two-stage or a multistage stochastic programming problem, the simplest way to tackle it is modelling it as single problem, such as in [18, 93, 157, 161, 169, 173–179]. However, this approach creates intractable problems when considering a large number of scenarios. Thus, many approaches use a scenario reduction technique to have a few scenarios that are representative of the uncertainty, such as in [13, 14, 19, 68, 180–184]. In [185], instead of using Monte Carlo simulation to generate the scenarios, they use the probabilistic collocation method with the aim of reducing the number of scenarios needed for a good representation of the uncertainty.

The performance issues have also led to the use of decomposition methods, such as the Benders decomposition (BD) technique, which can be seen in [56,57,186]. In [55], particularly, the authors implement the Benders-based Branch-and-Cut, that works by verifying whether every examined integer solution is optimal or not. If it is not, a Bender cut will be added and the same problem that returned the integer solution will be solved again, this will be done until it returns an optimal integer solution, or it returns a fractional solution, or it becomes an infeasible problem. This algorithm removes the need to solve a MILP problem several times, improving BD's performance significantly.

Another way to tackle the performance issues is using heuristics to solve the problem. In [187], the authors use the PIES algorithm to solve the problem, and, in [188], the Particle Swarm Optimization (PSO) algorithm is used. Heuristics are also applied in multi-objective problems, such as in [154], where a multi-objective multi-criteria decision making heuristic is applied, and in [189], where a genetic algorithm is used to solve the model. In [190], instead of using an heuristic, the authors apply Lagrangian relaxation to the original model and they solve the new model in an iterative fashion.

Besides that, there is the issue that risk is not often well represented, which has prompted some authors to take into account risk measures. One can observe this in [175, 184], where the proposed models use the Conditional Value-at-Risk (CVaR) measure to model the risk that is associated with the decisions made. In [191], the authors propose the use of the fuzzy stochastic CVaR to measure the risk adequately, since they aim to measure the risk associated with the wind power and DR uncertainties. In [55], the authors use the Average Value-at-Risk instead of CVaR as a risk measure.

Finally, because of the lack of information about the uncertainty data distribution, in some cases the uncertainty of some parameters is modeled using the information gap decision theory (IGDT), such as in [192]. Consequently, they develop a hybrid IGDT-stochastic optimization model.

Robust Optimization

The most straightforward approach to tackle an optimization under uncertainty problem with robust optimization (RO) is considering a single stage RO problem, such as in [193–196], which is solved the so called static robust counterpart (SRC).

Nonetheless, in many cases, there may be some decisions that need to be taken before the uncertainty is realized leading to a multi-stage RO problem, which can be reformulated by finding its adjustable robust counterpart (ARC), such as in [155,163,164,197–199]. In general, due to performance considerations, decomposition methods are used to tackle this kind of problem. In some cases BD is applied, as seen in [197], but in most cases the column and constraint generation (C&CG) algorithm is used, since it has a better convergence speed, such as in [155].

In some cases, it is possible to know the distribution of some of the uncertain parameters of the problem, and a hybrid stochastic-robust optimization approach is used, such as in [199, 200].

Besides that, some authors approach the uncertainty with the IGDT, such as [201–203]. IGDT is very similar to RO, however, it considers variable uncertainty sets, that is, the upper and lower bounds of the uncertainty set are not fixed.

Finally, in [204], the authors take into account adjustable uncertainty sets and use the affinely adjustable approach, generating an affinely adjustable robust counterpart (AARC), which is less conservative than the ARC.

Chance-constrained Optimization

When solving a chance-constrained problem, one builds a non-linear optimization problem, which can be solved directly, as can be seen in [160]. However, non-linear optimization problems can often be hard to solve. This has led to the use of solution methods or problem reformulations that make the model more tractable. In [205], the authors use the Big-M method to linearize the model, and, similarly, in [206], a MILP reformulation of the chance constraints is used. Sometimes heuristics are employed in order to find a good quality solution in a reasonable amount of time. In [207], the authors propose an improved version of the jaya algorithm, which is a population-based method. Particle swarm optimization (PSO) is also employed in some cases, such as in [208], in [209], the authors employ PSO together with some of the Genetic Algorithms operators, such as the Mutation and Crossover operators.

6.4 Expansion planning

When operating the power grid over a long-term horizon, other issues have to be considered. Because energy consumption grows over time, it is highly probable that the generating capacity will be not enough to supply all of the energy demand. Also, the transmission system may not be able to transport enough energy to supply costumers demands anymore. As such, there is a need to plan the expansion of the generating capacity as well as of the transmission system. When tackling this problem, one can only consider one of the types of expansion planning, or one can take both types into consideration. Besides that, the models also have to consider what kind of DR program will be considered and how they will be implemented in the model. In this section, we go over the various expansion planning models, both for generation and transmission expansion planning problems.

Finally, power grid representations can choose how the transmission system will be represented, if it is represented. Most of the models either do not consider a transmission system or consider a DCOPF model. There are some models, however, that take into consideration an ACOPF representation, such as [210–213].

6.4.1 Transmission expansion planning

There are several approaches in which transmission expansion planning takes into account the impacts of DR, such as in [210, 212–217]. Taking DR into consideration when planning the expansion of the power system has several possible goals.

There are models that consider DR resources to mitigate the renewable energy generation fluctuation, such as in [210, 214]. In [210], the authors also consider system reliability, using DR as a tool to guarantee it when a power grid has an important amount of renewable energy.

In [218], the authors consider the problem of guaranteeing a reliable and secure power system taking into consideration the possible generating units and transmission lines outages. Besides that, congestion management issues are also a problem that needs to be considered, as seen in [219].

In some cases, DR has the objective of reducing the need for new transmission lines or reinforcing existing ones, such as in [216]. It should be noted, however, that the natural consequence of using DR resources is often delaying building or reinforcing transmission lines.

Besides that, in certain cases, the impact of DR is evaluated on the daily power grid operation in order to verify if a given transmission expansion plan is optimal, such as in [215].

Finally, one also should note that it is not always that the addition of DR implies considering a specific variable and constraints for it. In fact, in [213–216], DR is not calculated directly, it is rather the new demand, after DR is requested, that is calculated directly. In [213, 215], this new demand value is calculated based on the price elasticity and on the electricity price. In [216], besides these two factors, incentive is also taken into consideration.

6.4.2 Generation expansion planning

The impacts of DR in generation expansion planning are taken into account in articles such as [220–223]. However, taking into consideration DR when planning the expansion of the generating capacity has several possible goals.

Most approaches in the literature consider DR resources in order to minimize or delay investments on new energy plants, such as in [222, 223].

In some cases, in addition to delaying investments, DR is also used to mitigate renewable energy generation fluctuation, such as in [221]. In [224], the authors also consider the need to minimize greenhouse gas emissions in their model and DR is also used with that objective.

Some authors, such as in [220], only account for DR with regards to how it impacts the operation of the power grid. The operation of the power grid is used to verify if the proposed expansion schedule is optimal.

Finally, although DR is often represented through a specific variable, such as in [220–222], it is not always the case. In [223], DR is represented by calculating the new demand directly considering the electricity price.

6.4.3 Transmission and Generation expansion planning

The impact of DR on generation and transmission expansion planning is taken into account by authors such as [111, 211, 225–232]. However, taking into account DR when planning the expansion of the system and of the transmission system has several possible goals.

In general, the proposed models consider DR resources to minimize or delay investments on new power plants as well as investments on new transmission lines, such as in [211, 227, 228].

Not only DR can be used to delay investments, but it can also be used to manage the supply and load balance in face of the intermittent energy generation through renewable energy, such as in [225, 226, 229, 230].

In [225], the authors also consider the reliability of the grid after applying the proposed expansion plan. In this specific model, the reliability is measured by using the loss of load expectation (LOLE) measure, which has to respect the LOLE limit established previously.

In some cases, the impact of the DR resources in the proposed expansion plan is analyzed in the daily operation after applying that plan, such as in [228]. More precisely, the idea is to analyze the impact on the peak load and how adequate the expansion plan proposed is for the operation of the power grid considering DR.

Besides that, the problem of the optimal location and siting of DR resources in the power grid is also taken into consideration by a couple of models, such as in [231, 232].

In [111, 231] there is also a preoccupation with regards to the environmental impacts when proposing an expansion plan. To mitigate those impacts, CO_2 emissions constraints are considered as well as carbon capture technologies.

Furthermore, in some cases the DR is modelled through an aggregator, such as in [211], which facilitates the procurement of DR resources by the system operator.

Finally, it should be noted that, in general, DR is directly represented through a variable when solving this type of problem, as we can see in [111, 211, 225, 226, 228, 230–232]. However, this is not always the case, and [227] is a good example of that.

6.4.4 Expansion Planning under uncertainty

Stochastic Optimization

Similarly to what was seen in the operation planning models, most authors model the SO problem as a single deterministic problem containing all the scenarios, such as in [224, 233–236]. However, because of the performance issues of that approach, some authors use a scenario reduction technique to use only the most representative scenarios, such as in [237, 238].

Nonetheless, in order to consider more scenarios and larger problems, some papers rely on decomposition algorithms. In [238, 239, 239, 240], the authors use the BD algorithm to solve their proposed models. Because BD has performance issues, enhancements to this method are employed in articles such as in [218], where the authors use an improved BD algorithm, which they call hierarchic BD (HBD). It works by solving, in a first phase, a relaxed version of the original problem, and, then, solving the original problem with the Benders cuts generated in the first phase.

Besides that, there are some authors who develop multi-objective SO models, which are often solved with heuristics. [219, 241] employ the nondominated sorting genetic algorithm to solve their models. [242] use the multi-objective evolutionary algorithm MOEA/D.

Finally, because often risk is misrepresented in SO problems, some approaches take into consideration risk measures, as we can see in [238, 243]. In [239], the authors CVaR as a risk measure in other to generate risk-averse solutions.

Robust Optimization

When using the RO approach, initially, one only needs to consider an uncertainty set, find its robust counterpart and solve it, which is the SRC, which can be seen in [217]. However, investment decisions will impact future decisions under uncertainty. In this case, we face a multistage problem and an ARC formulation can be used to solve it, as in [244, 245]. Because these problems can be hard to solve, decomposition methods are often used, such as in [246]. Finally, one may know the distribution of the uncertainty for using a SO approach, however the knowledge of this distribution is incomplete. In these cases, one can use the Distributionally Robust Optimization (DRO) approach, as seen in [246]

6.5 Conclusion

This survey has presented a review of operation and expansion planning models integrated with DR resources. In the operation planning models, DR use can have many goals, such as mitigating the renewable energy fluctuation and mitigating transmission congestion. In the expansion planning models, the DR usage main objective is mitigating the need for new power plants and the construction of new transmission lines. However, it can have several adjacent objectives, such as mitigating the energy generation fluctuations of new renewable energy plants.

In most cases, no transmission system or a DCOPF model is considered; ACOPF is very rarely employed in both the operation and expansion planning models. Although this is understandable due to the fact that ACOPF makes problems computationally challenging to solve, this choice may lead to optimistic solutions. Considering that there are convex relaxations for the ACOPF model, models with a better representation of the transmission system can be developed, allowing to find more accurate and less optimistic solutions.

With respect to DR modelling, one can see that, often, aggregators are not considered, which may cause issues when tackling large-scale grids with many DR resources. It would be interesting to explore the impacts of aggregators on large-scale grids and how they can facilitate the use of DR in them.

Besides that, in most of the expansion planning models, the impact of DR coupled with the expansion schedule is not analyzed in a daily operation perspective. Considering that the impact of using DR is more perceptible in the day-ahead operation, it would be important to analyze how DR would impact in the choice of an expansion schedule.

Also, one can also observe that there are several models that take into consideration uncertainty. However, when we analyze the SO models, we see that only a few of them employ decomposition techniques, and, even in these cases, most of them do not consider any enhancement methods to improve the performance of those decomposition methods. Considering the performance issues of decomposition algorithms, a possible performance improvement could be derived from employing enhancement techniques, which would allow to apply the models to large-scale power grids.

With regards to RO, we can observe that it is sparsely used when tackling uncertainty. Also, it would be interesting to explore the potential of applying more advanced methods, such as DRO.

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CHAPTER 7 GENERAL DISCUSSION

7.1 Summary of Results

We, first, developed a deterministic short-term optimization model to allocate both DR and extra generation resources for supplying external demand after the dispatch decision is made. Analyzing the results of this model, we observe that the use of DR resources has allowed the generators to supply more external demand. In fact, when analyzing the first case study, with the IEEE RTS-96 test grid, we can see that, when overall energy demand was higher, DR resources had a significant participation on supplying the external demands. And, in both cases, we can see that there was often a pronounced use of DR resources. This proves that DR can be used for congestion management successfully and that it can also guarantee that more external demand is supplied.

Besides that, using a semidefinite relaxation to obtain a good starting point to solve our problem in a reasonable amount of time has proven itselfa very good approach. When analyzing the execution time for the IEEE RTS-96 test grid, we observe that in the latter we had an improvement of 31.71% when using our approach. For the ACTIVSG500 test grid, not using a good starting point to solve the problem has not even allowed us to find a solution, whereas using our approach we were able to find an optimal solution.

We are also able to verify that the relaxation chosen is able to give us a very good starting solution for our problem. In fact, in the first case study, the optimization gap was 4.13%, and, in the second case study, is 28.05%.

Afterwards, in Chapter 5, we have considered more aspects of our problem, which are the UC problem and the uncertainty of some of the problem's parameters. As a consequence, we have developed a stochastic short-term UC model considering the renewable energies and the external demand offer as the uncertain parameters to optimally allocate DR resources and to optimally commit and dispatch the generating units. To solve this problem, we have decided to apply the GBD algorithm. Because of the slow rate of convergence of the chosen algorithm, enhancement methods for the GBD algorithm were employed. When analyzing comparatively the impact on the performance of the chosen methods using the IEEE RTS-96, we can see that all of them have contributed to an improvement on the execution time, on the number of iterations of the GBD algorithm, and on the quality of the solution found. It should be noted, however, that the most significant contribution on the algorithm performance was brought by the use of Pareto-optimal cuts.

Finally, in Chapter 6, we have explored thoroughly the body of works of both power grid operation and expansion planning models that consider DR. One can see that DR can have several different objectives in the operation and in the expansion planning models. These objectives can range from mitigating the renewable energies generation fluctuation to delaying the construction of new power plants.

However, there are several possible future research directions. First, modelling this problem taking into account an ACOPF model or a convex relaxation of the ACOPF model would significantly improve the accuracy of the given solutions. Likewise, a more accurate modelling of DR resources and aggregators could contribute to find better quality solutions. Besides that, when considering uncertainty, most works do not consider any method to improve the performance of the solution algorithms, which could make a significant impact on the solution time of these models. Finally, with regards to robust optimization, it would be interesting to explore more advanced methods.

7.2 Limitations

Although we have developed a model that represents well the original problem, and that considers the uncertainties inherent to this kind of problem and we have implemented a solution algorithm that guarantees us that it will return an optimal solution in a reasonable amount of time, there are still some limitations to our modelling and solution approach.

In our model, we have significantly simplified the representation of the hydroelectric and thermal plants by not considering all of their physical aspects and constraints. More specifically, hydroelectric plants energy generation is also dependent on the water inflow, on the reservoir's state, and on the plant's geographic position on the river. Besides that, depending on the type of thermal plant, there are different operational constraints, which include up-time, downtime, and ramping constraints. We have approached DR and aggregators similarly by also employing a simplification of their representation.

Besides that, when implementing our approach to solve the stochastic UC model that we have developed, we have not taken any advantage of the possible improvements in performance that can be brought by multi-threading. When solving the second stage sub-problems in Chapter 5, we solve them sequentially, even though they are independent and, thus, we could solve them simultaneously, which makes us lose an opportunity to further improve the algorithmic performance. Similarly, we sequentially explore the Benders based branch-and-cut tree, when we could, in fact, explore several nodes simultaneously.

Finally, when solving the NLP problems proposed in Chapter 4, we use a solver that does not take advantage of multi-threading, which is a possible bottleneck in terms of performance.

CHAPTER 8 CONCLUSION AND RECOMMENDATIONS

In this thesis, we developed a short-term optimization model to optimally allocate DR resources, through aggregators, and generation considering external demand supply after a dispatch decision is made considering a detailed representation of the transmission system. In addition, we have also tackled the uncertainties inherent to this type of problem, which has led to the development of a non-linear stochastic optimization model. To solve this stochastic NLP problem in a reasonable amount of time, we have employed several enhancement techniques to the algorithm initially proposed to solve our problem.

We have seen that DR has a very important impact on managing the transmission system congestion, allowing more external demand to be supplied by the generators. Besides that, with DR resources being supplied by an aggregator, the complexity of optimizing their allocation has been significantly reduced. Finally, considering a more realistic representation of the transmission system topology has allowed us to find a more adequate solution to our problem.

8.1 Future Research

Considering the limitations presented in Chapter 7 as well as other possible improvements to the model, we can summarize paths for possible future research as follow:

- Modelling more accurately the hydroelectric plants and the thermal plants. Considering their technical constraints would guarantee us a more accurate solution.
- Taking advantage of multi-threading capabilities when solving the subproblems of the stochastic optimization model proposed, allowing us to solve several subproblems simultaneously. Thus, we would be able to improve the problem's solution time.
- Implementing a parallel Benders based branch-and-cut algorithm, which would allow us to further improve its performance. With this new implementation, different nodes could be explored simultaneously. However, we would have to make sure that as soon as a node with an integer feasible solution is found, the solution of other nodes would be halted. After this node's problem is solved, the new feasibility and optimality cuts should be added to the pool of cuts and the algorithm would resume the nodes' exploration. Otherwise, we would not have accurate solutions for all of the branch-and-bound tree nodes. See [247] for further details.

- Add constraints to approximate the transmission losses in the master problem, further lifting the lower bound. This could potentially lower the number of GBD iterations needed to find the optimal solution, which would have a positive impact on the solution time.

- Considering a more detailed representation of the aggregators. Being able to more accurately represent how aggregators procure DR resources and how they offer these DR resources would contribute to having a more accurate solution for our problem.

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