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Renewable Energy and Flexibility Integration on the Electricity Market

by

Mathilde Badoual

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Engineering - Civil and Environmental Engineering

in the

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of the

University of California, Berkeley

Committee in charge:

Professor Scott J. Moura, Chair
Professor Duncan Callaway
Professor Alexandra von Meier
Professor Alexandre Bayen

Fall 2021

Renewable Energy and Flexibility Integration on the Electricity Market

Abstract

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Mathilde Badoual

Doctor of Philosophy in Engineering - Civil and Environmental Engineering

University of California, Berkeley

Professor Scott J. Moura, Chair

Electricity is the most common way to transport, transform and consume energy. However, the total electricity generation accounts for 40% of worldwide CO_2 emissions. With the threat of climate change, it is crucial to lowering emissions related to electricity generation and grid operation.

While renewable energy sources provide a solution to decarbonize the electric grid, they bring new challenges due to their inherent volatility. The grid requires balancing capacity to maintain a stable frequency and storage to adapt generation hours to consumption hours. Meanwhile, 54% of the world's electricity consumption happens in countries that rely on competitive markets for efficient dispatch [4]. Therefore, it is essential to provide correct incentives and dispatch mechanisms on the electricity markets to integrate renewable energies and develop new market mechanisms for balancing renewable energy variability.

This dissertation explores methods to integrate flexible resources into the electricity market. First, we develop an optimal bidding strategy for grid-scale storage on a wholesale electricity market. The specific role of the storage system creates market power which challenges the design of the bidding algorithm.

Secondly, the dissertation focuses on flexible resources located on the distribution grid. Indeed, the simplest way to lower overall CO_2 emissions with a decarbonized grid is to electrify all energy use. This electrification entails the deployment of electric vehicles, electric heaters, or electric stoves. In addition, rooftop solar panels, household batteries, and other local energy resources are installed on the distribution grid, known as distributed energy resources (DERs). As a result, the distribution grid faces dramatic changes and requires precise monitoring and maintenance. Controlling DERs and integrating them into the electricity market could provide new flexibility to the grid. This dissertation introduces a new market dispatch model for the day-ahead wholesale electricity market where DERs are integrated as stochastic sources of flexibility.

However, the control and integration of DERs on the distribution grid rely on having a complete and accurate distribution grid model. Because the distribution grid lacks sensors and monitoring equipment, developing a detailed grid model is challenging for the system operator. Research on this subject is recent but provides diverse solutions dependent on modeling assumptions and data acquisition. In order to give future researchers a good understanding of existing methods and challenges left to tackle, this dissertation provides a detailed review and analysis of methods to estimate distribution grid topology.

One must still have chaos in oneself to be able to give birth to a dancing star.

Friedrich Nietzsche, "Thus Spoke Zarathustra"

To my parents, my sister and my brothers.

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Acknowledgments

When I look back on when I started this Ph.D., I was almost convinced that I would not finish. But here I am, graduating. This was harder than I thought, but not for what I expected. A Ph.D. is hard because it challenges your self-confidence and exposes you constantly to your own doubts. I finished this Ph.D. because I was surrounded by amazing people who helped me and trusted me during those years.

First, members of the eCAL lab, starting with Scott Moura, who leads this group with energy, humanity, and intelligence. I started this Ph.D. because he believed in me, and I am grateful for his trust that guided me through those years.

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Chapter 1

Introduction

This dissertation explores the integration of renewable energy on the electrical grid through three research projects. This chapter briefly introduces power systems, electricity markets, and current challenges. We also explain the background motivations that led to this research. This chapter is organized as follow:

First (1.1), we provide a brief definition of the power system and market actors for the clarity of the discussion.

Secondly (1.2), we describe the new challenges faced by the electrical grid, the inevitable transition to low carbon energy, and the need for additional flexibility resources. We raise the importance of storage systems and DERs monitoring to provide flexibility. We explain the critical role of electricity markets in the grid transition and the integration of flexibility providers.

Thirdly (1.3), we go through the ideas, reflections, and real-world experiences, that led to the formulated research projects.

Finally (1.4), we expose the contributions of the resulting research that is developed in the following chapters of this dissertation.

1.1   Power System Actors

In the following work, we will frequently refer to several electrical grid and market actors. This first section provides a dictionary of those terms for a clearer understanding. Those definitions are inspired by the work of D. Kirschen [55] and A. Von Meier [66].

Distribution Grid refers to the final stage of the electrical grid, which distributes electricity to homes, industry, and other end users. The power level is reduced by step-down transformers, which lower the voltage of the electricity from dangerous levels (over 1 kV) to safer levels (100 - 400 V). The entire distribution grid includes lines, poles, transformers, switching, and protection circuits that deliver safe electrical power.

Distribution System Operator (DSO) or Distribution Utility owns and operates distribution networks. It is responsible for distributing and managing energy from the gener-

ation sources to the final consumers. In a traditional environment, they have a monopoly for selling electrical energy to all consumers connected to their network. In a fully deregulated environment, the sale of energy to consumers is decoupled from the distribution network's operation, maintenance, and development.

Transmission Grid refers to the lines, poles, and transformers that move bulk electricity from the generation sites over long distances to substations closer to areas of electricity demand. Transmission equipment has voltages of over 100 kV.

Transmission System Operator (TSO) owns transmission assets such as lines, cables, transformers, and reactive compensation devices. They operate this equipment according to the instructions of the independent system operator. The TSO is usually a natural monopoly, and as such, it is often subjected to regulations.

Independent System Operator (ISO) has the primary responsibility of maintaining the security of the power system. An ISO monitors the power system in real-time, plans for future energy needs, and dispatches power resources. It is called independent because, in a competitive environment, the system must be operated to favor or penalize one market participant over another.

Regulator is the governmental body responsible for ensuring the fair and efficient operation of the electricity sector. It regulates monopolies, guarantees independence, ensures competition, and protects consumers—examples of regulators: CRE (France), FERC (United-States).

Retailer buys electricity on the wholesale market and resells it to consumers who do not wish, or are not allowed, to participate in this wholesale market. The DSO is often one of the retailers.

Market Operator runs the electricity dispatch that matches the bids and offers that buyers and sellers of electrical energy have submitted. It also takes care of the settlement of the accepted bids and offers. In some markets, the TSO or ISO runs the last-minute markets (balancing or real-time markets). Examples of market operators: CAISO (California), ERCOT (Texas), EPEX (Europe), AEMO (Australia).

Distributed Energy Resources (DER) DERs are electricity generation units, typically from 1 to 10MW, connected to the distribution grid: "DERs may include electric storage, intermittent generation, distributed generation, demand response, energy efficiency, thermal storage or electric vehicles and their charging equipment" [46].

1.2 Motivation

The grid is facing inevitable changes and has to adapt

From the time of Nikola Tesla and Thomas Edison in the late 19th century, the electrical grid has developed at a breathtaking pace into what was said to be "*the most complex machine ever built by humans*". In the 21st century, it is hard to imagine that the grid is more complex than data centers, nuclear power plants, or the International Space Station.

However, its complexity lies in many aspects. First, in its size, the electrical grid covers continents, connects countries through underwater DC lines or long high voltage AC lines up to remote farms in the middle of desert areas. In the United States, there are about 600 000 miles of transmission lines and 5.5 million miles of distribution lines. Secondly, the grid is made of various devices, from lines, poles, transformers, switches, and sensors, all manufactured at different times with different ratings. This variety and the age of the electric grid complexify grid management and operation. Finally, the grid is essential for our society. Every step in our modern life depends on electricity, computers, lights, food conservation, heaters, and soon, cars. No one questions if the light turns on when we press the interrupter, the grid is expected to work. This implies that the lines reach everywhere human life and provide electricity for every use at any time.
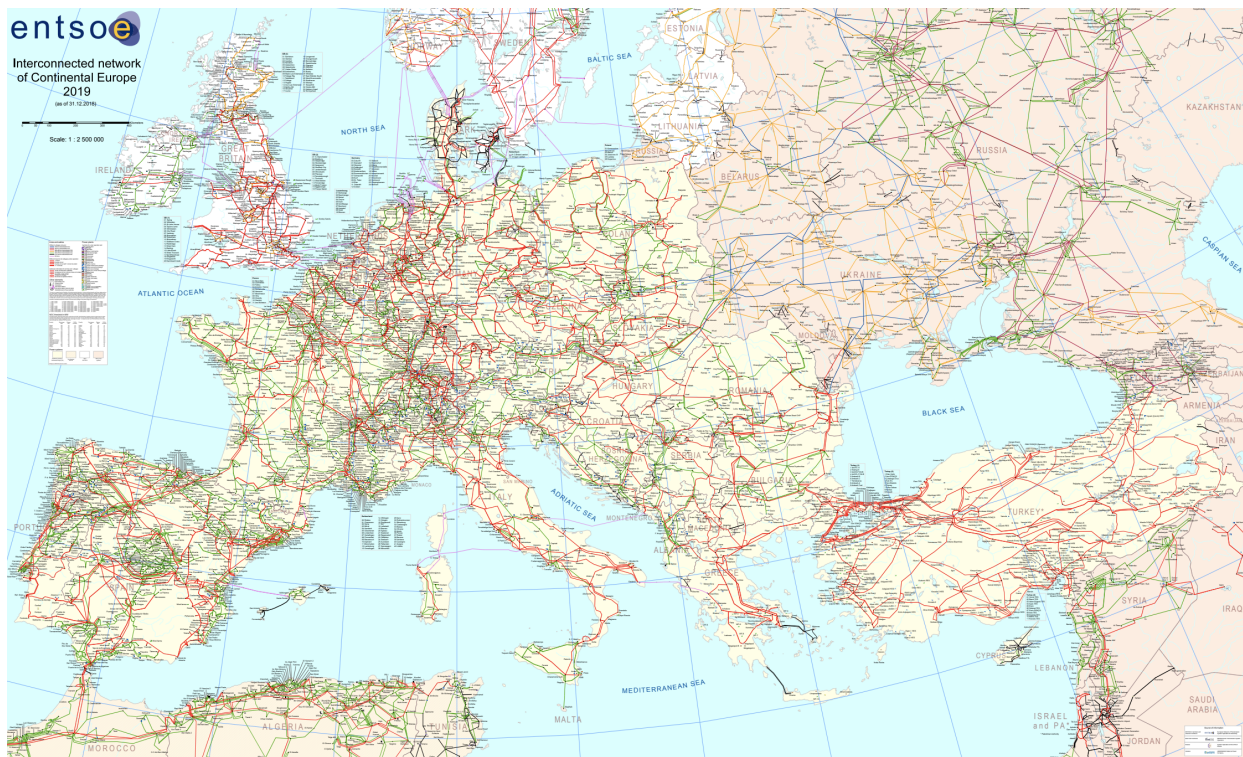
Figure 1.1: Interconnected Network of Continental Europe 2019 - ENTSO-E [42]

Today, this highly complex system is under pressure. The aging of the equipment, the lack of recent investments, and climate risks as extreme fires or hurricanes [25], are increasing power outages and threaten the grid operation. However, another threat is progressively becoming a major issue for the grid: the integration of renewable energy and the electrification of our society.

Climate change is, in my opinion, the most threatening problem for our generation. It

puts our lives on this planet at risk, and it is clearly shown that humans are responsible for it. Cutting CO2 emissions is critical to reducing the greenhouse effect, mainly responsible for climate change. The integration of renewable energy as solar and wind, in addition to the use of nuclear and low carbon energy, is, for now, our best solution to shift our energy dependency from fossil fuel. Fortunately, this shift is on its way; Fig. 1.2 shows the net annual renewable capacity added in the world by region in 2021. It shows the high adoption of solar and wind in America and Europe and the massive shift in Asia Pacific towards renewable energy. Those additions will likely continue over the century as several countries adopt political goals towards a 100% carbon-free grid. Then why are renewable energies simultaneously a solution and a threat to our grid?
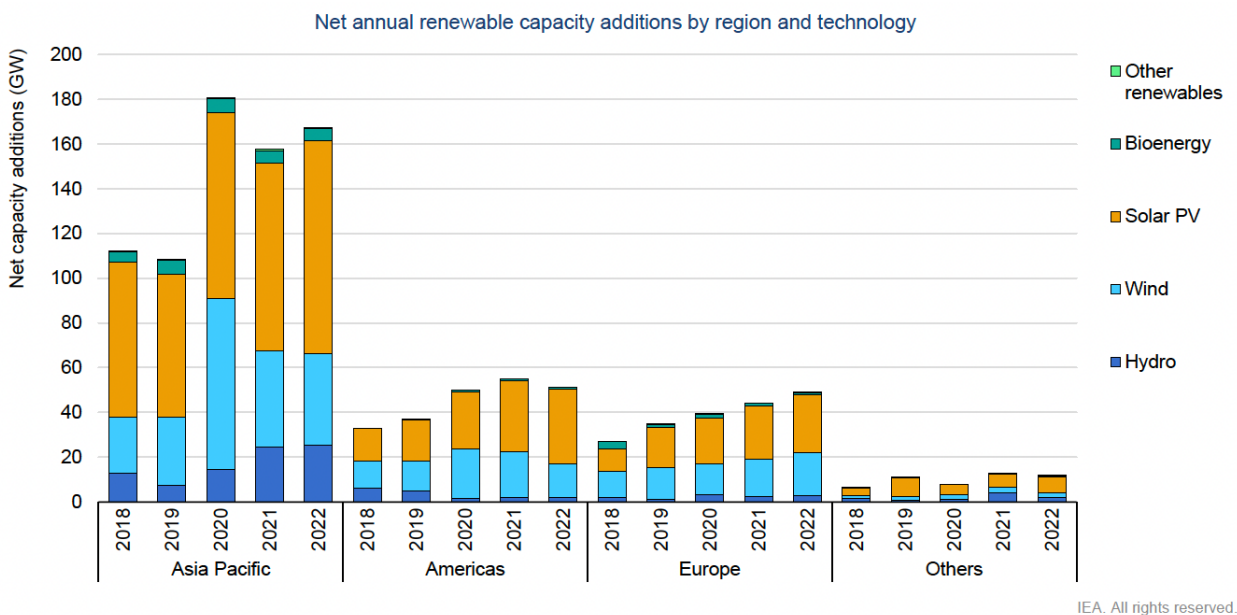
Figure 1.2: Net annual renewable capacity additions by region and technology. Source: IEA, *Renewable Energy Market Update 2021* [5]

First, renewable energies depend on natural resources like wind and solar, which are variable and hard to predict. Wind can stop blowing, and a cloud can pass between the sun and the solar panel. Those brutal interruptions cause frequency variations that damage grid equipment. In addition, generation cannot be scheduled and can happen when the grid does not need extra electricity. This is well known in California as the "duck curve": the electricity is produced during the day with solar panels, while the consumption peak is later in the day, after sunset. Fig. 1.3 illustrate this curve, with the red part of the curve being the increase in net load (demand minus solar generation). One of the most efficient solutions is using a grid-scale storage system as lithium-ion batteries to provide the grid with reserve and balancing services. Indeed, storage systems can store (i.e. buy) electricity when

it is produced the most (i.e. at the lowest cost) and release (i.e. sell) that electricity when the consumption is higher (i.e. the prices are higher). Finally, non-synchronous generation sources like wind and solar panels do not provide inertial like rotating machines and thus need controlled inverters that follow grid frequency [3].
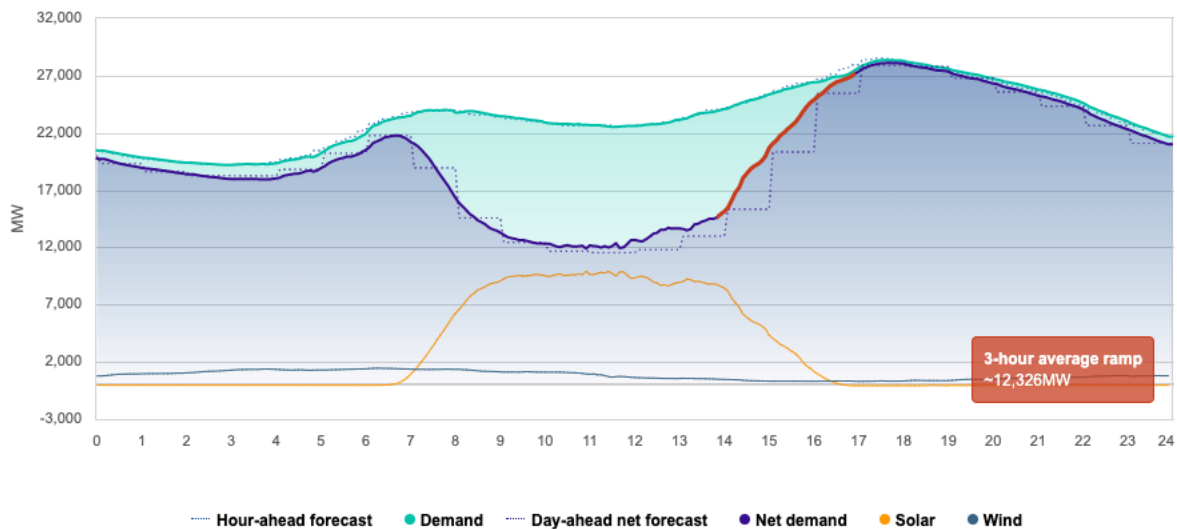
Figure 1.3: California Independent System Operator (CAISO) Total Load and Net Load: November 22, 2021 [1]

However, the problem of renewable energy integration on the grid is not localized only at the transmission level. Indeed, at the distribution level, rooftop solar panels are causing several issues and prevent the DSO from guaranteeing voltage levels to customers and protecting equipment. Distributed energy resources (DERs) could offer generation where consumption is located but also create back-flow, unpredictable demand, and noise from DC-AC inverters. Developing the grid infrastructure to face distribution generation has a cost and requires optimal control [24] [22].

Integrating grid-scale storage or DERs on the grid requires designing adapted control mechanisms and price incentives. The grid will need to increase dispatchable peaking units, storage facility, demand-side flexibility, and improve regulations to allow the use of other sources of flexibility [3]. This dissertation will take a close look at the market mechanisms to integrate those resources.
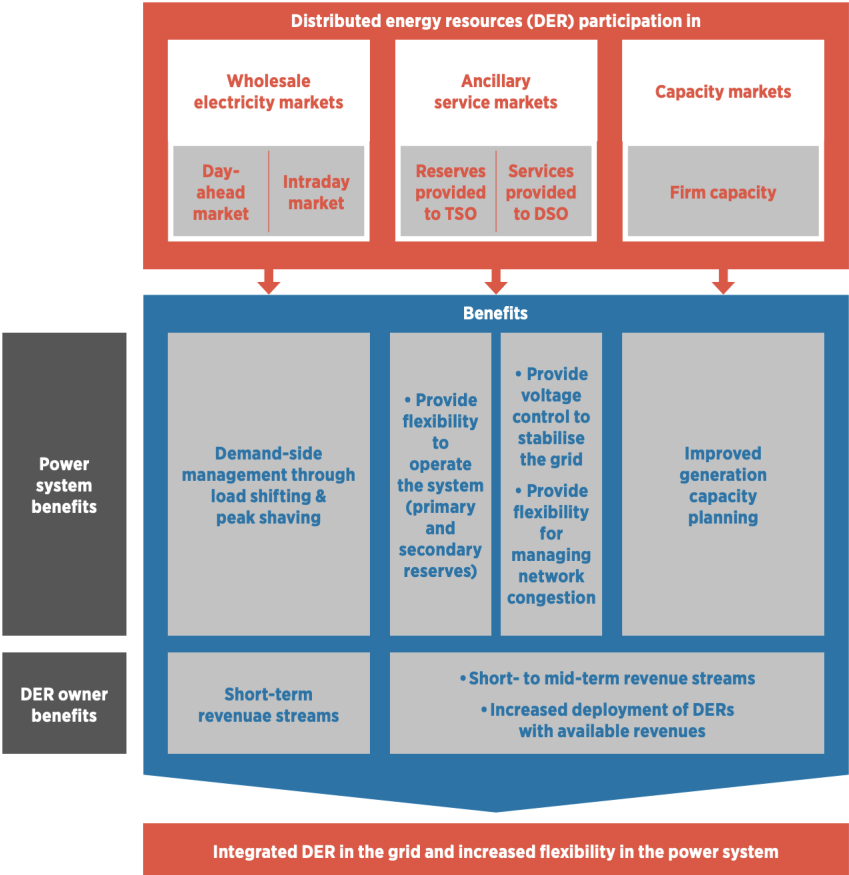
Figure 1.4: Distributed Energy Resources Integration in Electricity Market

The critical role of electricity markets

In a deregulated market, electricity production and consumption result from an auction, where producers (resp. consumers) bid a quantity and a price to sell (resp. buy). The market operator runs a dispatch that maximizes social welfare under physical grid constraints. The highest price cleared is called the *clearing price*. Two types of markets exist, *uniform price auction* market, where the players are paid with the clearing price, and the *pay as bid auction*, where the price paid is the bidding price.

The electricity trade depends on demand and generation predictions; the ISO provides a demand forecast at the time of delivery, and each actor predicts their production. The accuracy of those predictions is weakened by the use of renewable energies and the increase of DERs on the consumer side. Thus, the market runs multiple dispatches to allow the actors to adapt their bids while the accuracy improves closer to the delivery time. There exist many different electricity markets around the globe, but they all share some basic structures. As

shown in Fig. 1.5, the wholesale electricity market runs three main dispatches: the Day-Ahead (the day before), the Intra-Day (during the day), and the Real-Time (between 5 to 15 min before the delivery time).
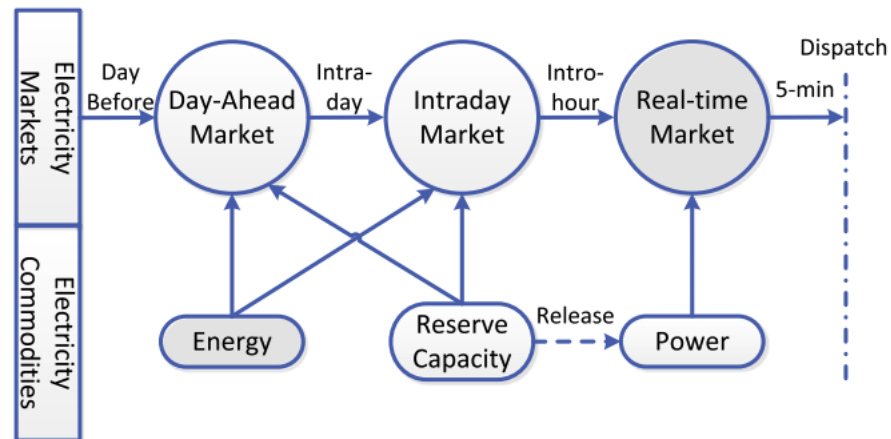
Figure 1.5: Basic market architecture in modern power systems [96]

A well-functioning market incentivizes generation when needed, and as a result, the use of storage to balance renewable energy generation. Markets are also adapting to reserve capacity to respond to higher grid variability. Those markets are usually called ancillary services markets, where actors can provide backup reserve or frequency regulation. Indeed, at the time of delivery, some failures happen, or uncertainty in the prediction remains, and renewable energy providers might expect some volatility in their production. Adjusting to those small variabilities is done by allocating capacity in day-ahead markets and calling this capacity in real-time through an automatic gain control (AGC) signal.

Many countries have shifted or are in the process of from regulated monopolies to deregulated markets to incentivize through competition the most efficient technologies. Coupled with the right carbon market, those mechanisms can lower grid $CO2$ emissions while adapting to current and future challenges.

Regulators and governments are well aware of the power of markets and develop new regulations, pilot projects and studies, to find optimal market rules. The recent FERC 2222 order is one significant example of those changes: "*This rule enables DERs to participate alongside traditional resources in the regional organized wholesale markets through aggregations, opening US organized wholesale markets to new sources of energy and grid services. It will help provide a variety of benefits including: lower costs for consumers through enhanced competition, more grid flexibility and resilience, and more innovation within the electric power industry.*"

The European Network of Transmission System Operators for Electricity (ENTSO-E) represents 42 TSO across Europe and provides analysis and policy recommendations for electricity markets. Their recent white paper on *Market Design and System Operation towards 2030* [43] they specify that: "*Ongoing transformation of the power system, in particular increasing variable and unpredictable flows on all voltage levels, will require step-wise improvements of current models on both system operation and market design.*"

Several challenges and market improvements are raised in those reports. First, ancillary services markets do not always provide the right signal incentive, some grid needs are not well converted into prices (as congestion or frequency regulation), and thus, some actors are not integrated efficiently. Secondly, wholesale market rules are designed for traditional generators that can plan their generation but are not well suited for renewable energy generation that brings unpredictable variability. Finally, the prices are not yet coupled with global CO_2 emissions. Indeed, electricity is not an electron that comes from a location and is used somewhere else; every generation and consumption has a global effect on the grid; if renewable energy produced needs frequency control from a gas power plant, the total CO_2 emission per watt consumed is not zero.

DERs are well-positioned to respond to flexibility and frequency control on the grid; however, integrating resources connected to the distribution grid is challenging. Many of those reports are working on developing new market designs to fix those issues [57]. The third chapter of this dissertation will look more closely at a new market design to integrate DERs.

Distribution grid modeling, the missing tool

Achieving those goals and optimally operating the grid requires a good knowledge of the existing grid and infrastructure. It is vital for TSO, DSO, or regulators to have a good grid model that allows them to run power flow models, detect outages, plan for maintenance, and make the right decisions. Historically, the distribution grid was built to handle one-way power flow and standard load shapes and has been under-equipped with sensors and monitoring devices. Increasing sensors, data collection, and data analysis are essential to gain more knowledge on the grid. M. Bariya provides a deep understanding of available and new tools to collect and use grid data to increase DSO/TSO *situational awareness* [14]. This dissertation will give a detailed review of distribution grid topology estimation.

1.3 Research Overview

This research results from a four-year maturation process in a world that was realizing the threat of climate change, facing more frequent climate disasters, and fighting a worldwide epidemic that brought several energy crises. Choosing a research subject on a problem that responds to current issues cannot be done behind the closed doors of a University laboratory. Thus, several existing problems I encountered during my work in the industry inspired this

research. This section gives the reader explanations of those problems and how they inspired the following chapters.

The Hornsdale Power Reserve

In 2017, the Hornsdale Power Reserve was built in South Australia, the first 100MW and 129MWh grid-scale battery integrated into the Australian market. The integration of the battery led to another technical progress: an automatic bidding algorithm to trade the battery electricity on the electricity market. Indeed, while other generators could fix their bids to their marginal costs and manually design their trading policy, a battery has no marginal cost and needs to account for future prices to optimize its revenues. The actual charge and discharge of the Hornsdale Battery, depending on prices, is shown in Fig. 1.6. The basic behavior is to charge during low prices and discharge at high prices. Two other prices are mentioned in that figure, "FCAS lower" and "FCAS raise" Frequency Control and Ancillary Services (FCAS) markets allow specific devices to provide frequency control to the grid.

The performances of the Hornsdale battery on the FCAS markets led the battery to have market power on those markets; in other words, its bids impact the clearing prices. The battery has to consider this situation to design an optimal bidding strategy, which is not a simple task in practice. Modeling the market to include it in the optimization problem is complex and requires knowledge challenging to access.
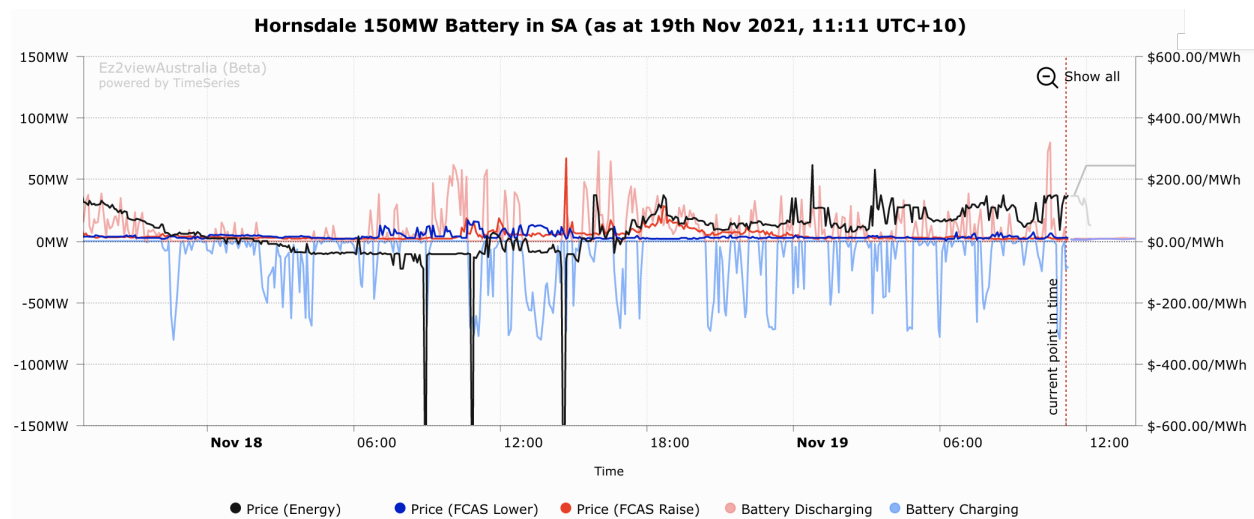
Figure 1.6: Hornsdale Power Reserve charge and discharge depending on prices over the last 36 hours [50]

Gird-scale batteries are necessary to guarantee grid reliability while integrating renewable

energies. However, building grid-scale batteries has a cost that must be covered by a good return on investment during operation. Thus, developing optimal bidding algorithms for grid-scale batteries on electricity markets is essential to increase economic incentives and attract more actors.

In recent years, reinforcement learning has been gaining in performance, and in attention [32]. The use of those *black box* techniques is interesting for power systems as they overcome modeling complexity. Fig. 1.8 shows the general framework of reinforcement learning; an action is decided from a control policy and is then applied to an environment, the resulting information is then used to update the policy and deduce the next action. The second chapter of this dissertation presents a reinforcement learning algorithm for optimally bidding on a market where the battery is a price-maker.
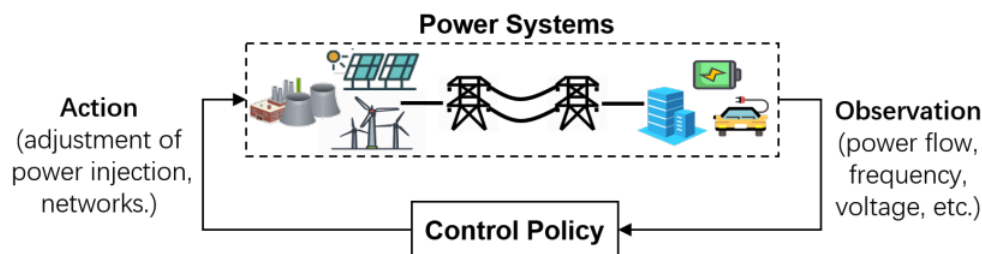
Figure 1.7: Reinforcement Learning schemes for the control and decision-making in power systems [32]

DERs in New Mexico Distribution Grid

Kit Carson Electric Cooperative (KCEC) is an electricity retailer and a DSO located in New Mexico. Like many in the United States, this electricity cooperative is transitioning to a 100% renewable energy grid while facing changes in consumers load. In 2020, KCEC has approximately 19.8 MWs of solar renewables online (and 21MWs planned in 2021), accounting for 56 % of the daytime load. In addition, KCEC customers are massively installing rooftop solar panels and adopting electric vehicles. However, those DSOs are not equipped with advanced metering and rely on outdated grid models. The practical expertise of their power system engineers is enormous but relies on their experience. When an outage happens, the analysis and repair are done mainly by sending someone to inspect the lines manually. While this method suffices in most situations, the distribution grid changes and requires better monitoring. Those improvements are possible by deploying sensors as PMUs and smart meters and better modeling of the distribution grid topology and parameters.
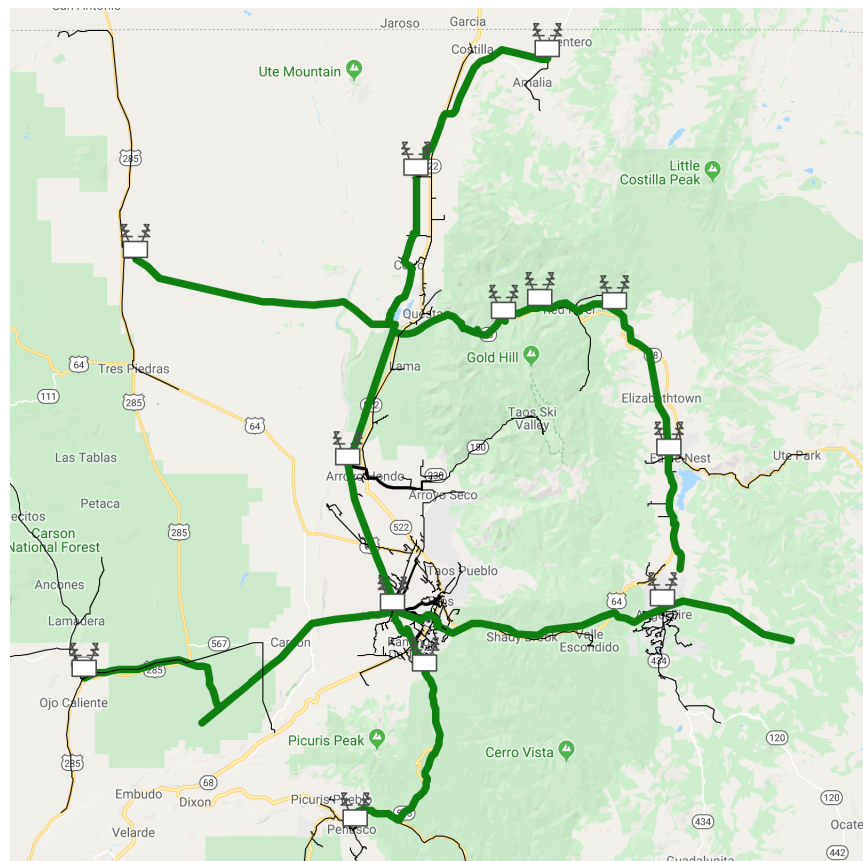
Figure 1.8: Kit Carson Electric Cooperative Grid

While installing more sensors is underway, the process takes time. More complex estimation algorithms have to be used to overcome the lack of sensors and grid modeling. The fourth chapter of this dissertation gives an overview of existing literature on topology estimation algorithms.

1.4 Contributions and Outlines

The rest of the thesis is organized as follows:

Chapter 2 presents an optimal bidding strategy for the price-maker grid-scale storage system. Developing an optimal bidding algorithm to respond to battery-specific market behavior is essential to provide batteries with the right incentives. The algorithm uses reinforcement learning to improve the bidding optimization and include the price-maker behavior. The paper provides an implementation that guarantees a safe performance during the neural network learning process. The novel contributions of this chapter are:

- Develop a new Supervised Actor-Critic algorithm. The supervisor technique reduces the action space dimension and thus accelerates the learning process while ensuring that the algorithm tries less dangerous actions. The supervisor is a naive and model-based algorithm, MPC, with the assumption that the battery is a *price-taker*. This algorithm is deterministic and does not take dangerous actions.

- Combine a new algorithm with a *shield* to protect the battery from charging or discharging above limits. And we add a penalty term to the reward function to inform the algorithm of dangerous actions.

- Provide a discussion on the use of reinforcement learning for bidding on electricity markets and the risks and benefits of such a technique.

Chapter 3 tackles the problem of integrating DERs on the electricity market. The paper provides a new day-ahead dispatch that considers the use of DERs flexibility to provide real-time balancing capacity. The novel contribution of this chapter is:

- Develop a co-optimization of the day-ahead energy market and balancing capacity market dispatch that integrates distributed energy resources as an uncertain source of flexibility.

- Aggregate DERs into a non-market player stochastic balancing reserve and the risk associated with their uncertain response is included using the conditional value at risk metric.

- Develop a data-based method to model the aggregated DERs stochastic response.

- Study the potential of using aggregated DERs into the balancing capacity market, despite the risk induced.

Chapter 4 reviews the problem of distribution grid topology estimation. To manage and integrate DERs on the electricity market, distribution system operators must have a good grid model that would be well suited for optimal power flow, event detection, equipment, or maintenance. The lack of sensors and available data complexifies distribution grid model estimation. In this chapter, we aim to provide a review of existing methods. The contributions of the chapter are:

- Describe the problem of topology detection and the challenges of real-world implementations.

- Classify the research papers solving the issue of distribution grid topology estimation.

- Provide a clear understanding of the remaining gap in the literature with regards to real-world issues.

Chapter 2

A Learning-based Optimal Market Bidding Strategy for Price-Maker Energy Storage

This chapter introduces an optimal bidding strategy, using reinforcement learning techniques, to tackle the specific situation of a price-maker grid-scale battery. This bidding algorithm provides a better understanding and integration of grid-scale flexibility resources on the wholesale market.

Load serving entities with storage units reach sizes and performances that can significantly impact clearing prices in electricity markets. Nevertheless, price endogeneity is rarely considered in storage bidding strategies and modeling the electricity market is a challenging task. Meanwhile, model-free reinforcement learning such as the Actor-Critic are becoming increasingly popular for designing energy system controllers. Yet implementation frequently requires lengthy, data-intense, and unsafe trial-and-error training. To fill these gaps, we implement an online Supervised Actor-Critic (SAC) algorithm, supervised with a model-based controller – Model Predictive Control (MPC). The energy storage agent is trained with this algorithm to optimally bid while learning and adjusting to its impact on the market clearing prices. We compare the supervised Actor-Critic algorithm with the MPC algorithm as a supervisor, finding that the former reaps higher profits via learning. Our contribution, thus, is an online and safe SAC algorithm that outperforms the current model-based state-of-the-art.

This chapter was originally presented at the *American Control Conference* in 2021 and may be cited as follows:

Mathilde D. Badoual and Scott J. Moura. "A Learning-based Optimal Market Bidding Strategy for Price-Maker Energy Storage". In: *2021 American Control Conference (ACC)*. 2021, pp. 526–532. DOI: 10.23919/ACC50511.2021.9483213

2.1   Introduction

Background & Motivation

Large-scale energy storage systems can solve a number of issues that can arise on electric power systems with high penetration of intermittent renewable energy generation. Energy storage and more specifically, lithium-ion batteries which are particularly fast to charge and discharge, can help to keep the voltage within bounds, stabilize grid frequency, and provide reserves that can be called on should a contingency occur. Storage can also address issues related to surplus that can occur when renewable sources produce more electricity than consumers demand, and can mitigate *congestion* when the transmission capacity of the system is exceeded. Because legacy grid technologies are unable to store electricity once produced, electricity prices vary significantly between times of surplus and shortage. This allows batteries to conduct *arbitrage*, and gives them a competitive edge on the energy market. [17] [27] [90].

In 2018, the U.S. Energy Information Administration [2] reported that operational large-scale battery storage represented 869 megawatts (MW) of power capacity and 1,236-megawatt hours (MWh) of energy capacity. Moreover, markets across the globe are implementing new regulations that will create new value streams for large-scale batteries [21]. In the US, the Federal Energy Regulatory Commission issued an order in 2011 requiring transmission grid operators – including Independent System Operators and Regional Transmission Operations (ISO/RTO) – to compensate fast-ramping resources on the frequency regulation market [54]. In Europe, the Frequency Control Regulation (FCR) market is updated to respond to the increased need for battery storage [49]. These new market rules favor grid-scale storage resources, which have response capabilities that conventional generation resources do not. These market incentives have led to increased investment in energy storage capacity.

The increase in storage capacity coupled with a unique position in the market has caused grid-scale energy storage to become a driver of the market price. In economic terms, energy storage is said to be a *price-maker*, or a monopolistic seller capable of influencing the market because no substitutes exist for their product. Conventional power plants, on the other hand, are said to be a *price-taker* with trivial influence on the market due to market size, suitability, or other anti-competitive factors. In a perfectly competitive market, all the sellers are *price-takers* and bid their marginal cost. More details on the price-maker/price-taker concepts can be found in [87] and [23].

One real-world example is the Australian Hornsdale power reserve. Upon entering the Australian market [94] [79] in December 2017, the battery achieved over 55% of the Frequency Control Ancilliary Services (FCAS) revenues in South Australia and prices went down by 90%. This occurred both due to the size of the battery and due to its fast-ramping capabilities that could not be matched by other market participants with pre-existing technologies.

Strategic bidding in markets with *price-makers* is a very challenging problem, due to the complexity of the market model as well as the lack of information about other players. Each agent must try to anticipate not only the demand but also the actions of other market

participants. However, agents generally do not have models that describe the bidding strategies of other market participants. The current work explores the use of adaptive control for optimizing the bidding strategy of a *price-maker* agent participating in a regular wholesale market.

Literature Review

Several papers explore optimal bidding algorithms on the electricity market when bids influence the clearing price, i.e. the market player is a *price-maker*. Some relevant examples include the following: Oren et al. [73] computed the optimal bidding strategy with dynamic programming by estimating other market players. Kwon et al. [58] review the optimization problem for bidding in the day ahead market. Velazquez et al. [93] base their bidding strategy on the study of the residual demand curve.

The bidding of energy storage capacity on the electricity market adds a layer of complexity. The battery has a limited capacity and accumulates revenue by scheduling efficiently generation and load modes. J. Arteaga et al. [10] develop a robust and stochastic optimization for the bidding on the Real-Time and Day-Ahead market in which the battery is a *price-taker*. They also study participation in the ancillary services market where the storage system is *price-maker* due to the battery efficiency in ramping up and down under emergency.

Throughout this literature, a common method to solve the optimal bidding strategy for a *price-maker* is used. A bi-level optimization program where the first layer maximizes the player's revenue and the second layer solves a dispatch problem to maximize the social welfare. This method is developed, among others, by Tómasson et al. [92] and Y. Ye et al. [98]. The resulting bi-level optimization problem is complex to solve and is commonly simplified using the Karush-Kuhn-Tucker (KKT) conditions relying on the convexity of the problem which is not guaranteed. Indeed, modeling the energy market dynamics as an optimization problem yields non-linearities. For instance, the dispatch can involve binary unit commitments. Perhaps more importantly, modeling the entire market requires knowledge of other players' strategies and predictions of their future behaviors. This can be difficult or even impossible due to lack of data and highly non-predictable behavior. Moreover, market prices can be volatile and depend on physical constraints, e.g. congestion, frequency instabilities.

A possible solution for this problem is to use learning-based and adaptive controllers, such as reinforcement Learning (RL) which learns a controller (or policy) via structured trial-and-error. Such techniques enable design of controllers for partially known systems. Moreover, the learned controller becomes a function mapping the state to an action (state-feedback control), which makes the controller computationally efficient. Glavic et al. [48] review the literature of Reinforcement Learning in electric power system decision making, presenting recent breakthroughs in Reinforcement Learning such as "safe RL" and "path integral control for RL". More recently Z. Zhang et al. [103] review the application of Deep Reinforcement Learning (DRL) – Reinforcement Learning with the use of Deep Neural Networks – in Power

Systems. They point out the benefits of DRL as an adaptive and model-free controller applied on electricity market trading in the case of incomplete information.

Among others, Gajjar et al. [47] use an Actor-Critic Algorithm to solve the bidding problem. The authors construct an Actor-Critic algorithm to model the behavior of generating companies, formalizing a mathematical model for competitor's behavior. However the battery is considered as a *price-taker* on the market. As a result, the paper does not investigate the use of DRL in an environment reacting to its action. Y. Ye et al. [98] use a form of Policy Gradient method in the case of a *price-maker* battery. The algorithm is a Deep Deterministic Policy Gradient with a Prioritized experience replay. In other words, Ye et al. use a policy gradient trained using a prioritized sample batch. The paper reports interesting results but does not tackle the safety issue of trial and error training on a real market, neither the complexity of building a realistic market environment for an off-line training. Indeed, the main justification for the use of RL and DRL lies in the complexity of the market model which makes the optimization of the bidding strategy a complex task. However, if this model can be built to train an adaptive algorithm, then optimization techniques will be more safe and reliable than a trial and error training.

Safety in DRL can take multiple definitions. In our context, safety is achieved when actions taken by the DRL algorithm, also called agent or policy, are not putting the system in states that are physically impossible to reach and that can lead to dangerous situations, such as discharging an empty battery.

Contributions

The main contribution of this paper is to ensure safety and improve performance via an online learning-based algorithm for optimal energy storage bidding, under *price-maker* conditions. Specifically, we develop a Supervised Actor-Critic algorithm. The supervisor technique reduces the action space dimension and thus accelerates the learning process while ensuring that the algorithm tries less dangerous actions. The supervisor is a naive and model-based algorithm, MPC, with the assumption that the battery is a *price-taker*. This algorithm is deterministic and does not take dangerous actions. In addition, we develop a shield, to protect the battery from charging or discharging above limits. Finally, we add a penalty term to the reward function to inform the algorithm of dangerous actions. We achieve a more efficient bidding strategy than the baseline model-based technique, while also ensuring safety during training.

Chapter Organization

Section II, details the market model and simulation. Section III introduces the Supervised Actor-Critic and Section IV describes the results.

2.2 Market and Storage System Model

In this section we describe the market setup and energy storage system operation used in our simulation.
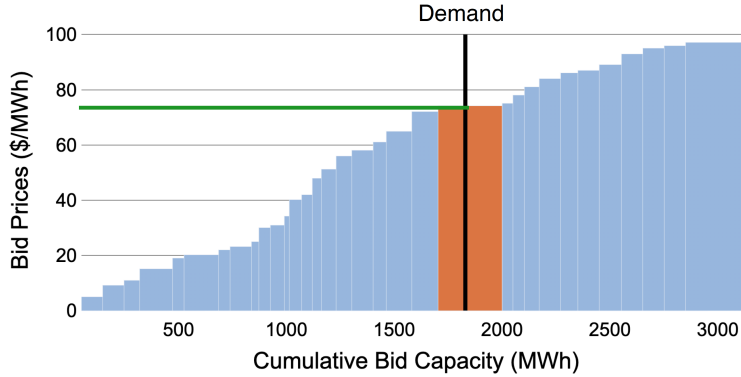
Figure 2.1: The Market Clearing Process as a Uniform-Price Auction

The electricity market is managed by the Independent System Operator (ISO) and maximizes the social welfare across generators and consumers so that enough generation is dispatched to serve a predicted demand. One step of the bidding process is represented in Fig. 2.1, where the demand is the vertical black line. At the point where the cumulative bid capacity reaches the demand, the market clears at this bid price, represented by the green line on the figure. This price is the so-called clearing price. The market used in this paper follows a *uniform-price auction* [8], i.e. the actors are paid the clearing price instead of being paid at their bidding price. The clearing process can be written as the following optimization problem (1)-(3):

$$\min_{P^t} \quad \sum_{i=0}^{n} c_i^t P_i^t \tag{2.1}$$

$$\text{s.t} \quad \forall i, \quad 0 \le P_i^t \le p_i^t \tag{2.2}$$

$$\sum_{i=0}^{n} P_i^t = \hat{d}_t \tag{2.3}$$

Each agent is represented by the index i and sends a bid at each time step t. A bid is of the form $\{c_i^t, p_i^t\}$ where c_i^t is the cost per unit energy and p_i^t is the capacity that the agent i can provide during time t. The variable $\hat{d}_t$ is the total predicted energy demand from retailers, industrial sites or storage systems. The market solves the social welfare maximization problem (1) by dispatching a capacity P_i^t for each agent while matching supply and demand (3). This capacity is either 0 when the bid is not cleared, or a number between

0 and p^t, the capacity bid by the agent (2). The optimization variable is $P^t = [P_0^t \ \cdots \ P_n^t]^T$ with n the number of agents.

The complete bidding process of the battery owner or agent can be described as follows, and represented in Fig. 2.2. The agent sends a bid to the market. The market clears the bids depending on the demand and according to the process described in Fig. 2.1. Then, if the battery bid is cleared amongst all bids to the left of the black line in Fig. 2.1, a command is passed to the battery to provide the capacity dispatched by the market at the cleared price. The combination of the market state and the battery state is sent back to the battery's bidding agent to compute a new bid at the next step.

Batteries generally have a larger impact on ancillary service markets and especially on frequency control markets. The reason is that, in small markets, the battery's fast response give them a competitive advantage over other players [19]. Here, we focus on the use and limitations of reinforcement learning as a bidding algorithm. We use a stylized representation of market dynamics in order to focus more specifically on the algorithm itself.

2.3 Bidding Strategy Algorithm

In this section we introduce two algorithms: the first is a common Model Predictive Control (MPC) algorithm that computes the optimal bidding strategy over a one day horizon. It will serve as our benchmark algorithm, and importantly it does not take into account that the battery is a *price-maker* on the market. The second and novel approach is an adaptive controller which learns and adapts to the *price-maker* situation. Specifically, the proposed controller is trained using a new SAC algorithm where the supervisor is the aforementioned MPC controller.

The online training of the SAC during the simulation is detailed in Fig. 2.2, and explained in the next sections.

Model Predictive Control as a RL Supervisor

Under the *price-taker* assumption, the energy prices are considered exogenous to the bidding strategy, and the optimal bidding strategy is computed regardless of its impact on the market price. In this case, the strategy relies on predictions of the clearing price: $\hat{\lambda}_{energy}^t$ and is
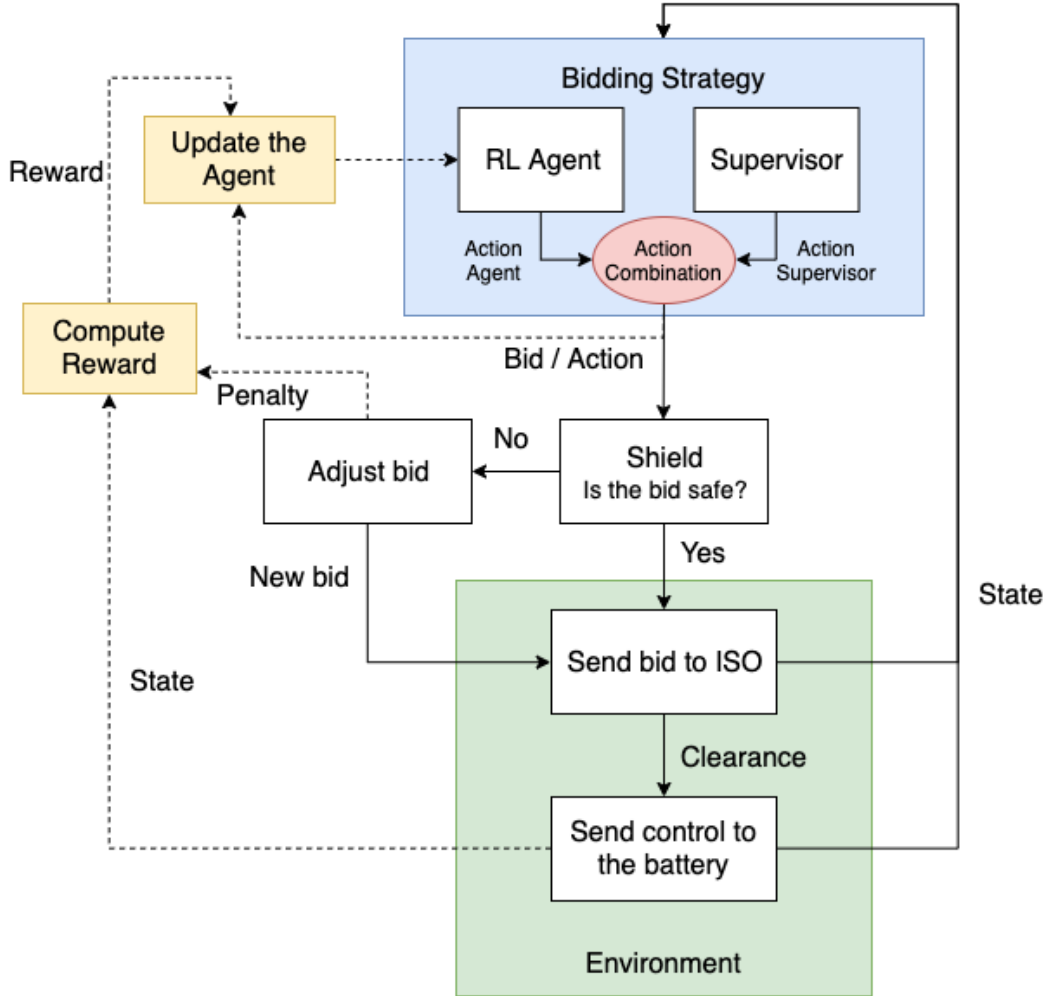
Figure 2.2: Learning and Bidding procedure for the proposed SAC. Bids are produced by combining actions from the MPC supervisor and the DRL agent. A shield adjusts bids to ensure physical and market constraints are satisfied by allowing only feasible bids. After the market clears and the battery state evolves, the reward (i.e. profit) is used to update the DRL agent.

formulated as a common deterministic Model Predictive Control algorithm:

$$\max_{p_l, p_g, soe, m \in \mathbb{R}^H} \quad \sum_{t=T}^{T+H} \hat{\lambda}^t (p_g^t - p_l^t) \tag{2.4}$$

$$\text{s. to:} \quad \forall t, \quad soe^{t+1} = soe^t - \eta_g p_g^t + \eta_l p_l^t \tag{2.5}$$

$$m^t \in \{0, 1\} \tag{2.6}$$

$$0 \leq p_l^t \leq m^t \overline{p_l} \tag{2.7}$$

$$0 \leq p_g^t \leq (1 - m^t) \overline{p_g} \tag{2.8}$$

$$\underline{soe} \leq soe^t \leq \overline{soe} \tag{2.9}$$

The cost function (4) is the cumulative revenue for the energy storage system owner over the horizon H. The variables p_l^t and p_g^t are the load and generation bids with price $\hat{\lambda}^t$. Equation (5) describes the storage system dynamics, with coefficients η_g and η_l referring to the charging and discharging efficiency coefficients. Since the storage system agent is not allowed to participate on the energy market as a load *and* a generator simultaneously, constraint (6) forces the solution to chose between one of the two products (7) and (8). The remaining constraints (9) are physical limits on the storage system capacities. Other physical constraints as temperature could be added in the form of linear constraints without changing the structure of the problem solved in this paper.

In a perfectly competitive uniform-price auction market the agents are bidding their marginal cost. The marginal cost of the battery can be seen as the cost of electricity at the time of generation, thus the battery bids the expected clearing price $\hat{\lambda}^t$. As a *price-taker* the battery will not impact the market clearing price and can be sure to clear if its bidding price is less than or equal to the market clearing price. The complete bid can be written as: $\{c^t, p^t\} = \{\hat{\lambda}^t, p_g^t - p_l^t\}$.

The problem is formulated for a horizon H, which allows the battery to plan its charging and discharging schedule depending on the variation of electricity prices. In MPC, only the first step of the solution bid is used and the problem is re-computed at every new time step t.

Supervised Actor-Critic Algorithm

Reinforcement Learning (RL) theory is based on the idea that we learn how to perform an *action* in an *environment* by structured try-fail cycles. In other words, after performing an action, we receive a *reward*, which measures the value of our action. We then learn how to increase that reward with subsequent actions. Sutton and Barto provide an excellent conceptual exposition of RL theory and application [89].

The system at time t is described by state s^t, and the agent's action is denoted by a^t. We define a reward function that quantifies the agent's performance, $r(s^t, a^t)$. The objective is to refine a policy π_θ that maximizes the expected cumulative reward of the trajectory $\tau = ((s^1, a^1), ..., (s^t, a^t))$:

$$J(\tau) = \sum_{t=1}^{\infty} \gamma^t r(s^t, a^t) \tag{2.10}$$

where γ represents a "discount factor" that priorities near-term gains over future and less certain events. We also introduce the value function:

$$V(s^t) = \mathbb{E}_{a \sim \pi_\theta}[\sum_{i=t}^{\infty} \gamma^i r(a^i, s^i)] \tag{2.11}$$

The value function $V(s^t)$ represents the expected cumulative reward, starting from state s^t until $t \to \infty$, under policy π. The value function satisfies Bellman's Equation, where s^{t+1} is

the state at $t + 1$ time step:

$$V(s^t) = \mathbb{E}_{a^t \sim \pi_\theta}[r(a^t, s^t) + \gamma V(s^{t+1})] \tag{2.12}$$

The Actor-Critic algorithm estimates the value function from data. To compute these estimates, we utilize Bellman's equation as a regression model. Namely, we define the temporal difference δ [88] as:

$$\delta^t = r(a^t, s^t) + \gamma V(s^{t+1}) - V(s^t) \tag{2.13}$$

The Actor-Critic algorithm involves an "actor" that runs the policy π_θ with parameters θ, and the "Critic" which is an estimate of the value function V_ω with parameters ω.

The Supervised Actor-Critic algorithm is similar to AC, with the addition of a "supervisor" policy that also proposes an action. The final action applied is a combination of the supervisor's and the Actor's action. Introduced by Rosenstein and Barto [81], the SAC is implemented as follows:

Initialization: We initialize the parameters of the Actor and the Critic, respectively θ and ω.

The Actor's parameters are first updated with the difference between the policy action a_A^t and the supervisor action a_S^t by one step of stochastic gradient descent on the following optimization problem:

$$\min_\theta \left\{ F_a(a_A^t, a_S^t) = \frac{1}{2}\|a_A^t - a_S^t\|^2 \right\} \tag{2.14}$$

Then the combined action is chosen using the risk parameter k, where $a_E^t \sim \mathcal{N}(0, \sigma)$ is an exploration term:

$$a^t = (1 - k)(a_A^t + a_E^t) + ka_S^t \tag{2.15}$$

Critic and Actor Updates: The Critic and the Actor's parameters are then updated using Temporal Difference and Bellman's Principle of Optimality equation with the updated value function. To update the critic, we again run one step of stochastic gradient descent on the following optimization problems:

$$\min_\omega \left\{ F_c(\delta^t) = \frac{1}{2}\|\delta^t\|^2 \right\} \tag{2.16}$$

Finally, we update the parameters of the Actor in order to increase the value function. The update is based on Bellman's principle of optimality:

$$\theta \leftarrow \arg \max_\theta \mathbb{E}_{a^t \sim \pi_\theta}[r(a^t, s^t) + \gamma V(s^{t+1})] \tag{2.17}$$

In practice (2.17) is computed using the Policy Gradient Theorem with "baseline", detailed by Sutton and Barto [89]. The "baseline" here is an estimate of the value function given by the Critic. The update is the following:

$$\theta \leftarrow \theta + \beta_2 \delta^t \nabla_\theta \ln \pi_\theta(s^t) \tag{2.18}$$

Algorithm 1 Supervised Actor-Critic

0: **Inputs**

0:     $V_\omega(s)$, Critic value function parameterized by ω

0:     π_θ^A, Actor policy parameterized by θ

0:     π^S, supervisor policy

0:     σ, exploration factor

0:     α, Critic step size

0:     β_1 and β_2, Actor step size

0:     $\gamma \in [0, 1]$, discount factor

0: **initialize** θ, ω randomly

0: **initialize** $s \leftarrow$ starting state

0: **repeat** for each time step, t

0:     $a^A \leftarrow$ action given by $\pi_\theta^A(s)$

0:     $a^S \leftarrow$ action given by a supervisor policy $\pi^S(s)$

0:     $\theta \leftarrow \theta + \beta_1 \nabla_\theta F_a(a^A, a^S)$

0:     $a^E \sim \mathcal{N}(0, \sigma)$

0:     $a \leftarrow (1 - k)(a^A + a^E) + ka^S$

0: **if** a is not safe **then**

0:         $a \leftarrow a^S$

0: **end if**

0:     **take** action a, **observe** reward, r, and next state, s'

0:     $\delta \leftarrow r + \gamma V(s') - V(s)$

0:     $\theta \leftarrow \theta + \beta_2 \delta^t \nabla_\theta \ln \pi_\theta(s^t)$

0:     $\omega \leftarrow \omega + \alpha \nabla_\omega F_c(\delta)$

0:     $s \leftarrow s'$

0:     Update $k \in [0, 1]$

0: **until** terminal state reached =0

Algorithm 1 details the implementation of the Supervised Actor-Critic.

The SAC algorithm allows the bidding algorithm to train online while satisfying physical and market constraints during exploration. When the RL agent yields higher rewards than MPC, then the coefficient k can be changed from $k = 0$ toward $k = 0.5$ to progressively weight in favor of the RL agent's bid.

To implement this algorithm within our environment, we specify the state, the action, and the reward formulation as follows.

The **environment** or system (i.e. the storage system and market) has the following state: t_{day} is the time step of the day, λ is a price either estimated, $\hat{\lambda}$, or exactly known, λ, and $\hat{d}_{up}$ is the estimated demand for the market. In math, $s^t = \left[\hat{\lambda}^t, \lambda^{t-1}, soe^t, t_{day}, \hat{d}^t \right]$.

The **action** is composed of the energy market bid at time t. A bid has the following structure: $a^t = \{\lambda^t, p_g^t - p_l^t\}$.

In order to propose safe actions (actions that lead to a feasible state) while learning,

we transform our reward function using a Lagrangian with predefined Lagrange multipliers. This is equivalent to adding penalty terms to the reward. The **reward** function is as follows:

$$r(a^t, s^t) = \hat{\lambda}^t(p_g^t - p_l^t) + \mu^T \mathcal{Y}(a^t, s^t) \tag{2.19}$$

where $\mathcal{Y}(a^t, s^t)$ refers to constraints (5) - (9) listed in the MPC formulation, and μ serves as weights to penalize constraints violations.

2.4 Experiment and Results

Experimental Settings

We run the simulation using electricity demand data from the Australian electricity market, also known as AEMO (Australian Energy Market Operator) [6]. The simulation is run over 5 months: June to October 2018. The other players are simulated as deterministic agents bidding a fixed quantity at a fixed marginal cost.

The parameters used for the supervised Actor-Critic are: We set $k = 0$ for the first 400

Table 2.1: SAC Parameters

Parameters	Values
γ discount factor	0.98
optimizer	Adagrad [51]
learning rate	10^{-4}
hidden layers	6
Activation function	Leaky Relu
exploration σ	1

steps in order to select the supervisor's action while the Actor-Critic agent is training. We then progressively increase the value of k until it reaches 0.5. The update of k is shown in Fig. 2.3.
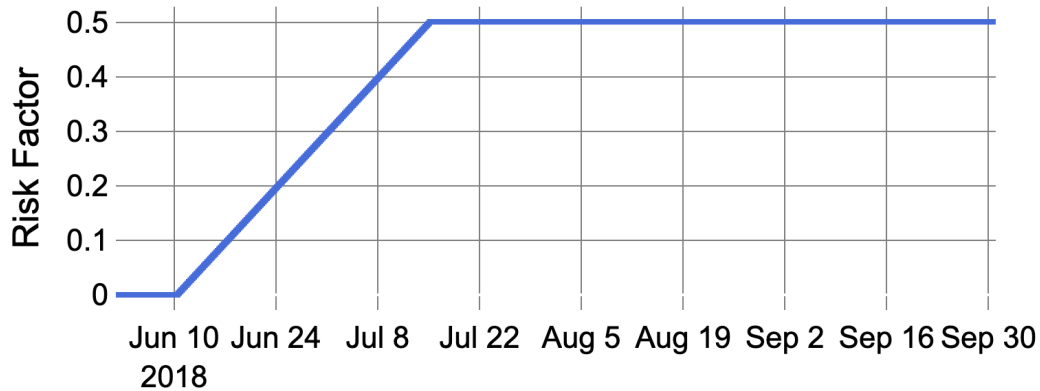
Figure 2.3: Risk Factor Update

The battery is designed with a capacity of 1029 MWh and a maximum capacity of 300 MWh. Those number are unrealistic but in order to simulate the behavior of a *price-taker* on the energy market we had to increase the battery capacity to create market power. We remind that batteries are *price-maker* on smaller markets as ancillary services markets. The charging and discharging efficiency rate are set to 1 for simplicity. When the battery behaves as a load, its bid is added directly to the total load of the grid. As a generator the battery bid is submitted to the clearing process described in Section 2.2.

Results

First, we evaluate that the MPC is behaving correctly, i.e. buying electricity at low price and selling at higher price. Figure 2.4 plots the simulation result over two days. The bar plot in the above figure represents the generation and load bids capacity that were cleared by the market. The black line is the cleared price and the green line is the battery's bidding price. The MPC bids as a generator when prices are high and as a load when prices are low. An interesting observation is that the MPC algorithm bids at the clearing price when behaving as a generator. That is, the battery plays the role of the orange bid in Fig. 2.1. In this case, the market cannot clear the entire capacity bid since this is the marginal bid. As a consequence the battery is not discharging as much capacity as predicted by the MPC, this is the main source of loss for the MPC algorithm. Another observation is that when the battery behaves as a load, it increases the demand and consequently increases the prices due to the price-maker condition occurring.

In addition to showing the expected behavior, Fig. 2.4 highlights the impact of the battery's bids on the market: Our system is a *price-maker* on this market.

We then apply the SAC algorithm to the same simulation. Our claim is that the SAC algorithm would recognize the battery's impact on the electricity market, and adapt. As

a result, it is interesting but expected to see that the clearing price distribution varies
depending on the bidding algorithm, as shown in Fig. 2.5.
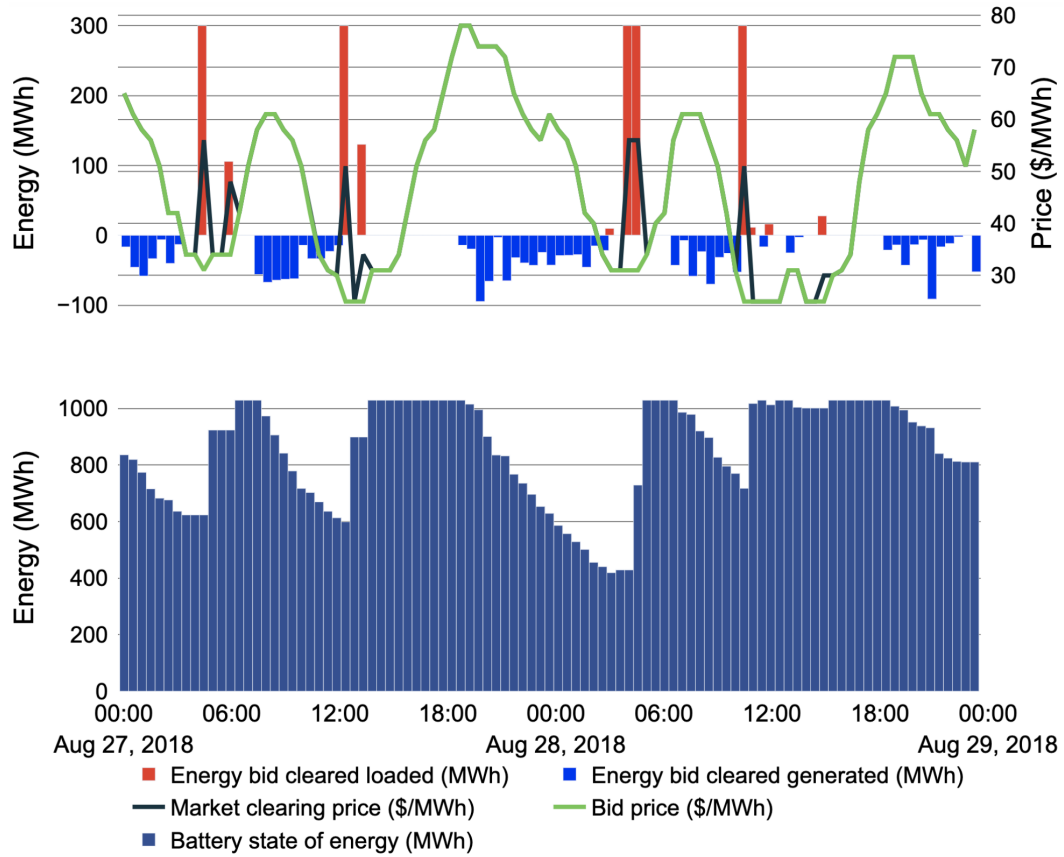
Figure 2.4: MPC strategy over two days of the simulation
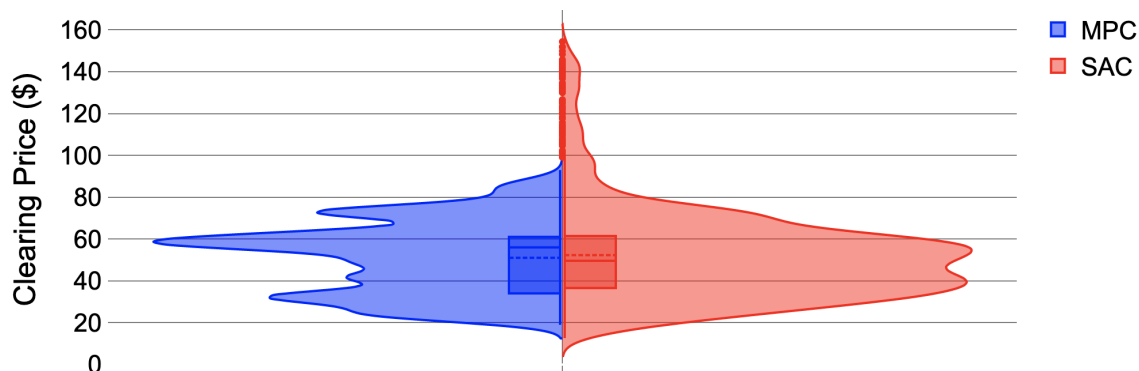
Figure 2.5: Market Clearing Price Distribution for MPC and SAC

To compare the SAC with the MPC algorithm, we compute in Table 2.2 the total revenue earned by the two algorithms. The SAC significantly outperforms the MPC algorithm by earning over 3.5 times more revenue on average. In Fig. 2.6 we can see the cumulative revenue increasing at a much faster rate after the increase of k over the time.

The SAC proves to be a safe algorithm: only 6% of the bids are charging or discharging the battery above limits. Fortunately our system is built with a shield that blocs those actions.

To understand the behavioral differences between the two algorithms we plot the distribution of the battery state of energy in Fig. 2.7, as well as the distribution of capacity bids in Fig. 2.8. The state of energy is varying across the entire range of possible values with SAC, taking full advantage of the battery's energy capacity. With MPC, the battery discharges less energy on the grid. This observation is related to the conclusion made on Fig. 2.4. Namely, the battery clears at the market clearing price and thus does not clear the entire capacity bid. We observe that the SAC algorithm solves this problem by recognizing the lower cleared quantity, and consequently adjusts the bid. This results in using the entire range of the battery capacity which leads to a significantly higher revenue.

Table 2.2: Bidding Strategies

	SAC	MPC
Average revenue per day	**599 $/day**	175 $/day
Average % of bids capacity cleared	**80%**	15%
Violations of battery capacity before shield	6 %	**0 %**
% of Generator bids	**66 %**	63 %
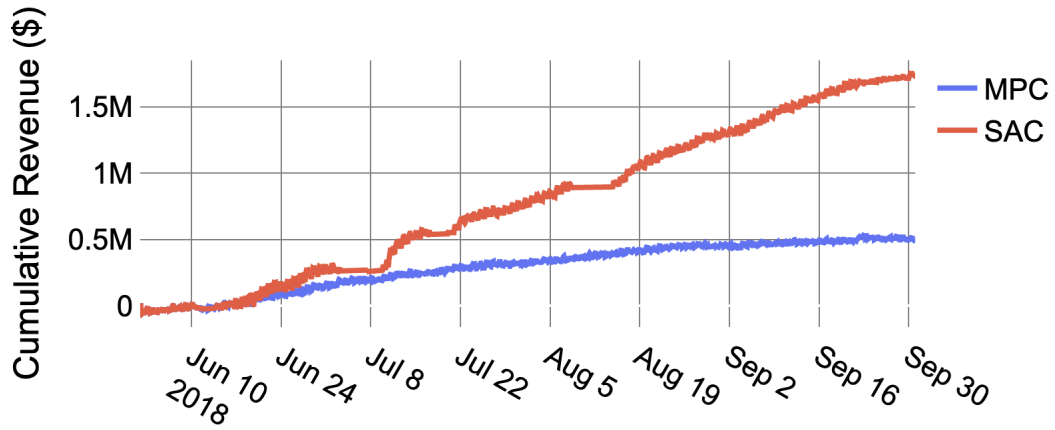
Figure 2.6: Cumulative Revenue for MPC and SAC
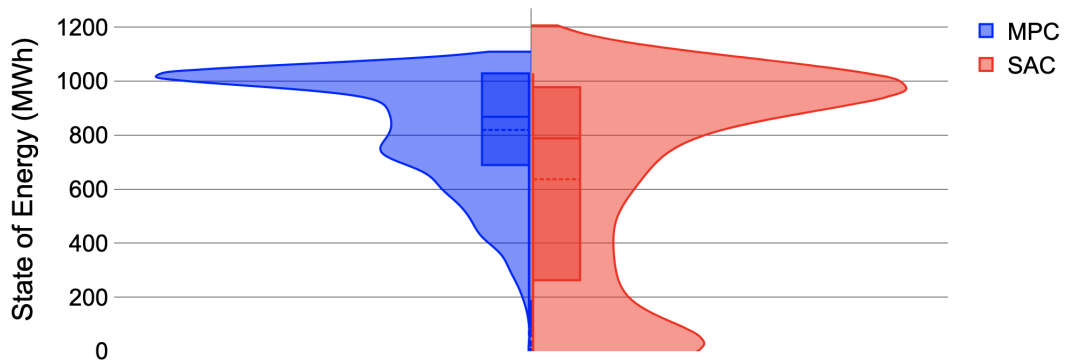
Figure 2.7: Battery State of Energy Distribution for MPC and SAC
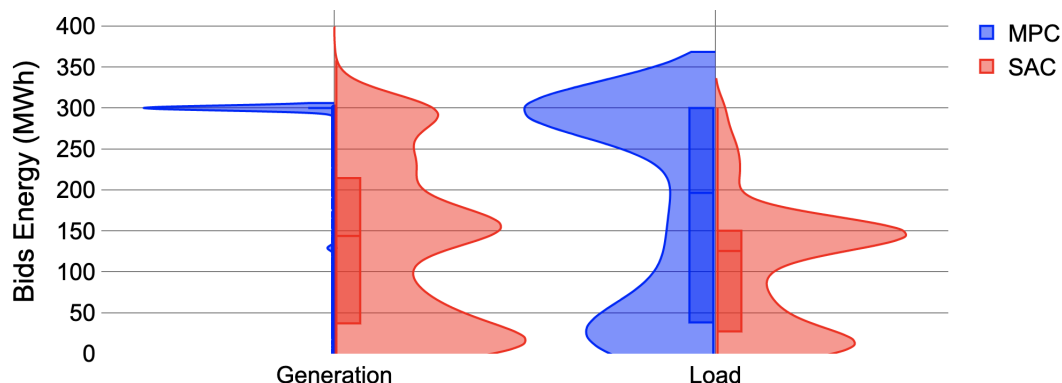
Figure 2.8: Generation and Load Bids for MPC and SAC

Yielding higher revenue charging and discharging cycles of the battery requires that the SAC generates more strategic bids. In Fig. 2.8 we compare the distribution of capacity bids between the two algorithms. The MPC constantly bids as a generator at a capacity of 300 MWh, which is the maximum. This strategy is normal since the battery is most of the time at high state of energy and thus can discharge at maximum rate. The SAC strategy cannot bid more than the battery capacity allows, which yields a broad distribution in Fig. 2.7. Another interesting behavior to point out is that the SAC generated load bids that are lower than MPC. However the load bids behave like an additional demand for the market and thus increases the clearing price a significant amount as seen in Fig. 2.4. Recall that the battery pays the market the clearing price when it operates as a load. The SAC recognizes that when the battery operates as a load, it inflates prices. Consequently, the SAC algorithm has lower capacity bids as to not inflate instantaneous costs.

2.5   Conclusion

Learning-based methods are particularly well suited to answer the need for optimal bidding algorithms. Indeed, markets have always been complex to model as they are multi-player and dynamic systems, but are necessary to understand when one player's bid impacts the clearing process, or when an ISO experiments with new market designs. For this reason, model-free or learning-based algorithms such as DRL are an appealing option. Those algorithms do not require a complete model of the system, and can adapt their actions in response to observed impacts on the system. DRL has proven its efficiency for controlling robots, playing video games, and targeting web content, but is rarely applied in energy systems. The main reason is because those algorithms learn through trial and error, and error can have dangerous consequences in real-world energy systems. Designing simulations to train these algorithms raises a paradox: if we can build a model of the environment, then why use a model-free algorithm?

To use DRL in real-world energy system, we must overcome the danger of training the algorithm. Techniques like developing shields to limit dangerous actions, adding penalty terms to the reward function, or using supervisors to reduce the search in the action space have the potential to solve this issue.

In this paper, we develop a Supervised Actor-Critic algorithm to optimally bid the energy of a *price-maker* grid-scale battery on the electricity market. In addition, we use a shield as well as a penalty term in the reward to avoid dangerous actions.

The results show that those techniques improve bidding performance relative to the baseline *price-taker* algorithm, while ensuring safety during algorithm training.

This first approach is experimental, and developing those techniques at an industrial level would require more theoretical work on the action space reduction and the effect of a shield. Moreover, future work could study the reaction of the SAC to a market with dynamic and multiple *price-maker* players.

Chapter 3

Stochastic DERs in a Co-optimized Balancing Capacity and Day-ahead Electricity Market

This chapter explores the integration of another source of flexibility, in the distribution system, defined as DERs.

As societies electrify loads and the electrical grid incorporates more renewable energy resources, new balancing control mechanisms are needed. Meanwhile, Distributed Energy Resources (DERs), such as electric vehicles and rooftop solar panels, are increasing load variability and uncertainty in the distribution grid. Yet DERs are also a potential source of flexibility when used and controlled as a balancing reserve. Designing a control system for DERs is challenging because a DER's response to control signals is uncertain and requires a specific market design. This paper introduces a new stochastic risk-aware co-optimization between day-ahead and balancing capacity dispatch that integrates DERs as an aggregate of stochastic reserve resources. In our approach the aggregate of DERs does not behave as a market player but only distributes the control command to DERs. We develop a data-driven method to model the DERs' aggregate uncertainty at the market level, and incorporate the risk implied by DERs' uncertainty via the conditional value at risk metric. Finally, We study the effect of the risk threshold on the dispatch results.

3.1 Introduction

Motivation

Decarbonizing society involves increasing renewable energy shares in the generation mix, and electrifying energy use. In recent years, this process has led to a proliferation of Distributed Energy Resources (DERs).

According to the Federal Energy Regulatory Commission (FERC) [46], DERs are electric-

ity generation units, typically from 1 to 10MW, connected to the distribution grid: "DERs may include electric storage, intermittent generation, distributed generation, demand response, energy efficiency, thermal storage or electric vehicles and their charging equipment" [46]. Due to their distributed, variable and consumer-centered nature, DERs cause unanticipated power flows and increase demand forecast errors [72]. On the other hand, the International Renewable Energy Agency (IRENA) reports that DERs can increase grid flexibility by enabling load shifting and peak shaving, or by providing ancillary services for voltage regulation, balancing control or congestion management [7]. However, despite their great potential for the grid, DERs are largely being installed without being fully internalized into grid modeling and operating tools. In addition, DERs' response to control signals are inherently unreliable as they are subordinated to variable capacity factors, human decisions and communication glitches. Integrating DERs requires one to answer three main questions: How should operators account for the DERs' unreliability? Who should be responsible for their aggregation? And how to compute their valuation? In this paper we will address the two first issues by proposing a new dispatch algorithm for the electricity market.

Background on Electricity Markets

Electricity markets are organized as a two-sided auction where producers, retailers and large consumers submit offers and bids [69]. The dispatch is first run, a day before delivery in the day-ahead market. Then generation dispatch is adjusted through the intra-day market. In addition, because the grid faces unpredictable events and uncertain loads or generation (such as wind generation), the dispatch requires real time adjustments, which are performed during the balancing market.

In most countries, day-ahead and intra-day markets are managed by market operators. In parallel, the Transmission System Operator (TSO) or Independent System Operator (ISO) performs a balancing or reserve capacity market, where some generators capacities are secured to back-up some balancing needs during real-time adjustments. After the day-ahead market clears, the market operator sends the dispatch results to the TSO/ISO who is then responsible for adjusting the grid frequency by calling reserves in a balancing or reserve energy market.

Literature Review

Many papers introduce DERs aggregators which behave as virtual power plants from the ISO/TSO's point of view. In most cases, the aggregator manages the risk of the uncertain DERs response. This is the case of the work of A. Papavasiliou et al. [74] which explores efficient designs with or without aggregators to use deferrable demand as a source of reserve, with a large penetration of renewable energy resources. P. Beraldi [18] develops a more detailed aggregator control integrating DERs' stochasticity. Finally, the work of H. Zhang [102] provides an aggregator dispatch algorithm that optimally bids on the regulation market while managing DER uncertainty. The economic value of aggregators as a transitory solution

to integrate DERs is studied by S. Burger et al. [26]. S. Burger et al. conclude that the value of aggregators comes from the lack of efficient information pipelines between the ISO/TSO and DERs.

However, DERs aggregators remain less reliable than other traditional generators and can interfere in ISO/TSO's grid management decisions. This represents a significant entry barrier to integrate DERs into electricity markets. Hence, the recent FERC 2222 order proposes that DERs aggregators be integrated in the wholesale market as particular market players [46]. In this order, the DERs control is given to third parties aggregators which are acting as black boxes under the scope of DSOs. In this paper, we argue that aggregators should not be integrated as market players but only as a communication layer between TSO/ISO and DERs.

In the meantime, the high variability of renewable energy has driven the needs for reserve capacity [7]. J. Morales [70] shows, using optimization models, that high penetration of wind creates an economic value for reserve. Similarly A. Papavasiliou et al. [75] develop a stochastic dispatch for balancing capacity markets that face wind power integration. The gap in the literature is the lack of electricity market designs that integrate DERs aggregators as a non market source of uncertain reserve.

DERs are known to provide reserve flexibility which is needed to balance renewable energy variability and should be used in balancing control mechanisms. DERs' characteristics and opportunities to enter the reserve market are analysed by J. Merinos et al. [67]. However, J. Merinos et al. emphasize the lack of existing procedures and market rules to optimally integrate DERs into market dispatch.

Without directly considering DERs, various works study market designs that integrate uncertainty from renewable energy resources. The book from J. M. Morales et al. [69] introduces the baseline for market design, with the use of two-level stochastic optimization in the day-ahead market to account for the real-time operational costs. In addition, the book presents a co-optimization between the capacity balancing market, and day-ahead dispatch. In [82], P. A. Ruiz et al. expose additional advantages of a joint stochastic unit commitment and balancing capacity market for uncertainty management.

In this paper, we formulate a day-ahead dispatch coupled with a balancing capacity market. This comes down to a two level stochastic optimization accounting for real-time operational cost. Here, the aggregated DERs are incorporated as uncertain source of reserve, available in real-time operation. However aggregators are not independent agents that maximize their profits. Instead, they only compute and send the local command to DERs following the reserve order from the ISO/TSO real-time operation dispatch.

Contributions

The main contribution of this paper is to develop a co-optimization of the day-ahead energy market and balancing capacity market dispatch that integrates distributed energy resources as an uncertain source of flexibility. DERs are aggregated into a non-market player stochastic balancing reserve and the risk associated with their uncertain response is included using the

conditional value at risk metric. In addition, we develop a data-based method to model
the aggregated DERs stochastic response. Finally the paper studies the potential of using
aggregated DERs into the balancing capacity market, despite the risk induced.

Paper Organization

Section II formulates the market mechanism and details the stochastic market dispatch
algorithm and the DER models. Section III introduces the risk averse dispatch problem,
and Section IV discusses simulation results and analysis.

3.2   Problem Formulation

Market Dispatch Framework

The following section describes the combined day-ahead and balancing capacity market dis-
patch, with high penetration of renewable energy.

The uncertainty induced by highly variable renewable energy increases the need for bal-
ancing control in real time, which requires a balancing capacity market to anticipate the
available reserve in advance. However, when the capacity required for balancing control is
reserved, generators cannot be cleared at full capacity. Then, in order to perform an optimal
grid management, the energy and balancing capacity markets are co-optimized [69].

Moreover, reserves are activated during real-time operation depending on the probabilistic
error of various forecasts. The need for real-time reserve impacts clearing decisions in the
balancing capacity market that is cleared a day before. Then, we add the anticipated costs
and decisions related to the real-time operations in the day-ahead dispatch.

For simplicity, we model the grid as one node with no loss. The time interval is 30 min
and the dispatch is run 24 hours before delivery. The model can be expanded to include
network or alternative time horizon, but here we focus on the challenge of integrating DER
uncertainty, on one node during one day horizon. The letter C represents the cost, p the
generated power, L the load, R the reserve which is allocated in advance. The blue variables
are decision variables, to ease readability.

The objective of the market dispatch is to maximize social welfare (1) while satisfying
electricity demand L for the horizon H (2). The N_G generators have a marginal cost of C^G
and are providers of energy p^G. For simplicity, we assume that when generators provide their
maximum production p^G_{max} they account for the ramping up and down constraints. The load
is the electricity demand minus the renewable generation. The simple day-ahead dispatch

can be modeled as:

$$\min_{p^G} \sum_{t=1}^{H} \Big[\sum_{i=0}^{N_G} C_{t,i}^G p_{t,i}^G \Big] \tag{3.1}$$

$$\text{s. to} \quad \forall t \in H, \quad \sum_{i=0}^{N_G} p_{t,i}^G = L_t \tag{3.2}$$

$$0 \le p_{t,i}^G \le p_{t,i,max}^G \tag{3.3}$$

Adding the balancing capacity market to the dispatch problem requires one to take into account the real-time operating costs. Generators provide a reserve R^+ and R^-, respectively upward and downward, for the balancing capacity market. The binary variable m ensures that generators are not providing upward and downward reserve at the same time (7)-(9). When the load and the renewable generation deviate from the forecast, the TSO activates the reserve $r^+ \le R^+$ and $r^- \le R^-$ to satisfy the unexpected demand $\tilde{L}$ (10)-(13). To guarantee that the problem is feasible, we introduce the variable L_{shed} which is the load shedding activated by the TSO to face extreme scenarios with a high cost of operation.

Since the activation of reserve depends on the uncertain forecast of demand and renewable energy, the real-time operating cost is stochastic. Then the cost is computed as the expected cost across all probable scenarios $\omega \in \Omega$ where, for all scenarios, the balancing constraint (13) is satisfied.

$$\min \quad \sum_{t=1}^{H} \Big[\sum_{i=0}^{N_G} (C_{t,i}^G p_{t,i}^G + C_{t,i}^{R-} R_{t,i}^- + C_{t,i}^{R+} R_{t,i}^+) \Big] + \tag{3.4}$$

$$\mathbb{E}_{\omega \sim \Omega} \Big[\sum_{i=0}^{N_G} (C_{t,i}^G r_{t,i,\omega}^+ + C_{t,i}^G r_{t,i,\omega}^-) + C_t^{LL} L_{t,\omega}^{shed} \Big]$$

$$\text{s.t.} \quad \forall t \in H, \qquad \sum_{i=0}^{N_G} p_{t,i}^G = \sum_{k=1}^{N_L} L_{t,k} \tag{3.5}$$

$$\forall i \in N_G, \qquad 0 \leq p_{t,i}^G - R_{t,i}^- + R_{t,i}^+ \leq p_{t,i,max}^G \tag{3.6}$$

$$m_{i,t} \in \{0,1\}, \tag{3.7}$$

$$0 \leq R_{t,i}^+ \leq R_{i,max}^+ . m_{i,t} \tag{3.8}$$

$$0 \leq R_{t,i}^- \leq R_{i,max}^- . (1 - m_{i,t}) \tag{3.9}$$

$$0 \leq r_{t,i,\omega}^+ \leq R_{t,i}^+ \tag{3.10}$$

$$0 \leq r_{t,i,\omega}^- \leq R_{t,i}^- \tag{3.11}$$

$$0 \leq L_{t,\omega}^{shed} \leq L_t \tag{3.12}$$

$$\forall \omega \in \Omega,$$

$$\sum_{i=0}^{N_G} (r_{t,i,\omega}^+ - r_{t,i,\omega}^-) = L_{t,k,\omega}^{shed} + \tilde{L}_{t,\omega} \tag{3.13}$$

3.3 Scenario Generation

Accounting for renewable energies, such as solar and wind power, in the dispatch requires probabilistic predictions. Multiple models for probabilistic forecasts are described by J. Morales et al. [69]. However, due to multiple sources of error in the forecast, the market dispatch should solve a stochastic optimization problem [52].

Scenario-based stochastic optimization is introduced in the text by Shapiro et al. [83]. The market operator collects historical data, runs associated prediction models, and obtains distributions of the prediction error, or the residuals. When building the optimal dispatch, scenarios are created by sampling data from the distributions of forecast residuals. The process is explained by A. Papavasiliou et al. [75] and improved by R. N. King et al. [53]

In this work, we utilize ARIMA models to perform forecasts of wind, solar and demand [85]. The demand minus the variable generation is represented by the demand variable L_t in the model.

Control and modeling of DERs

Many studies have classified DERs depending on their impact on grid flexibility, see e.g. [7] or [67]. In our paper, we define four categories as well as the equations modeling their response to the grid request for reserve.

Flexible Loads refers to consumer demand response. The amount of reserve provided $r_t^{d,fl}$ is bounded by the maximum available reduction of load by the consumer for each hour of the day. In addition, the consumer sets a limit on the total energy it is able to reduce during the day $r_{total,max}^{d,fl}$. The random variable η_t models the uncertainty of the response, and follows a Bernoulli trial with a probability $\mathbb{P}(\eta_t = 1)$.

$$0 \leq r_t^{d,fl} \leq r_{t,max}^{d,fl} \cdot \eta_t$$

$$\sum_{t=0}^{H} r_t^{d,fl} \leq r_{total,max}^{d,fl} \tag{3.14}$$

Storage systems are local or community battery storage. Initial condition soe_0 is the initial battery state of energy and soe_{max} is the maximum capacity. The reserve power $r^{d,s}$ is the power (multiplied by the bidding time period) added or removed from the battery. Similar to flexible loads, the variable η_t models the uncertainty of the response in the case of disconnection or unavailability of the storage system.

$$0 \leq soe_0 + A \cdot r^{d,s} \leq soe_{max}$$

$$A = \Delta t \begin{bmatrix} 1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 1 & \dots & 1 \end{bmatrix} \quad \text{and} \quad r^{d,s} = [r_0^{d,s}, \dots, r_H^{d,s}]^T \tag{3.15}$$

$$r_{min}^{d,s} \cdot \eta_t \leq r_t^{d,s} \leq r_{max}^{d,s} \cdot \eta_t$$

Shapeable loads are loads that are able to delay their use of electricity but need a fixed amount of energy soe_{des} at the end of the day or of the time horizon H [59]. The model is similar to a storage system since the delayed electricity use can be seen as energy given to the grid, which is taken back when the consumer decides to use it at the delayed time. The minimum energy $soe_{t,min}$ limits the discharge to guarantee that soe_{des} is met at the end of the day. Additionally, soe_{max} is the maximum capacity, the reserve power $r^{d,st}$ is the power added or removed from the battery. Again, η_t represents the uncertainty of the response. For example, the shapeable load could be a plug-in electric vehicle that randomly connects and disconnects to the grid.

$$soe_{t+1} = soe_t + r_t^{d,sl}$$

$$soe_{t,min} \leq soe_t \leq soe_{max}$$

$$r^{d,s} = [r_0^{d,sl}, \dots, r_H^{d,sl}]^T \tag{3.16}$$

$$r_{min}^{d,sl} \cdot \eta_t \leq r_t^{d,sl} \leq r_{max}^{d,sl} \cdot \eta_t$$

$$soe_{t,min} = max(soe_{des} - r_{max}^{d,sl} \cdot (H - t), 0)$$
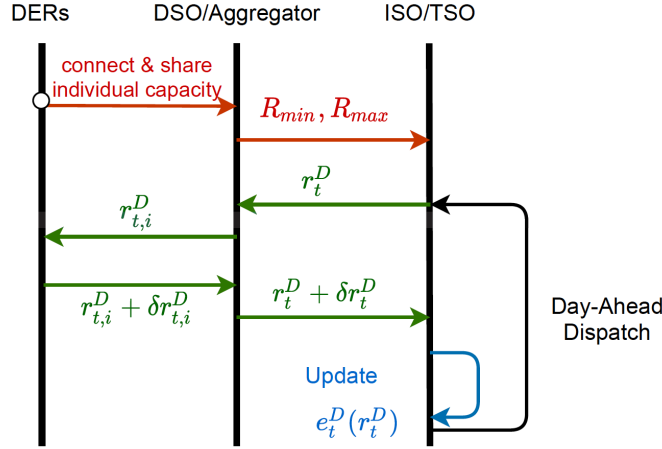
Figure 3.1: Market System - Coordination between the TSO/ISO, one aggregator and DERs

Distributed generation includes community wind and solar plants or privately owned rooftop solar panels. The reserve power required is $r_t^{d,g}$, bounded by the maximum power available at time t. The unused power is curtailed. Symbol $\hat{r}_{t,max}^{d,g}$ is uncertain because the generators are solar or wind power, which are highly variable resources.

$$\forall t \leq H, \quad 0 \leq r_t^{d,g} \leq \hat{r}_{t,max}^{d,g} \tag{3.17}$$

When the TSO/ISO dispatches the balancing control command, the DSO sends individual commands to local DERs to match the reserve requested by the TSO/ISO. Fig. 4.1 shows the coordination between the TSO/ISO, one DSO and the DERs. DERs are connected to their local DSO and share characteristics such as capacity and maximum rate of charge. The DSO aggregates this information to communicate the maximum and the minimum total reserve at time t, respectively $R_{total,max}^D$ and $R_{total,min}^D$ with the TSO/ISO. Thus, the reserve requested is picked between those bounds and is plotted on Fig. 3.2. In this paper we do not consider any reward or incentive given to the DER owners in exchange for their participation in grid regulation. Indeed, many studies show that the reward or incentive could be designed using behavioral analysis [95][101] and can be managed case by case by the electricity retailer. The aggregator or the DSO dispatches the reserve requirement among the DERs connected to the distribution grid to match the reserve demand r_t^D:

$$\sum_k r_{k,t}^{d,fl} + \sum_i r_{i,t}^{d,s} + \sum_m r_{m,t}^{d,sl} + \sum_j r_{j,t}^{d,g} = r_t^D \tag{3.18}$$

$$\text{s.t } (3.14, 3.16, 3.15, 3.17)$$

Using the models introduced in equations (3.14, 3.16, 3.15, 3.17) with the characteristics described in Table 3.1, we solve (3.18) for 24 hours and show the results in Fig. 3.2. Despite

the uncertainty on the DERs' responses shown in Fig. (3.3), the reserve delivered is close to
the reserve requested.
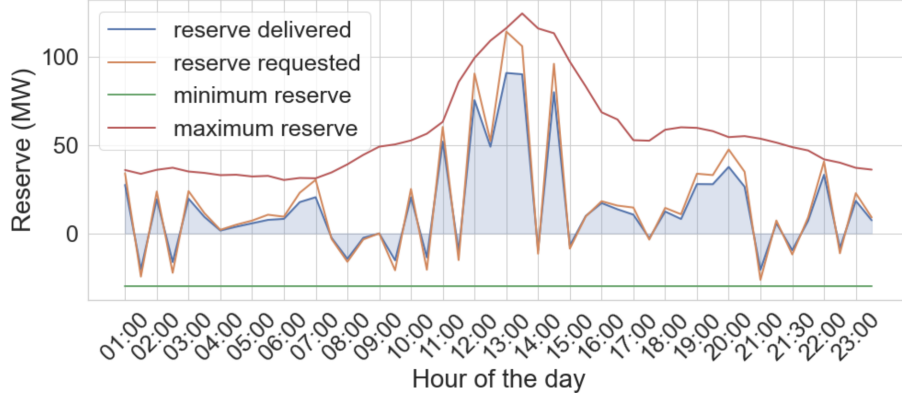
Figure 3.2: DER aggregator reserve control over one day. Note the delivered reserve tracks
the requested reserve, with some undershoot from randomly unresponsive DERs.

Characteristics of the aggregator's response error

As described in Fig. 4.1, the aggregator receives a reserve request r_t^D but delivers $r_t^D + e_t$,
where e_t is the error. This error might be caused by a device disconnection (technical issue
or intentional disconnection if the device is mobile) or from a different user consumption (not
following the power reduction command). Characterizing the error of reserve delivered with
regards to the amount requested is key for the TSO/ISO dispatch. We show in the following
section that the aggregated error can be characterized using data analysis techniques.

We gather the errors distribution between the requested and delivered reserve sampled
over 200 simulations with the requested reserve picked between the maximum and minimum
available. Fig. 3.4 shows the scatter plot of the error with regards to the requested reserve
for two different hours of the day. From the plots, we assume a linear relation between the
mean and variance of the responses and request. This assumption is rather intuitive: the
more the ISO requests, the bigger the error and the larger its spread. We characterize the
error as:

$$e_t(r_t^D) \sim \mathcal{N}(\mu(r_t^D), \sigma^2(r_t^D)) \tag{3.19}$$

Table 3.1: Characteristics of DERs used for simulation

Parameters	Flexible Load	Storage	Shapeable Load	Generation
number	100	100	50	50
capacity kWh	0.1 to 0.5	3 to 10	0.4 to 1	0.1 to 0.7
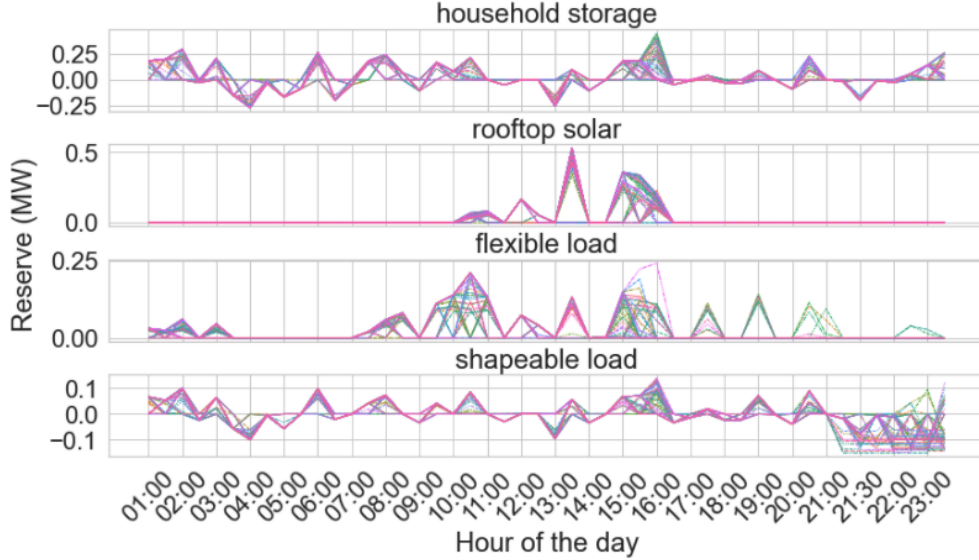
Figure 3.3: Each DER's response to the individual controls sent by the aggregator during one day.

Where $\mu(r_t^D) = a_t r_t^D + b_t$ and $\sigma^2(r_t^D) = c_t r_t^D + d_t$. The fitting process is described in the Appendix. It makes the use of a weighted least squares to evaluate the best linear estimator for the variance $\sigma^2(r_t^D)$. Note that in the results, we learn those parameters in an offline setting. As an extension, we could use statistical learning methods such as assuming a prior between those coefficients, or using covariance functions to decrease model complexity and ease the fitting process.

3.4 Stochastic Risk Averse Dispatch

To integrate DERs, we must account for the uncertainty of their response which implies a risk of not meeting the demand. In our paper we design the aggregator as a controller, and not as a market player. Thus, the risk of the DERs participation in balancing control is managed by the TSO/ISO. For a dispatch algorithm, a risk is seen as an additional cost that should be minimized: if the balancing capacity does not meet the demand, the TSO will have to bear additional operational cost to meet demand.

Conditional Value at risk

In order to account for the cost of a decision under the DERs' uncertainty, we use the Conditional Value at Risk metric (CVaR), also known as the expected shortfall. The choice of CVaR is motivated by the fact that CVaR is continuous, convex and is a coherent and spectral
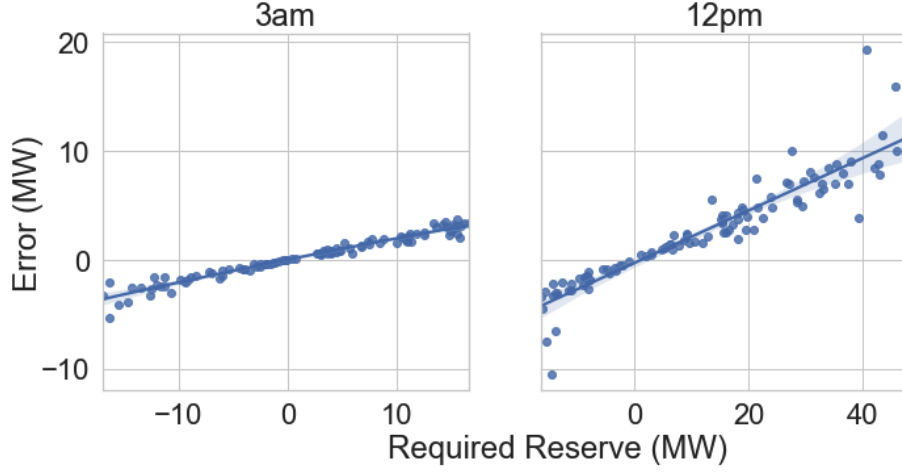
Figure 3.4: Error between the requested and delivered reserve, for 3am and 12pm hours, over 200 simulations. Note the error depends on the requested reserve.

risk measure [80], [56]. To define the CVaR, we introduce a cost function $C(x, \xi)$, where x is the decision variable and ξ is the uncertainty. Then we define the cumulative distribution function of losses $\psi(x, \xi)$ as the probability that the cost does not exceed threshold α:

$$\psi(x, \alpha) = \mathbb{P}_\xi[C(x, \xi) \leq \alpha] \tag{3.20}$$

Now we define the Value at Risk, $VaR_{1-\epsilon}$ and the Conditional Value at Risk, $CVaR_{1-\epsilon}$, where ϵ is a threshold set on the function ψ:

$$
\begin{aligned}
VaR_{1-\epsilon}(x) &= VaR_{1-\epsilon}(C(x, \xi)) \\
&= \min(\alpha | \psi(x, \alpha) \leq 1 - \epsilon)
\end{aligned}
\tag{3.21}
$$

$$
\begin{aligned}
CVaR_{1-\epsilon}(x) &= CVaR_{1-\epsilon}(C(\mathbf{x}, \tilde{z})) \\
&= \mathbb{E}_\xi[C(x, \xi) | C(x, \xi) \geq VaR_{1-\epsilon}(C(x, \xi))]
\end{aligned}
\tag{3.22}
$$

Equation (3.22) shows that $CVaR$ is the mean of the $1 - \epsilon$-tail distribution of the loss $C(x, \xi)$.

When the loss follows a normal distribution $\mathcal{N}(\mu, \sigma)$, then the CVaR is defined as:

$$CVaR_{1-\epsilon}(x) = -\mu(x) + \sigma(x) \frac{\phi(\Phi^{-1}(1 - \epsilon))}{1 - \epsilon} \tag{3.23}$$

Where ϕ is the standard normal density function and Φ is the standard normal quantile.

Risk of DERs as a balancing reserve

The complete risk adverse dispatch algorithm is summarized as follows:

$$\min \quad \sum_{t=1}^{H} \Big[\sum_{i=0}^{N_G} (C_{t,i}^G p_{t,i}^G + C_{t,i}^{R-} R_{t,i}^- + C_{t,i}^{R+} R_{t,i}^+) \Big] +$$

$$\mathbb{E}_{\omega \sim \Omega} \Big[\sum_{i=0}^{N_G} (C_{t,i}^G r_{t,i,\omega}^+ + C_{t,i}^G r_{t,i,\omega}^-) + C_t^{LL} L_{t,\omega}^{shed} +$$

$$\sum_{l=0}^{N_D} \alpha_l CVaR_{1-\epsilon}(e_{t,l,w}^D(r_{l,t,w}^D)) \Big]$$

$$\text{s.t.} \quad \forall t \in H, \qquad \sum_{i=0}^{N_G} p_{t,i}^G = \sum_{k=1}^{N_L} L_{t,k}$$

$$\forall i \in N_G, \qquad (6) - (12)$$

$$\forall \omega \in \Omega,$$

$$\sum_{i=0}^{N_G} (r_{t,i,\omega}^+ - r_{t,i,\omega}^-) + \sum_{l=0}^{N_D} r_{t,l,\omega}^D - \mu_t^D(r_{t,l,\omega}^D) = L_{t,k,\omega}^{shed} + \tilde{L}_{t,\omega}$$

$$\forall l \in N_D, R_{t,l,min}^D \leq r_{t,l,\omega}^D \leq R_{t,l,max}^D$$

The optimization problem is now in the form of a two level stochastic program. The first level contains the uncertainty from renewable energy forecasts. The second level contains the uncertainty of the DER aggregator's response. The coefficient α adjusts the risk value to be coherent with other costs.

3.5 Simulation Settings and Results

Simulation data

The data is collected on the Open Power System Database [71]. We use the total load, solar and wind generation in Great Britain in 2019 as published on the ENTSO-E Transparency Platform, scaled for the purposes of this simulation.

Results

We use Cvxpy [40] to solve the extensive form of the stochastic optimization problem. First, we run the dispatch using the DER aggregator model detailed in Section 3.3. Then, we simulate the DERs' response from the control r^D. The results for one day are plotted in Fig. 3.5. The upper figure shows the total reserve needed in one of the scenarios considered during the dispatch. In this simulation, the risk threshold is $\epsilon = 0.05$. Thus the DER reserve

is called over the traditional reserve, except when the total requested reserve is higher (lower) than the DER maximum (minimum) reserve. The lower plot is highlighting the precision of the linear regression forecast on the DERs' response error. The forecast of the aggregation of DERs is precise due to the large number of DERs controlled by the aggregator. The law of large numbers reduces the impact of each individual DER. Fig. 3.6 compiles the relative errors from multiple simulations at each step of the day.
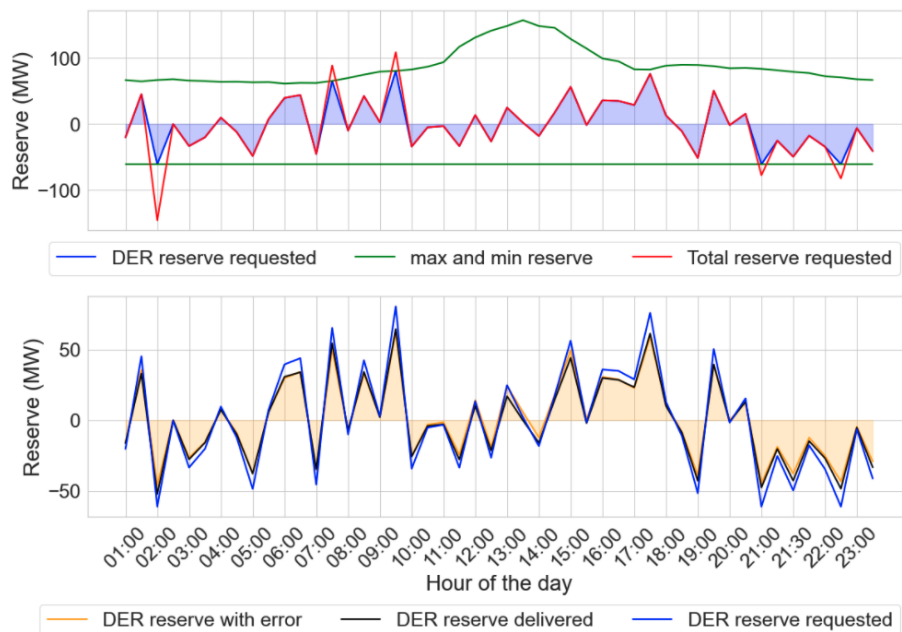
Figure 3.5: day-ahead dispatch results and simulation results for $\epsilon = 0.05$.

Accounting for aggregated DERs in the stochastic dispatch will decrease the cost but increase the risk. Indeed, in our simulation settings, DERs are less expensive as they do not need to be reserved in the day-ahead market, yet are available in real-time operations. However their control response is uncertain and thus DERs are a risk for the grid operator who has to balance the grid. The risk threshold ϵ sets the level of risk that the grid operator is willing to take. When ϵ is close to 1, the cost of risk is set high and traditional generators will be preferred over DERs. Similarly, when ϵ is close to 0, DERs are considered since the grid operator estimates a lower cost of risk. Fig. 3.7 shows the effect of ϵ on the dispatch results. In the upper figure, when the DERs are chosen over the traditional reserve, the DERs unreliability cost increases as well at the tails of the cost distribution over scenarios (represented by the blue area). The risk taken is indeed higher when ϵ is closer to 0, but its weight on the optimization cost is lower due to the CVaR mechanism.
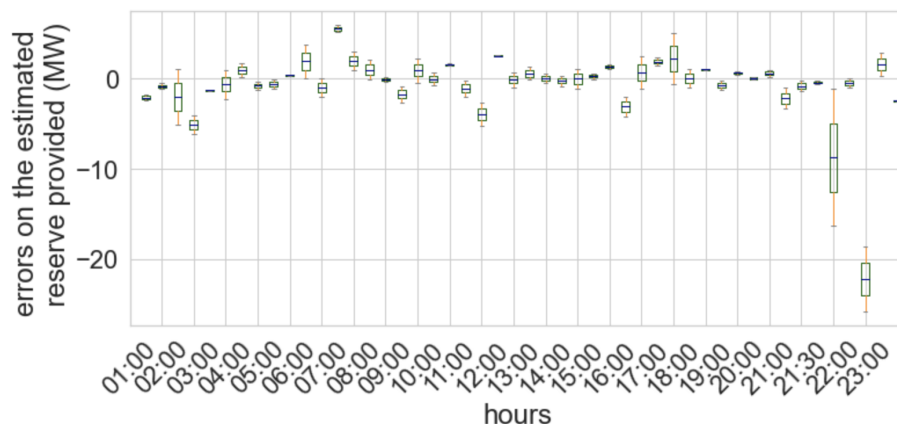
Figure 3.6: Relative Error on the Estimation of the Reserve Mismatch
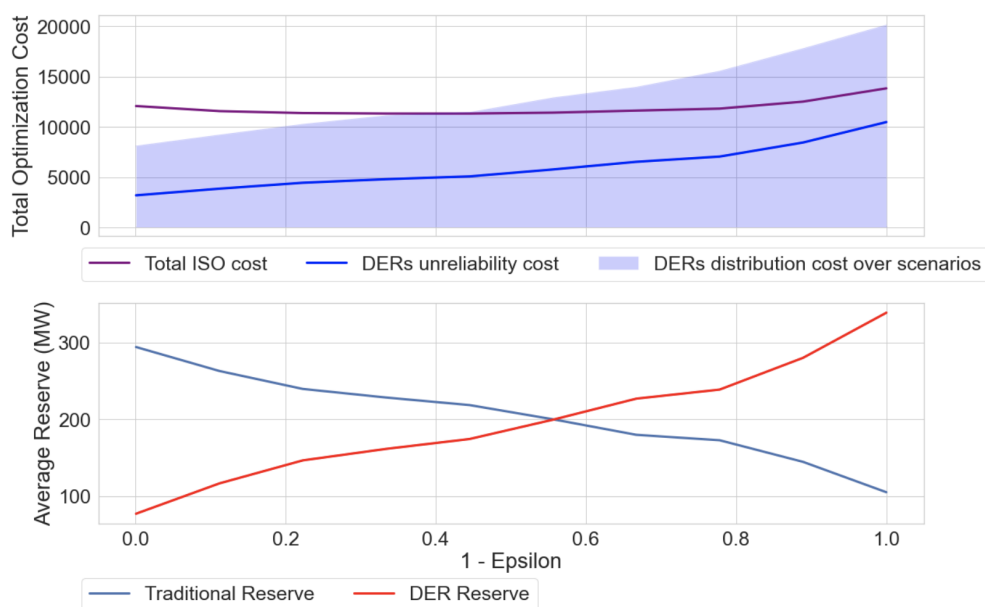
Figure 3.7: Average total ISO cost and planned reserve by the day-ahead dispatch when ϵ varies. As ϵ increases we are less risk adverse and more DERs are dispatched.

3.6   Conclusion and Future Work

The integration of DERs requires to adapt market dispatch. In this paper we proposed a new market design that tackles two main issues of DER integration: their aggregation in the market dispatch and their inherent unreliability. First, DERs are integrated through an

aggregator that does not participate in the electricity market, but acts only as a conceptual intermediary to the balancing control signal. Designing the aggregator as a controller, with no economic incentives, allows for a transparent communication between the aggregator and the ISO/TSO. Second, the uncertainty of the DERs' response is managed through a bi-level stochastic optimization, and the error in the response is characterized via data-driven techniques. The uncertainty induces a risk for the market operator who sets a risk threshold. The dispatch chooses between reliable traditional reserves, which must be contracted in advance at a high cost, and DERs that are uncertain but available at low cost during real-time operation. This paper shows that the market design is efficient in capturing the DERs uncertainty while providing a good risk control for the market operator.

Future work could improve the model by adding physical grid constraints to the market dispatch. Indeed, in addition to the impact of congestion on the dispatch results, DERs are located at the distribution level which gives them a competitive advantage to perform balancing control on the distribution grid. Moreover, for a more detailed market design, coordination between the aggregator and the Distributed System Operator should be studied.

Acknowledgment

Appendix

Best Linear Estimator of the Variance

Let X, Y be respectively the independent and observed random variable. We define as m and σ the conditional moments of order 1 and 2 of Y given X. I.e. $m(x) = \mathbb{E}[Y|X = x]$ and $\sigma^2(x) = \mathbb{E}[(Y - m(x))^2|X = x]$. We assume that m is known and we seek to estimate $\sigma^2(x)$.

Given X, the residuals are $R|X = (Y - m(X))^2$. By definition, $R|X$ has an expectation of $\sigma^2(X)$. Following [44], [45], we first define the local linear estimator such that $\sigma^2(x) = \hat{\alpha}x + \hat{\beta}$. These estimators possess high statistical efficiency in the asymptotic minimax sense and are design adaptive. They are estimated through the following least-square procedure:

$$(\hat{\alpha}, \hat{\beta})(x) = \arg\min_{\alpha, \beta} \sum_{i=1}^{n} \left(r - \alpha - \beta(X_i - x)\right)^2 W\left(\frac{X_i - x}{h}\right) \tag{3.24}$$

where W is a density function, and $h > 0$ is the bandwidth. We look for a, b such that the linear estimator is globally optimal:

$$\min_{a, b} \sum_{j=1}^{n} \sum_{i=1}^{n} \left(r_i - a - b(X_i - X_j)\right)^2 W\left(\frac{X_i - X_j}{h}\right) \tag{3.25}$$

This is now a standard weighted least-squares problem. In this work, W is taken as the Epanechnikov kernel and h is selected as to maximize the fitting score.

Chapter 4

Review on Topology Estimation Methods for Distribution Power System

This chapter provides a review of existing solution to estimate distribution grid topology, which is essential to efficiently integrate DERs.

The integration of renewable energies and the massive electrification of energy demand are essential to lower carbon emissions. As a result, the distribution grid is facing new challenges: voltage variations, overloading, frequent outages, and requires more precise monitoring and control. This, however, relies on reliable distribution grid models. However due to frequent re-configurations and a paucity of sensor and monitoring investments, distribution system operators typically only have access to an approximated or outdated grid model and topology. The estimation of distribution grid topology is a recent but important research question where solutions are diverse and highly dependant on modeling and data assumptions. This paper provides a comprehensive explanation of the topology problem, and details the main existing solutions, in order to guide the reader to existing gaps between real world challenges and state-of-art research results.

4.1   Introduction

Motivation

As electricity production is moving toward the goal of 100% clear energy, the power grid and especially the distribution grid is facing fundamental changes. *Distribution grid* refers to the final stage of the electrical grid which distributes electricity to homes, industry, and other end users. The voltage is reduced by step-down transformers from high levels (over 1 kV) to lower levels (100 - 400 V). The entire distribution grid includes lines, poles, transformers, switching and protection circuits that deliver safe electrical power [66].

Reports have shown that widespread electrification of demand will increase total U.S. electricity consumption by 20% in 2050, relative to the reference [64]. Distribution lines will be subjected to significant change due to new construction and urban development. Thus, to lower maintenance and operating costs, distribution lines have been historically overdesigned with almost no sensors to control power flow. However the fast increase of electricity consumption combined with the aging of the grid infrastructures have pushed the distribution grid capacity to its limits. Investments to increase capacity are needed, as well as significant innovation in monitoring and control.

In addition, the nature of the electricity consumption is evolving. First, electrification dramatically shifts load shapes. For instance, the adoption of electric water heaters or electric vehicles increase the electricity needs at certain hours. Secondly, large-scale deployment Distributed Energy Resources (DERs) will alter both consumption and local generation. The Federal Energy Regulatory Commission (FERC) defines DERs as follows: "DERs may include electric storage, intermittent generation, distributed generation, demand response, energy efficiency, thermal storage or electric vehicles and their charging equipment" [46]. Due to their distributed, variable and consumer-centered nature, DERs can cause unanticipated power flows and increase demand forecast errors. Those new assets, installed in a grid built for one way power flow, add additional stresses and uncertainty to the grid infrastructure.

To address the dual problems of aging infrastructure and rapidly evolving consumption patterns, developing more efficient grid management is essential [91]. This includes proactive maintenance, such as carefully planned infrastructure investments, replacement strategies, and condition-based monitoring that pro-actively mitigate equipment damage. This also includes security management, such as outage/fault detection, isolation and service restoration.

All that said, grid management usually requires grid models to make decisions or interpret sensors signals. The grid model refers to the grid *topology* and the grid device *parameters*. This model is often used in power flow equations to deduce the grid state given a set of sensor data.

Contributions

This paper aims to: (i) Describe the problem of topology detection and the challenges associated with real-world implementation. (ii) Organize and classify the published literature on distribution grid topology estimation. (iii) Provide a clear understanding of the remaining gaps in the literature with regards to translating the stat-of-art research to real-world settings.

Paper Structure

Section 4.2 introduces the main mathematical concepts for grid modeling relevant for power network monitoring. Section 4.3 presents the common assumptions made in the literature

about grid models, grid configurations, and available data. Section 4.4 explains the methodology and techniques used in the literature to solve the topology estimation problem. Then, Section 4.6 challenges the assumptions and methods developed in the existing literature with real-world issues. This section aims to orient the reader toward future challenges and remaining gaps. Finally, Section 4.7 concludes the paper.

4.2 Background on Power System and Grid Modeling

This section aims to give the reader a fundamental background on existing grid topology modeling, as well as basic knowledge on distribution grid monitoring. The mathematical concepts described in this section will have context later in the manuscript, when describing specific power system models in the literature.

The Power Flow Equations

The distribution grid is mathematically described as a graph: $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$ where $\mathcal{N}$ is the set of nodes and $\mathcal{E}$ is the set of edges or lines. We denote n the number of nodes and m the number of edges. Each line, donated by a pair of nodes $(i, k) \in \mathcal{E}$, is characterized by an impedance: $z_{i,k} = r_{i,k} + jx_{i,k}$ (where $r_{i,k}$ and $x_{i,k}$ are the resistance and the reactance) or the admittance $y_{i,k} = z_{ik}^{-1} = g_{i,k} + jb_{i,k}$ (where $g_{i,k}$ and $b_{i,k}$ are the conductance and the susceptance). The state of the grid can be described by the following variables: complex voltage $\mathcal{V}$ and current $\mathcal{I}$ with phase θ, the real power P and the reactive power Q. Finally, the total complex power is $S = P + jQ = VI^*$, also known as apparent power. Kirchhoff's current law applied to all nodes $i \in \mathcal{N}$ of the system gives the following relation: $I_i = \sum_{\{k|(i,k)\in\mathcal{E}\}} I_k = \sum_{\{k|(i,k)\in\mathcal{E}\}} y_{ik}V_k$, from which we deduce the power flow equations: $\forall i \in \mathcal{N}$,

$$\begin{aligned}
S_i = P_i + jQ_i &= V_i I_i^* \\
&= V_i \left(\sum_{\{k|(i,k)\in\mathcal{E}\}} y_{ik}V_k \right)^* \\
&= \sum_{\{k|(i,k)\in\mathcal{E}\}} |V_i||V_k|y_{ik}e^{j(\theta_i - \theta_k)}
\end{aligned} \tag{4.1}$$

$$\begin{aligned}
P_i &= V_i \sum_{\{k|(i,k)\in\mathcal{E}\}} V_k(g_{ij}\cos(\theta_i - \theta_k) + b_{ik}\sin(\theta_i - \theta_k)) \\
Q_i &= V_i \sum_{\{k|(i,k)\in\mathcal{E}\}} V_k(g_{ik}\sin(\theta_i - \theta_k) - b_{ik}\cos(\theta_i - \theta_k))
\end{aligned} \tag{4.2}$$

where P_i and Q_i are the real and reactive power, and V_i and θ_i are the voltage magnitude and voltage phase angle at node $i \in \mathcal{N}$.

The *state* of the grid is given either by the set of $\{P_i, Q_i\}_{i \in \mathcal{N}}$ or $\{V_i, \theta_i\}_{i \in \mathcal{N}}$. Solving the power flow equations means to find one set given the other. The grid model is then the combination of the graph $\mathcal{G}$ and the parameters g_{ik}, b_{ik}.

Linear Coupled Power Flow (LC-PF)

It is easy to see that the equations (4.2) are coupled and non-linear. To simplify the computation, it is common to *linearize* (4.2) around an optimal point of operation. Indeed, in normal operation, the voltage angle difference between nodes is relatively small and thus we can approximate $\cos(\theta_i - \theta_k) \sim 1$ and $\sin(\theta_i - \theta_k) \sim \theta_i - \theta_k$. This gives the following equations:

$$
\begin{aligned}
P_i &= V_i \sum_{k, \{i,k\} \in \mathcal{E}} V_k(g_{ik} + b_{ik}(\theta_i - \theta_k)) \\
Q_i &= V_i \sum_{k, \{i,k\} \in \mathcal{E}} V_k(g_{ik}(\theta_i - \theta_k) - b_{ik})
\end{aligned}
\tag{4.3}
$$

which can be written compactly as:

$$
\begin{aligned}
P &= H_g V + H_b \theta \\
Q &= H_b V - H_g \theta
\end{aligned}
\tag{4.4}
$$

where $V = [V_1, \ldots, V_n]$ and $\theta = [\theta_1, \ldots, \theta_n]$, and H_b and H_g are the weighted Laplacian matrices associated with the graph $\mathcal{G}$ (see paragraph 4.2).

DC Power Flow

Some papers use DC Power Flow equations, which are obtained by assuming that reactance is negligible relative to resistance. Thus the equations (4.4) are decorrelated into:

$$
\begin{aligned}
P &= H_b \theta \\
Q &= H_b V
\end{aligned}
\tag{4.5}
$$

While this assumption generally holds true for the transmission grid, the distribution grid has a higher reactance over resistance ratio [66], and thus the DC power flow approximation is less appropriate for distribution circuits.

Laplacian Matrix

In graph theory, a *Laplacian matrix* is the matrix representation of a graph. The matrix is defined as: $L = MM^T$ where M is the *oriented incident matrix*, defined by the columns

$[\boldsymbol{m}_{ik}]_l$ for $l \in \mathcal{N}$ and for all edges $\{i, k\} \in \mathcal{E}$:

$$[\boldsymbol{m}_{ik}]_l = \begin{cases} -1 & \text{if } l = i \\ 1 & \text{if } l = k \\ 0 & \text{otherwise} \end{cases} \tag{4.6}$$

In addition, the Laplacian matrix is positive semi-definite and has the following *null space properties*:

$$L\mathbb{1} = 0, \quad L^T\mathbb{1} = 0 \tag{4.7}$$

The *weighted Laplacian matrix* is defined as $L_w = MWM^T$ where $W = diag(w_i)$ is a diagonal matrix of weights. In the case of the LC-PF equations, $H_g = MGM^T$ and $H_b = MBM^T$ with $G = diag(g_{ik})$ and $B = diag(b_{ik})$.

In Section 4.4 we will describe methods to compute the Laplacian matrix and find the grid topology. A common practice in those approaches is to use the *reduced graph Laplacian matrix*, which is the Laplacian matrix without the rows and columns corresponding to the substation node. Indeed, one can fix phase and voltage at those substations as "slack buses", $\theta = v = 0$. The reduced matrix is then full rank, invertible and block-diagonal.

The *Adjacency matrix* is also frequently used to model the distribution grids as a graph. It can be defined using the Laplacian matrix L as the matrix A such that: $L = D - A$. The matrix D is the degree matrix of the graph, for $\{i, k\} \in \mathcal{N}$:

$$D_{ik} = \begin{cases} deg(i) & \text{if } i = k \\ 0 & \text{otherwise} \end{cases}$$

The degree of node i, $deg(i)$, is the number of edges (or lines) terminating at node i.

4.3 Assumptions or Hypotheses

The main difficulty in power system studies is the wide range of assumptions that can be made by researchers on the grid models and data. While all papers referenced in this article are proposing various approaches to solve the topology estimation problem, they rely deeply on hypotheses such as the existence of certain sensors, or the efficiency of a grid model. In this section, we present several common hypotheses, their usages, and their limitations.

Grid Model

Meshed or Radial Grid

The distribution grid is either modeled as *radial* or *meshed*. In reality, the grid operates usually as a *radial* network but is built as *meshed*. Indeed, some lines are disconnected
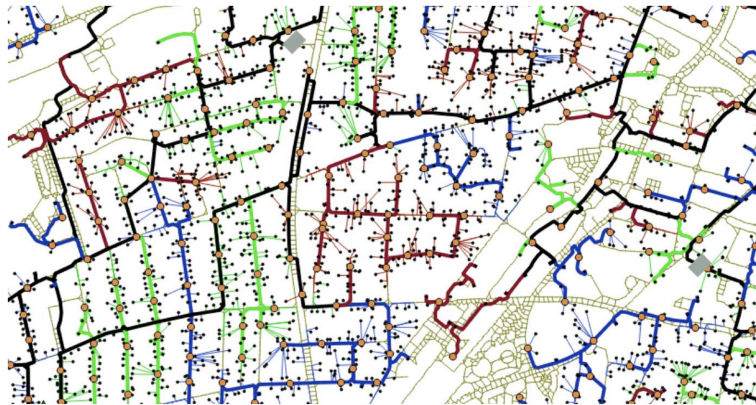
Figure 4.1: Distribution grid visualization. Lines in black are three phases and red, green and blue represent one phase each. This graph was built at NREL [65] under that Synthetic Models for Advanced, Realistic Testing: Distribution Systems and Scenarios (SMART-DS) project

through switches [66]. In the case of a *radial* grid, the graph representation is a tree where the root node is the feeder node that connects to the transmission grid, and the leafs are the end-users nodes. Several papers assume the power network as radial, such as M. Bariya et al. [16] [15], D. Deka et al. [35], S. Park et al. [76] [77], Y. Liao et al. [62].

While assuming a *radial* grid is not unrealistic, other papers solve the topology estimation problem assuming a *meshed* grid. This is the case of J. Yu et al. [99], Y. Liao et al. [61] and Z. Soltani et al. [86].

Grid Parameters

Grid parameters refer to lines' impedance (reactance and resistance), which are necessary to build a complete grid model. When topology is unknown it is common to recognize that the line parameters are also unknown. While some papers are solving parameter and topology estimation problems jointly [99] [77], some develop techniques that do not rely on those parameters [61], [39] or that assume the line reactance over resistance ratio is uniform over the distribution grid, for instance S. Bolognani [20].

Grid Power Flow Model

In power system theory, it is common to linearize the AC power flow equations around an optimal point of operation in normal use, as described previously. It is also widely assumed, that in the distribution grid, contrary to the transmission grid, the reactance-to-resistance ratio is not zero. This means the DC power flow model is not well-suited for the distribution

grid. Nevertheless, if the reactance can be neglected, M. Babakmehr [12] [11], X. Li [60] and D. Deka [36] [37] use the DC power flow equations to model the distribution grid.

One phase or Three Phases

The distribution grid is a three phase AC grid. However modeling a three phase grid is complex. It is common to simplify the analysis by modeling the grid as single phase. This simplification relies on the assumption that the magnetic coupling between lines is negligible and that the grid phases are balanced. While those assumptions can be discussed, only a few papers solve the topology estimation problem for three phase distribution grids, such as D. Deka et al. [39], M. Bariya [15]Y. Liao [**liao2019**] and O. Ardakanian et al. [9].

In a three phase model, active and reactive power, voltage and current have three components indexed with a, b, c for each phase:

$$S_i = \begin{bmatrix} p_i^a \\ p_i^b \\ p_i^c \end{bmatrix} + j \begin{bmatrix} q_i^a \\ q_i^b \\ q_i^c \end{bmatrix}, \quad V_i = \begin{bmatrix} v_i^a e^{j\theta_i^a} \\ v_i^b e^{j\theta_i^b} \\ v_i^c e^{j\theta_i^c} \end{bmatrix} \tag{4.8}$$

$$\text{and} \quad Z_{ik} = \begin{bmatrix} z_{ik}^{aa} & z_{ik}^{ab} & z_{ik}^{ac} \\ z_{ik}^{ba} & z_{ik}^{bb} & z_{ik}^{bc} \\ z_{ik}^{ca} & z_{ik}^{cb} & z_{ik}^{cc} \end{bmatrix} \tag{4.9}$$

$$\forall i \in \mathcal{N}, S_i = \sum_{\{k|(i,k)\in\mathcal{E}\}} diag(V_i(V_i^H - V_k^H)Y_{ik}) \tag{4.10}$$

where Y_{ik} is the inverse of the reduced matrix Z_{ik} (without the substation nodes) and V_i^H is the Hermitian transpose of V_i. Equation (4.10) is the three phase AC power flow equation.

Balanced or Unbalanced

Imbalance in the grid is caused by unequal system impedances and unequal distribution of single phase loads [66]. In other words, Z_{ik} in (4.9) can have $z_{ik}^a \neq z_{ik}^b \neq z_{ik}^c$. When the nodes are only connected through one or two phases, the corresponding impedances are 0. An unbalanced grid can accelerate fatigue of electrical infrastructure. Consequently, it is important to model precisely the topology of unbalanced networks. This is the case of the work from D. Deka [39]. However, when the grid is unbalanced because of missing phase connections between nodes, it is important for the grid monitoring systems to detect the bus phase as presented by Y. Liao [63] and M. Bariya [15].

Data Sources

Historically, the distribution grid has not been equipped with sensors and monitoring systems. However, in the last decades, smart meters have been massively deployed to monitor user consumption. In addition, Phasor Measurement Units (PMUs) are receiving more attention from distribution system operators.
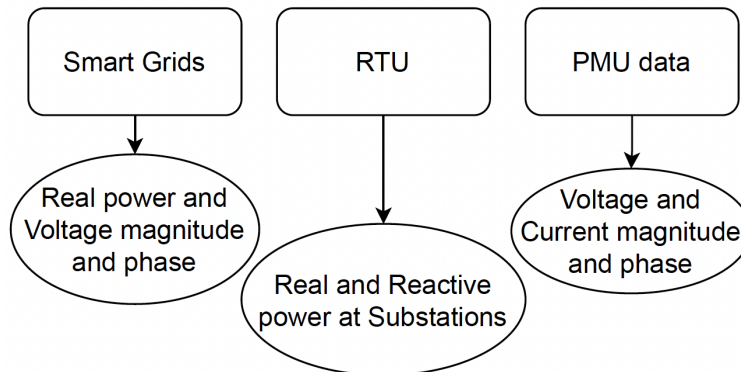
Figure 4.2: Data sources from grid sensors on the distribution grid

Smart Meters

Smart meters record voltage and real power at end points of the grid to monitor user consumption. Most distribution networks are now equipped or equipping their customers with such sensors, which make them the principal source of data for distribution grid monitoring. X. Li et al [60] base their algorithm on "injection data", which refers to real power at terminal nodes, gathered by smart meters measuring consumed power and gathered by the SCADA (Supervisory Control and Data Acquisition) system at the feeder station connecting the distribution grid to transmission grid. Similarly, D. Deka et al. [35] [38], S. Bolognani et al. [20] and S. Park et al. [76] [77] assume knowledge of injected power at the terminal node from smart meters and/or SCADA systems.

Remote Terminal Units (RTUs)

RTUs are electronic devices that transmit data to the SCADA system. In the distribution grid, RTUs are installed at substations, where the distribution grid is connected to the transmission grid. The recorded data is usually the power injection, which is often a necessary data source for the algorithms analyzed in this review paper. RTUs can also record voltage, current magnitude and phase.

Phasor Measurement Unit (PMU)

PMUs are high speed sensors that provide time-synchronized phasor measurements, estimating the magnitude and phase angle of sinusoidal quantities such as voltage or current at a specific location and gives each measurement a precise time-stamp [91]. On the distribution grid, the lower distance between devices impose the use of micro-PMUs (μPMU) which run at a micro-second resolution. Indeed, if two devices are installed at a shorter distance, a higher resolution is necessary to detect differences in measurements. Today, PMUs are

widely deployed in the transmission grid but less so in the distribution grid. However, as the needs for monitoring the distribution grid increases, more PMUs are being installed in distribution circuits.

PMU data is well-suited for topology estimation, thanks to its high-frequency and sychronized time stamps. The work from M. Bariya et al. [15] [16], K. Moffat et al. [68], Z. Soltani et al. [86], Y. Liao et al. [62] and G. Cavraro [28] [29] all use μPMUs, which are assumed to partially or entirely cover nodes on the distribution grid.

While the choice of sensor data is an important topic for topology estimation, some authors do not specify the data source and assume access to data at every node [38]. This assumption might be justified by the future installation of PMUs at every node.

4.4 Approaches - methodology

Methods and algorithms listed in this review paper vary depending on their data, grid model assumptions, and the approach used. While this paper focuses on topology estimation, not all papers solve the same problem – some focus on topology estimation, or topology recovery, while others jointly solve the topology and parameter estimation problem [9] [99].

A closely related literature tackles the problem of topology detection. This problem refers to the detection of changes in switch status over time. While algorithms developed to answer these problems are interesting for topology estimation, we will not cover this literature in this review. Refer to the work of G. Cavraro et al. [28] for instance.

Iterative or Greedy Methods

We call "iterative methods" methods that use power flow equations to iteratively build the grid topology. D. Deka et al. [36] [37] [34] [35] [38] [39] and M. Bariya et al. [15] developed algorithms based on this approach.

Greedy Algorithm with Voltage Data

In [38], D. Deka et al. reconstruct a radial grid sequentially from the leaves to the root by using the statistical second moments of voltage data. From the LC-PF equations (4.4), the authors derive relations between second moments of voltage angle and magnitude data and deduce "rules" between parent nodes and from the reduced incidence matrix structure. Three algorithms are proposed, based on the same approach: First, the algorithm tests each node's connections using the following relationship between the second order moment data and the covariance matrices of injected power Ω_p, Ω_q and Ω_{pq}. If node k is a parent of node i, then:

$$
\begin{aligned}
\mathbb{E}[(V_i - \mu_{V_i}) - (V_k - \mu_{V_k})]^2 = \sum_{\{l,m\}\mathcal{D}_i} r_{ik}^2 \Omega_p(l,m) \\
+ x_{ik}^2 \Omega_q(l,m) + 2r_{ik}x_{ik}\Omega_{pq}(l,m)
\end{aligned}
\tag{4.11}
$$

where $\mathcal{D}_i$ is the set of descendants of node i and μ_{V_i} is the mean of voltage measurements at node i.

The second algorithm does not require knowledge of the covariance matrices and replaces the previous relationship by the following. If node k is a parent of node i, then

$$k = \arg\min_{l \in \mathcal{N}} \mathbb{E}[(V_i - \mu_{V_i}) - (V_l - \mu_{V_l})]^2 \tag{4.12}$$

Finally, the authors propose a third algorithm where some nodes are missing, i.e. the data at this node is not available. The technique uses the same relations (4.11) and (4.12) with graph structure conditions to identify the missing node placement.

The method described in this previous section was also published in earlier works [36] and [37]. In [35], D. Deka et al. generalize the above algorithm to the situation where only terminal node voltage measurements and injection statistics are accessible. The algorithm follows the same procedure with a relation similar to (4.11), but adapted to detect nodes with similar parents.

Greedy Algorithm with Phase Recovery

Next we consider networks with three phases that are potentially unbalanced. M. Bariya et al. [15] is a generalization of the paper from D. Deka et al. [38] considering the case of three phases and unbalanced grid. As in [38], the algorithm uses voltage measurement at every node and voltage statistics at every node for each phase. First, the topology is reconstructed using equations (4.11) generalized for three phases. Then, the phase identification is done by applying trend observation along phases. For example, if the node k is a parent/child to node i for phase ϕ, then it satisfies

$$k = \arg\min_{l \in \mathcal{N}} Var(V_i^\phi - V_l^\phi) \tag{4.13}$$

Recursive Grouping Algorithm

In this subsection, we consider methods that use recursive grouping algorithms. In [76], S. Park et al. propose an iterative algorithm that reconstructs the grid topology and impedances using only terminal node measurements. Based on the same LC-PF models as in [38], the authors estimate matrices $H_{1/r}^{-1}$ and $H_{1/x}^{-1}$, the inverse of the weighted Laplacian matrix with weights $1/x$ and $1/r$ the inverse resistance and reactance, based on the following equations:

$$\begin{aligned}
\mathbb{E}[V_i P_k] &= H_{1/r}^{-1}(i,k)\mathbb{E}[P_k^2] + H_{1/x}^{-1}(i,k)\mathbb{E}[P_k Q_k] \\
\mathbb{E}[V_i Q_k] &= H_{1/r}^{-1}(i,k)\mathbb{E}[P_k Q_k] + H_{1/x}^{-1}(i,k)\mathbb{E}[Q_k^2]
\end{aligned} \tag{4.14}$$

Then, the topology is recovered using a Recursive Grouping Algorithm. The algorithm reconstructs a radial network from real-valued information distances between the "observed" nodes, defined here as the set of nodes for which the information distances are known but the parent node is unknown. By comparing the pairwise quantities, the set of "observes"

nodes is recursively shrunk until the tree is reconstructed. The distance used by [76] is the resistance distance defined as:

$$
\begin{aligned}
d_r(i, k) &= \sum_{\{l,e\} \in \mathcal{K}_{ik}} r_{le} \\
&= H_{1/r}^{-1}(i, i) + H_{1/r}^{-1}(k, k) - 2H_{1/r}^{-1}(i, k)
\end{aligned}
\tag{4.15}
$$

The set $\mathcal{K}_{ik}$ is the set of nodes in the unique path from i to k. The Recursive Grouping Algorithm is also used by K. Moffat et al. [68] and generalized to complex-valued distances.

In an extended journal paper [77], S. Park et al. include new theoretical results on sample complexities that prove the correctness for the performance of the algorithms at finite samples.

Maximum Spanning Tree with Correlation Matrix

Now we focus on a modeling approach known as maximum spanning trees. Using μPMU voltage measurements, M. Bariya et al. [16] formulate an algorithm that relies on the synchronicity of measurements as it detects correlation across voltage signals. The authors build a *proximity matrix* $\mathcal{P}$ that is passed to a Maximum Spanning Tree (MST) algorithm to estimate the topology. The *proximity matrix* elements are the average correlation coefficients for each edge $\{i, j\} \in \mathcal{E}$, such that:

$$
p_{ij} = \frac{1}{e_i} \sum_{k=1}^{e_i} \rho(V_i(t_k^{(i)}, t_{k+T}^{(i)}), V_j(t_k^{(i)}, t_{k+T}^{(i)})))
\tag{4.16}
$$

$$
\mathcal{P}_{ij} = \min(p_{ij}, p_{ji})
\tag{4.17}
$$

where ρ is the Pearson correlation coefficient between voltage magnitude measurements, and $V_i(t_k^{(i)}, t_{k+T}^{(i)})$ is the vector of voltage measurements between t and $t + k$ at node i. The MST algorithm uses the proximity matrix as the adjacency matrix of the graph.

Following the approach of formulating the problem into a MST algorithm, S. Bolognani et al. [20] develop an algorithm that estimates grid topology from smart meter voltage data. However, in this method, the covariance matrix is not used directly in the MST algorithm, but is the base to build the *concentration matrix* $\hat{K}$ (Lemma (6) in [20]).

Bolognani et al. describe graphical properties contained in the *concentration matrix* $\hat{K}$, which is then used to deduce the grid topology through an MST algorithm: Prim's algorithm. It is interesting to note that the *concentration matrix* has an interesting relation to the Laplacian matrix: $\hat{K} = U_N^2 L \Sigma^\dagger L \mathbb{1}$ where U_N is the nominal voltage, Σ the voltage covariance matrix, L the Laplacian matrix and $\mathbb{1}$ the column matrix of ones.

Maximum Spanning Tree with Mutual Information

Next, we discuss methods that utilize MSTs with a statistical property called "mutual information". Using the MST algorithm, Y. Liao et al. [62] present an algorithm based on

the voltage measurements' *mutual information*. Suppose we define $\mathcal{V}$ as the probability distribution which generates voltage measurements. Then the *mutual information* is defined as:

$$\mathcal{I}(\mathcal{V}_i, \mathcal{V}_k) = \int_{\mathcal{V}_i} \int_{\mathcal{V}_k} p(v_i, v_k) \ln \left(\frac{p(v_i, v_k)}{p(v_i)p(v_k)} \right) dv_k dv_i \tag{4.18}$$

The goal of the algorithm is to find the Chow-Liu representation of the joint probabilistic distribution from mutual information. In [63], Y. Liao et al. generalize the method to 3 phase unbalance grids with phase detection.

Similarly, Y Weng et al. [97] develop a topology reconstruction algorithm using mutual information. However, they generalize the algorithm in [62] to meshed networks. In order to detect loops on a grid, the authors use Kullback-Leiber (KL) divergence.

Graphical Model Learning

Next we examine statistical learning methods for graph models. D. Deka et al. [34] develop a framework to detect grid topology from voltage and phase measurements. Their approach is based on graphical model learning where the node connections are deduced form conditional independence tests (see Theorem 1 in [34]). Learning the graphical model representation for the probability distribution of voltages is similar to the work of Y. Liao et al. [62]. This algorithm is then generalized to a three phase distribution grid in [39].

Optimization Based Algorithms

Optimization based methods solve what is often called the *topology estimation* problem. The approach is to first formulate the topology as a matrix, related to the associated graph Laplacian matrix. Then, estimate the matrix using available input data, through techniques like Maximum Likelihood Estimation or Maximum a Posterior Estimation. Next we will examine several sub-categories of optimization based algorithms.

Inverse Power Flow

The inverse power flow problem aims to find the admittance matrix Y from measurements at every node. Solving this problem is equivalent to solving the topology and parameter estimation problem. An advantage of the inverse power flow problem literature is that it provides a fundamental understanding and several mathematical guarantees. In [100], Y. Yuan et al. provide a complete analysis of the problem and show that the admittance matrix can be uniquely identified with measurements on every node. Then, they show that a Kron-reduced admittance matrix can be determined in the case of hidden nodes, i.e. nodes without measurements.

Maximum Likelihood Estimation (MLE)

Maximum-likelihood is a common technique to find the grid topology. The main principle of maximum likelihood estimation is to find parameters that maximize the probability of observing the collected data y, knowing the parameters θ. Thus, the method relies on the formulation of the conditional probability: $\mathbb{P}(y|\theta)$.

The advantage of the Maximum Likelihood approach relies in that it fits parameters representing the grid topology in the presence of noisy data. MLE can be interpreted as a linear regression that incorporates the noise distribution in the fitting process. For instance, if the noise is Gaussian, then MLE applied to a linear regression is equivalent to Least Square regression.

G. Cavraro et al. (2019) [30] use a maximum likelihood method to learn the active lines in a known grid. For the grid operator, this is similar to estimating the switch status. Alternatively, if certain connections are not perfectly known, the active/inactive status can determine the existence of a line. In this approach, G. Cavraro et al. estimate the variable $\boldsymbol{b} \in \{0,1\}^m$, a binary vector such that $b_i = 1$ if the line i is active and $b_i = 0$ otherwise. Here, the maximum likelihood problem fits vector $\boldsymbol{b}$ over the voltage data gathered over a certain time period. In other words, they minimize the value $\mathbb{P}(\boldsymbol{V}, \boldsymbol{b})$ defined as:

$$\mathbb{P}(\boldsymbol{V}, \boldsymbol{b}) = \frac{|\Sigma(\boldsymbol{b})|^{-T/2}}{(2\pi)^{NT/2}} \exp\left(-\frac{1}{2} \sum_{t=1}^{T} \boldsymbol{V}_t^T \Sigma^{-1}(\boldsymbol{b}) \boldsymbol{V}_t\right) \tag{4.19}$$

Here, $\boldsymbol{V}$ is the voltage data and $\Sigma(\boldsymbol{b})$ represents the covariance matrix of the voltage measurements.

Y. Sharon et al. [84] develop a similar version of the MLE algorithm and propose an alternative approach based on the support vector machine algorithm. Following the same idea, J. Yu et al. [99] used the MLE technique to iteratively estimate the parameters and the topology of a distribution grid. As in [30], they estimate the connected and disconnected buses. Solving the parameter estimation problem jointly with the topology estimation problem answers a practical need in grid management, as the entire model is usually unknown or partially known.

Maximum A Posteriori (MAP)

The Maximum A Posteriori approach is closely related to Maximum Likelihood Estimation (MLE), but incorporates prior information on the estimated variable. In the case of estimating energized lines (4.19), the prior is a sparcity enhancing prior on the parameter $\boldsymbol{b}$. G. Cavraro et al. show in [31] how the sparsity enhancing prior is defined from the Bernoulli distribution:

$$-\log \mathbb{P}(\boldsymbol{b}) = \sum_{i \in \mathcal{E}} b_i \beta_i - \log(1 - \pi_i) \tag{4.20}$$

where $\mathbb{E}(b_i) = \pi_i$, and $\pi_i = 1$ if the line is known to be energized, $\pi_i = 0$ otherwise, and $\pi_i = 0.5$ if there is no prior information on the line. The prior is then incorporated in the

maximum log-likelihood approach and using Bayes' rule, the topology estimation problem
can be formulated as:

$$\hat{b} = \arg \min_{\bm{b} \in \{0,1\}^m} \frac{T}{2} f(\bm{b}) + \beta^T \bm{b} \tag{4.21}$$

X. Li et al. [60] propose a Maximum A Posteriori (MAP) approach. Specifically, the prior
is a sparsity-enhancing term on the topology matrix, defined using the Laplacian distribution.
The grid model used in this work is the DC power flow equations which consider the ratio
of resistance to reactance to be sufficently low. This decorrelates the equations (4.1). The
resulting model is given by:

$$P = B\theta \tag{4.22}$$

where $P = [P_1, \ldots, P_n]^T$, $\theta = [\theta_1, \ldots, \theta_n]^T$ and $-B$ is the weighted Laplacian matrix where
the weights are the reactance values. The solution is then similar to the MLE presented in the
previous section [30] [99], where the unknown topology is contained in the Laplacian matrix
B. The sparsity-enhancing prior incorporates information on the sparcity of the matrix B.
While X. Li et al. [60] brings an interesting approach by using the MAP technique, the
DC power flow equations are often not well-suited to distribution grids as the assumption
that reactance is significantly smaller than the resistance usually does not hold. A more
generalized approach is developed by D. Xiaowen et al. [41] for learning the Laplacian
matrix using sparcity enhancing prior.

Compressive Sensing-Based and Sparse Recovery

Compressive sensing is a graph theoretic concept [33], used by M. Babakmehr et al. [12]
[11] to describe the topology estimation problem. The problem solved by M. Babakmehr
et al. in [11] is similar to X. Li et al. [60], which is to solve equation (4.22). However, M.
Babakmehr et al. assume that matrix B is sparse, and then use a sparse recovery algorithm.

Sparse recovery problems are optimization problems in which the goal is to recover an
S-sparse signal $y \in \mathbb{R}^K$ from a set of linear observations (measurements) $p = Ay \in \mathbb{R}^M$ where
$A \in \mathbb{R}^{MxK}$ is the sensing matrix with $M < K$.

The sparse recovery algorithm used in this paper is the greedy *Orthogonal Matching
Pursuit (OMP)* algorithm and the LASSO estimator. In addition, M. Babakmehr et al.
bring an interesting approach by using the *clustered sparsity* of the Laplacian matrix (see
Definition 4 in [11]) in the OMP algorithm, while raising the issue of correlation between
grid data resulting in a *highly coherent* sensing matrix A.

In [11], the LASSO optimization is used in the OMP algorithm. However, other algo-
rithms could be used. The goal is to use a formulation equivalent to a basic pursuit de-noising
which provides recovery guarantees for sparse matrices (see Theorem 2 in [11]) and is defined
as the following optimization problem:

$$\hat{y} = \arg \min_{y} \|y\|_1 \quad \text{subject to} \quad \|p - Ay\|_2 < \epsilon \tag{4.23}$$

In [12] the authors detail more variations of problem (4.23) including *Re-weighted $\ell 1$-Minimization* or *Noisy Re-weighted $\ell 1$-Minimization*, which account for noisy measurements.

It is interesting to note that the fundamental structure of this problem is similar to the maximum likelihood estimation problem in the case of Gaussian noise.

LASSO estimation and Conditional Inference

The method exposed by Y. Liao et al. in [61] relies on the definition of node measurements as random variables, denoted $\mathcal{V}_i$. The collection of random variables for a certain set s is denoted by $\boldsymbol{\mathcal{V}_s}$. Assuming current injections are independent, the joint probability distribution of nodal voltages is proven to be equal to:

$$\mathbb{P}[\boldsymbol{\mathcal{V}}_\mathcal{N}] = \prod_{i=1}^{n} \mathbb{P}[\mathcal{V}_i | \mathcal{V}_{\mathcal{T}(i)}] \tag{4.24}$$

If we additionally assume that the random variable $\boldsymbol{\mathcal{V}}_\mathcal{N}$ follows a multivariate Gaussian distribution, then the authors establish that, for each node $i \in \mathcal{N}$:

$$\mathcal{V}_i = \boldsymbol{\mathcal{V}}_{\mathcal{N}\backslash\{i\}}\beta^i + W_{\mathcal{N}\backslash\{i\}} \tag{4.25}$$

where the coefficient β^i indicates the statistical dependence between two nodes, and $W_{\mathcal{N}\backslash\{i\}}$ is a zero mean Gaussian variable error term. This equation shapes the topology estimation problem into a linear regression problem:

$$\hat{\beta}^i = \underset{\beta^i(1)=0}{\arg\min}\left\{ \sum_{t=1}^{N}(V_i^t - (\boldsymbol{V}_{\mathcal{N}\backslash\{i\}}^t)^T\beta^i)^2 + \lambda\|\beta^i\|_1 \right\} \tag{4.26}$$

The Lasso formulation seeks to enforce the sparsity of the vector β^i, whose elements are zero for unconnected lines. This method is similar to other optimization based methods described in this section, since the LASSO formulation seeks to induce sparsity while fitting weights in the face of uncertainty. However, this approach differs in the sense that the nodal voltage measurements are treated as random variables, and the LASSO problem is solved for every node iteratively. The authors adapt this algorithm to multi-phase grids in [63], combining the optimization based approach with an iterative method described in Section 4.4.

Adaptive LASSO

Next we describe adaptive variations of LASSO. O. Ardakanian et al. [9] use a LASSO formulation to solve the three phase topology estimation problem with current and voltage measured from PMUs at all nodes. Similarly to previous algorithms, the authors adopt the LASSO formulation to induce sparsity in the admittance matrix. However, the paper explores a more interesting structure, as the possible bias between data or the existence of an approximate impedance matrix.

Finally, the authors show how the algorithm can be incorporated into an online event detection algorithm. The algorithm is divided into two steps: change detection and localization. Change detection is done by comparing the change in state estimation with the current model and measured data. Localization is next performed by running the previous LASSO based algorithm with knowledge of the past impedance matrix.

Mixed-Integer Quadratic Optimization (MIQP)

Z. Soltani et al. [86] formulate the problem as a MIQP. The formulation is based on the AC optimal power flow equations. The parameter and topology estimation problems are solved alternatively, similar to [99]. In [86], the objective or cost function is a loss function representing the error between measurement data and the linearized model. The constraints are the power flow equations.

4.5 Discussion

In the following section we discuss methods from the literature described in Section 4.4 in terms of: (i) the integration of grid data uncertainty, and (ii) the efficiency and implementation of the algorithm.

Integrating Uncertainty

The grid is a complex system extended across large areas and exposed to various environments. Sensors and communication equipment can fail, and records of device models and parameters might be inexact. This uncertainty from input data must be taken into account by topology estimation algorithms. Consequently, an exact topology estimate and model parameterization is, in practice, hard to achieve. The challenges of uncertainty can be decomposed into at least two categories: missing data and noisy data, which we discuss next.

Missing Data

Even as more sensors are being installed, the distribution grid remains mostly unequipped or partially equipped with sensors, such as PMUs or even smart meters. In addition to unrecorded data, the grid operator has to face the problem of missing data, resulting from sensor deficiency or connection issues. Most authors who use PMU data in their algorithm take into account that PMUs might not be installed at every node of the system. Recursive or iterative algorithms tackle the case where data is missing at one node by finding children relationships between nodes. This is the case of D. Deka et al. [37] [38] and S. Park [76].

However, in most papers, the existence of the missing nodes is known, and the algorithm only finds the best path through the nodes. In practice, this is not usually the case and some nodes might not be known. In [16], M. Bariya et al. present an algorithm that finds

the topology only from nodes that do have measurements. If the sensors are well-placed, then this approach can recover a useful subset of the topology. M. Bariya et al. provide recommendations, based on their topology estimation algorithm, on how to place PMUs sensors in order to recover a useful topology, i.e. one that can detect switches.

Noisy Data

Most papers that tackle the data uncertainty problem consider incoming data as random, modeled with probabilistic distributions, or by adding Gaussian noise.

This is the case of Y. Liao et al. [62] [61] and all the papers considering the MLE or MAP method, G. Cavraro et al [29], J. Yu et al. [99], M. Babakmehr et al. [11], X. Li et al. [60], D. Xiaomen [41]. In almost all cases, the random variable is assumed to follow a normal distribution.

In recursive approaches, the data uncertainty is included by considering the second order moments of the voltage or angle data. The work from D. Deka et al. is based on this technique [36] [37]. While this allows the algorithm to use noisy data, the time required to gather sufficient data is long and the topology might have evolved during that time.

M. Bariya et al. [16] uses signal shapes in contrast to signal values to side step noise from instrument transformers. The authors raise the issue of the *low-rank nature of synchrophasors*: short and high resolution windows show uniformly low correlation while long and lower resolution windows show uniformly high correlation. Consequently, M. Bariya et al. [16] select event points of data to overcome this issue.

Algorithm Efficiency & Performance

Depending on the objective of the topology estimation algorithm, multiple aspects of algorithm efficiency and performance can be considered. Most of the literature mentions that topology estimation and grid models can be used to control and integrate DERs, which implies solving the optimal power flow problem. In this application, the topology must be estimated and optimal power flow re-computed after each change in switch status or if a change is detected. The paper from G. Cavraro et al. [28] and Y. Weng et al. [97] develop techniques to detect changes in switches and adapt the data collection to avoid unnecessary noise from switches.

The efficiency of a topology estimation algorithm can be measured using the "recovery ratio" or average relative error, as presented in most papers [76], [36] [37] [61] [63] [62]. However, since the input data is uncertain, a more rigorous metric like the confidence interval on the estimated topology could be used. The work from G. Cavraro et al. [30] and Y. Sharon et al. [84] use line error probability and approximated error rate, respectively, to present their algorithm results.

This review divides the methods used in the literature into two categories: recursive and optimization based techniques. While the efficiency of each algorithm depends on many assumptions, we try next to compare the two approaches.

4.6 Gap Between Real World Needs and the Existing Literature

Real Grid Challenges

Traditionally, power system modeling and operation has focused on the transmission grid network, since more sensors have been installed and better modeling techniques have been developed. Less attention and infrastructure investments have been made on the distribution grid. Instead, distribution grids are oversized by design. These historical decisions are now responsible for a lack of sensors and communication protocols to monitor operation in distribution circuits. Specifically, data can be missing at some nodes, have low precision, and/or have incorrect timestamp records. To perform an efficient topology estimation, algorithms should take these issues into account.

In addition, the distribution grid operator usually lacks a high fidelity model. However, they may have a low fidelity model and experience that can provide prior information for topology estimation. It is useful to incorporate this information, or validate it in the process of topology and parameter estimation. This is particularly true for papers assuming knowledge of the impedance values – post verification methods are needed.

Imperfect prior knowledge of the grid can also prevent grid operators from recovering the topology of the full network. In the literature, most papers assume the reconstruction of topology between known nodes only. Figure 4.3, reproduced from [62], illustrates this challenge. The red points are nodes that exist and are known, but their connections are unknown. Meanwhile, the topology connecting white points is known. Considering the grid representation only from observable nodes is useful for grid management, as detailed in [16], yet still provides an incomplete picture.

More importantly, the distribution grid is built as a meshed network to provide redundant paths during, for example, maintenance or some outages. However, it operates as a radial network. While assuming a radial network is correct for modeling the distribution grid's active topology, reconfigurations are frequent and can happen automatically or manually. This motivates topology estimation algorithms that can produce accurate estimates with short periods of data, or leverage change detection algorithms.

Recommendations

Solving the topology estimation problem is a complex. It involves interesting graph learning and parameter estimation techniques. However, the grid is a complex, real-world physical system that was built over a century ago, which constrains the implementation of algorithms. In the last section, we exposed the challenges faced by a grid operator. In this subsection we aim to provide recommendations to the reader on areas that require future research, relative to the existing literature on topology estimation.

First, the available data could come from multiple sources. Smart meter data are widely installed, but do not always record voltage and power with high precision and synchronized
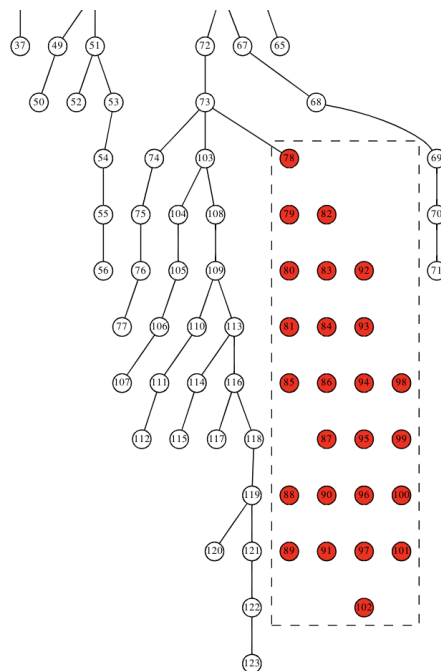
Figure 4.3: Part of 123-bus IEEE bus system. From Y. Liao et al [62]

timestamps. PMUs, on the other hand, record a large amount of data and are synchronized. However, they are not yet adopted by all distribution systems. Future work should consider algorithms based on both high-resolution PMU data (albeit at some nodes) and lower-resolution smart meter data.

Secondly, the use of prior knowledge on the grid model is a realistic assumption and improves the performance of grid topology estimation. Indeed, grid operators have approximate knowledge of some line connections and nodes. Since most equipment is similar for similar ratings, it is also possible to recover an approximation for line impedance by characterizing one line. High performance topology estimation algorithms should leverage these valuable sources of input.

Third, the distribution grid in the United States is highly imbalanced while in Europe distribution grids are more balanced. Given this fact, it would be useful to design a general topology estimation algorithm for three phase unbalanced grids.

Finally, the most important recommendation of this paper is to design an algorithm that provides confidence intervals on the estimated grid model. As mentioned, grid topology and a network model is needed to manage DERs and operate the grid under complex load constraints. The grid model will then be used in power flow optimization, failure detection algorithms, and maintenance decisions. While most of the papers listed in this review are providing detection rates with missing nodes or noisy data, only one provide a confidence

interval around the estimated topology [84]. Providing this metric would help grid operators to manage risk in decision making [78].

In addition to all these recommendations, the grid modeler and algorithm designer must always consider the model objective. Specifically, what is the purpose of constructing a given model? This purpose determines what level of confidence is required from topology and parameter estimation. For example, controlling switch status does not need the high-fidelity of a model used for estimating equipment age. Thus, carefully defining the modeling objective is a critical first step in any topology estimation algorithm design.

4.7 Conclusion

In this paper, we have provided a comprehensive overview of the challenges of distribution grid topology estimation. The review summarizes existing algorithms and methodologies. It also discussed important gaps between real world needs and the published literature. While this area of research is gaining more attention, due to the proliferation of sensing technologies and novel management algorithms, many challenges remain. There is a need for developing simple topology estimation algorithms that are robust to various grid changes and uncertainty, and that provide confidence intervals on results to enable effective decision making.

Chapter 5

Conclusion

5.1 Thesis Review

This dissertation explores diverse solutions to integrate renewable energy on the electrical grid through a better bidding strategy, new electricity market design, and understanding distribution grid topology.

Chapter 2 presents an optimal bidding algorithm, using reinforcement learning technique, to tackle the case of a price maker battery on the electricity market. This work studies the use of the reinforcement learning algorithm accounting for the safety and the practical implementation of the algorithm. We propose a new supervised Actor-Critic algorithm that uses traditional algorithms as Model Predictive Control. In addition, this work aims to provide reflections on the use of reinforcement learning techniques in real-world environments as electricity markets.

Chapter 3 proposes a novel day-ahead dispatch algorithm that integrates DERs as a source of flexibility. This source is located at the distribution level, is distributed, and more importantly, extremely variable and uncertain. The proposed dispatch accounts for the specific nature of DERs while using their flexibility potential. As a result, the dispatch co-optimizes balancing capacity and day-ahead market and uses stochastic formulations to integrate DERs uncertainty.

Chapter 4 reviews solutions to estimate distribution grid topology. Indeed, DERs are located on the distribution grid and require performing grid modeling to be controlled and integrated on the electricity market. The review provides a global understanding of topology estimation and presents real-world challenges caused by a lack of reliable sensors and prior knowledge. We explore the existing literature and expose available techniques depending on-grid and data assumptions. This work aims to give the reader the tools to develop future research that fills gaps in the literature and between research and real-world implementation.

5.2 Future Work

This dissertation tackles various aspects of flexibility integration in the electricity market. On each aspect, there are many possible future works to be done. We will list here subjects that are interesting to pursue and answer important challenges.

Efficiency of frequency control ancillary services markets

In chapter 2, we proposed a new optimal dispatch for grid-scale storage systems in the case of market power on the wholesale market. This work was motivated by the impact of batteries in the electricity market, and specifically on the frequency market. The battery's efficient frequency response creates significant market power. However, market power might disturb the frequency market, and it is essential to monitor the long-term effect of this power on frequency control. Future work could study the impact of grid-scale batteries on the ancillary services market and multiple batteries' impact on the same market. One should ask the two questions: How to guarantee fair competition that leads to a meaningful clearing price? And can batteries be profitable in a highly competitive market?

Role of reinforcement learning in power system

Chapter 2 uses reinforcement learning to improve grid-scale battery's bidding strategy. Reinforcement learning is an exciting tool for power systems. Indeed, the grid is complex, and modeling the entire grid can be difficult or impossible. As a black-box tool, reinforcement learning could simplify and improve control algorithms. Some possible use of reinforcement learning is markets dispatch, inverters control, demand response management, and optimal power flow. Future work will have to consider safety in using reinforcement learning in a real-world environment; indeed, as developed in chapter 2, reinforcement learning statistically chose the action to take and needs a learning process, which can lead to unsafe actions.

Communication process and optimal dispatch of DERs: DSO/TSO interface

In chapter 3, we propose a new market design for integrating distributed energy resources on the wholesale market as a source of flexibility. One aspect not studied in this research is the communication process between the ISO/TSO and the local DSOs. Indeed, the DERs are connected to the distribution grid managed by DSO, and while they have an aggregated impact on the transmission grid, they also impact the distribution grid. DSO must simultaneously control DERs in response to TSO/ISO order while maintaining a functioning grid.

Gaps between research and real-world challenges

Chapter 4 reviews existing work on distribution grid topology estimation. Most techniques rely on quality data and assume prior knowledge as parameters or nodes' existence. In practice, data is partially recovered and is highly correlated. Developing an exact topology recovery algorithm is challenging in practice and requires methods to account for noise and missing information. Future work could develop a topology estimation algorithm that uses multiple information sources and provides a confidence interval depending on the quality of input data. Those confidence intervals can then be used to assess the exactness of some power flow simulation or outage detections and improve the decision-making process.

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