Optimizing Long Duration Energy Storage Systems: A Forecasting and Modeling Approach Using Echo State Networks

by

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Thesis directed by Prof. Bri Mathias Hodge

As a global transition towards renewables is underway, proper management and scheduling of long duration energy storage (LDES) technologies is essential to maintain grid reliability, and address uncertainty within Variable Renewable Energy (VRE) generation. This thesis employs a dynamic Echo State Network (ESN) that generates price forecasts used in an optimization problem to optimize the schedule of varying sizes of LDES devices. The objective function of the model is to maximize energy arbitrage by choosing when to charge and discharge the storage devices. The optimization model makes use of a rolling horizon, optimizing over a period with extended foresight. The ESN is trained with price, VRE and load data from NREL's 118-Bus system to generate realistic price forecasts that are used as foresight in the optimization model. This work creates a framework that is better than deterministic models, by incorporating foresight of realistic price forecasts to inform the model. A multitude of simulations were conducted analyzing various lengths of foresight and sizes of LDES devices under two different market structures, a wholesale electricity market and an ancillary services (A/S) market. The operation dynamics of devices with shorter discharge durations were captured better with less foresight, while devices with longer discharge durations required more foresight. Smaller devices participating in the A/S market were influenced minimally by foresight horizon. Whereas larger devices saw a significant increase in value when simulated with a longer foresight. A vital takeaway is the impact on the value of storage devices of varying sizes when forecast error is present.

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Introduction

1.1 Motivation

Energy plays an essential role in almost every aspect of human life. Energy consumption is embedded in our education, entertainment, food, transportation, and more. As the global population grows and more technological revolutions occur, our energy consumption is increasing. Simultaneously, climate change and its implications are becoming increasingly prevalent; the need to quickly decarbonize has become apparent. For decades scientists have issued warnings regarding the climate crisis well before global temperatures began increasing. In 1965 President Lyndon B. Johnson issued a message, warning of the danger of fossil-fuel-based energy generation stating: "This generation has altered the composition of the atmosphere on a global scale through radioactive materials and a steady increase in carbon dioxide from the burning of fossil fuels"[18]. However, since this message global temperatures and carbon emissions have continued to increase, suggesting that mitigation efforts have not had the desired impacts [20].

As of 2024, the earth's temperature has risen by 0.11 Fahrenheit (0.06 Celsius) per decade since 1850, however, the rate of warming since 1982 has increased to more than three times that rate (0.36 Fahrenheit or 0.20 Celsius) per decade. It has also been observed that 2023 was the warmest year since temperature records began in 1850, and the ten warmest years have all occurred over the past decade [30]. These increased temperatures have cascading effects including increasingly extreme weather phenomena, like floods, droughts, and storms, and can also be linked to a worsening of certain diseases [45] [39]. Decreasing greenhouse gas emissions is imperative in slowing climate

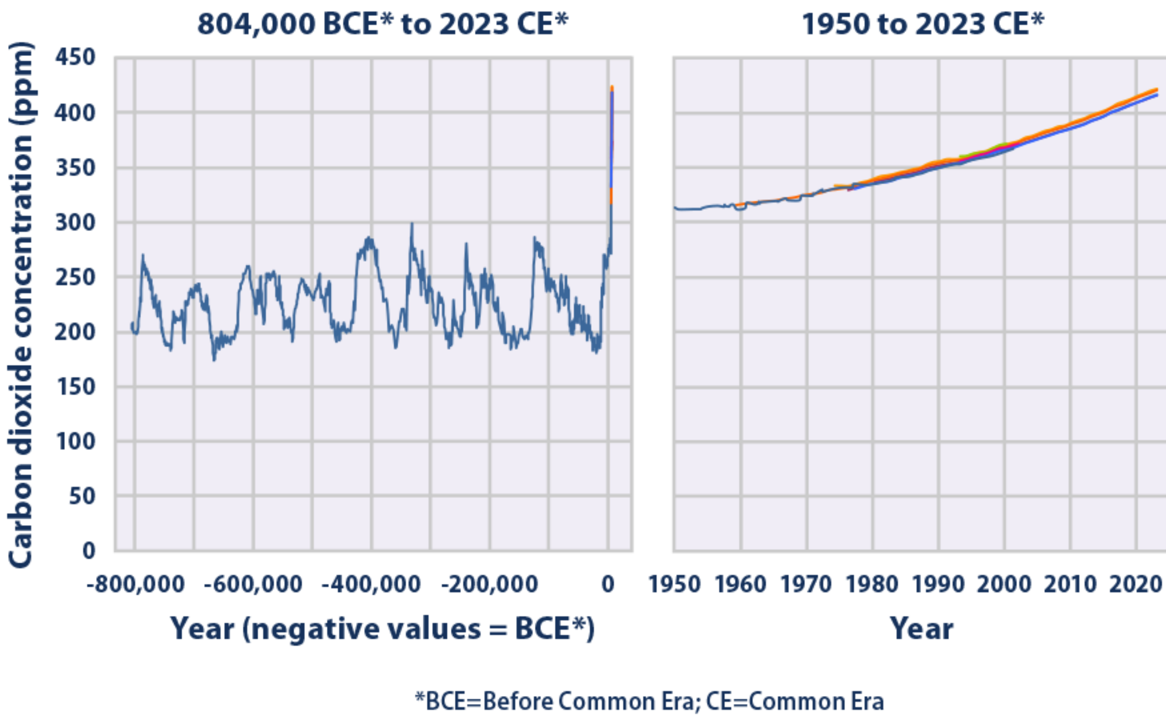

Figure 1.1: Global Atmospheric Concentrations of Carbon Diaxoide Over Time [50]

change and is dependent on global decarbonization. This global challenge includes improving the efficiency of current technologies, electrifying end-use sectors, integrating renewable energy technologies, improving direct air and ocean capture technologies, and encouraging social and behavioral changes. However, the most impactful avenue of decarbonization is the integration of more renewable energy technologies and moving the energy sector away from fossil-fuel based generation. The energy sector is the source of approximately 75% of total greenhouse gas emissions and is a key player in averting the worst of climate change.[13] Variable Renewable Energy (VRE) integration has been steadily increasing over the past couple of decades. As of 2023, wind energy was the source of 10% of the total U.S. utility-scale electricity generation, hydropower was 6% of the U.S. utility-scale electricity generation, solar photovoltaic and solar thermal pants provided approximately 4% of the total U.S utility-scale electricity, biomass accounted for about 1% of the U.S. utility-scale electricity generation. [49]

While the integration of VRE onto the current power grid is important, it does not come without technical and economic challenges. Namely, the fact that these resources are considered non-dispatchable, meaning their ability to generate power is not entirely tractable which can lead to variability and uncertainty. Additionally, there is often a temporal mismatch between the supply of VRE generation and demand. This mismatch can be seen on the hourly, diurnal and even seasonal time scales and becomes more pronounced as more VRE resources are integrated onto the grid [17]. For example, low or high wind speed regimes can last days to weeks, effectively causing wind generation electricity output to drop to nothing or soar. Furthermore, seasonal variability can be seen in the wind and solar electricity output. Wind generation tends to peak in the winter, while solar generation peaks in the summer [46]. Energy storage devices can smooth this variability by performing temporal arbitrage, charging during times of excess generation and discharging during times of high demand.

1.2 Long Duration Energy Storage

Storage technologies play a key role in the transition of the energy sector towards greater penetration of VRE [40], including Long Duration Energy storage (LDES) [1]. Broadly speaking, energy storage devices can be characterized in two ways: by their power capacity and energy capacity. Power capacity represents the maximum amount of electricity that the device can discharge at a given time, and is typically measured in kilowatts (KW) or megawatts (MW). The energy rating represents the total amount of energy that can be delivered until the device reaches 0% charge [48], and is typically measured in kilowatt-hours (KWh) or megawatt-hours (MWh). The energy industry has yet to define a standard for establihsing whether a technology is considered short or long term. However, there is a consensus that a device is considered long duration if it can discharge at it's maximum power rating for up to 10 hours or more [48]. The following table describes how different institutions define LDES.

While short duration storage can be used to capture diurnal mismatches between generation and demand [17], seasonal variations require larger amounts of energy to be stored and discharged.

Institution	Duration
DOE	10 + h
California Public Utilities Commission	8-12 h
California Energy Commission	10 + h
Advanced Research Projects Agency-Energy	10-100 h
LDES Council	8-24 h
PJM	4,6,8,10 h

Table 1.1: Long Duration Definition [48]

Figure 1.2 illustrate the load and resource balance for a 100% VRE grid in California, and indicated where LDES can be used during energy surpluses and deficits. Understanding the implications of integrating LDES onto a grid is highly complex and requires robust enough models to capture the true nature of these devices. This work aims to do just that.

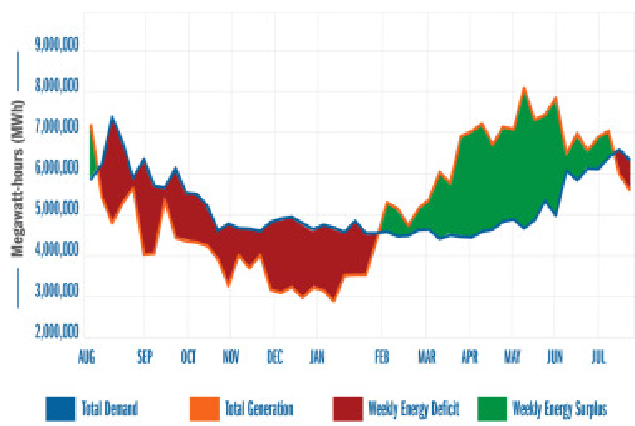

Figure 1.2: Simulated Load and Resource Mismatch for California [48]

Chapter 2

Literature Review

Increasing the penetration of renewable energy resources and transitioning away from fossil fuel-based power generation is critical to slow climate change. As of 2020, fossil fuels contributed 61.3% to global power generation [17]. However, renewable energy technologies are increasingly being relied on and contributing to overall power generation. Renewable energies including solar, wind, and hydro are variable energy sources because their generation is dependent on somewhat unpredictable weather conditions. This variability can be seen on the yearly scale, seasonally, diurnally, and even down to the second.[11] The variable and uncertain aspects of these sources leads to increased energy curtailment and the discrepancy between load and demand leading to a negative impact on pricing and power systems operations. Introducing long duration energy storage (LDES) can decrease energy curtailment, reduce start-up and shutdown costs, increase generator efficiency, increase energy arbitrage, and smooth out variability in location marginal prices. [54]. In theory, LDES devices operate in a straightforward fashion: during periods of excess VRE production, when energy prices are typically lower, it charges. In contrast, when demand is high and energy prices rise, the storage device discharges, generating a profit. Although energy storage is widely recognized as a key technology essential for integrating more renewable energy, studies on storage have been limited in breadth. Most studies have analyzed the operation of storage devices in the context of system-wide benefits, while other study the devices in isolation.

2.1 LDES Technologies

A multitude of potential LDES technologies have been proposed with differing round-trip efficiencies, locational constraints, and technology readiness levels (TRL). Some of the more common technologies include Pumped Hydro Energy Storage (PHES), Compressed Air (CAES), Thermal Energy Storage (TES) and Hydrogen Energy Storage (HES).

2.1.0.1 Pumped Hydro Energy Storage

Pumped hydro energy storage is a well-researched and effective system for utility-scale electric energy storage. As of 2022, 90% of the United States' energy storage comprised of pumped hydro. [40] Like a typical hydroelectric plant, the system consists of two reservoirs at different elevations. During times of low electricity prices, the system pumps water from the lower reservoir to the upper reservoir. During times of high energy prices, water flows through a turbine, producing electricity through a generator. Pumped hydro systems offer multiple benefits to the grid including flexibility and high energy capacity. According to Hino and Lejeune [19], PHES has fast startup and shutdown times, has the ability to quickly follow drastic changes in load, and can maintain voltage stability. [37] However, critical issues of PHES include geographical limitations and high construction costs. [37] These issues are being addressed through new technological developments, including a study by Connoly et al. [8] where a program was designed to scan terrain to identify potential PHES sites. [8]

2.1.0.2 Compressed Air Energy Storage

In 1949 Stal Laval proposed compressing air in underground caverns and subsequently catapulted the scientific community down the road of CAES [51]. During times of low energy prices, the air is compressed and stored in underground caverns at high pressures. This high-pressure air is then released during times of high electricity prices and driving an expander to generate electricity. The principle design of CAES is based on that of a traditional gas turbine [51]. Currently, there are two commercial CAES plants worldwide, a 290 MW plant in Huntorf, Germany, and a 110 MW plant in McIntosh, Alabama [24]. Like PHS, CAES can store energy during off-peak times generate power during times of high demand, and has a high energy capacity [4]. However, because the density of air is low, energy and power density are subsequently low. This limits the amount of energy that can be stored in a given volume [16]. The energy efficiency of CAES plants ranges from 40% to 70%, however, more advanced CAES systems such as A-CAES systems can reach energy efficiencies of 60% (e.g., Goderich facility in Canada) to 67% (e.g,. Feichegn in China) [25].

2.1.0.3 Thermal Energy Storage

Thermal energy storage (TES) is a broad term that can be broken down into three categories based on the storage medium used. Sensible heat is a process where energy is stored within a medium, and then an exchanger extracts the heat generating steam to pass through a turbine. This process can generate approximately 10-50 kWh/ton, depending on the medium used. [38] Latent heat manipulates the phase of a medium to store energy. When electrical demand is high, the medium is transitioned back to its original phase, releasing heat. [38] This process, also known as Phase Change Materials (PCM), can generate approximately 50-150 kWh/ton. [38] Thermochemical storage utilizes endothermic chemical reactions. A substance is split into molecules which are then stored separately. They are then reintroduced to release heat [38]. This process can generate 120-150 kWh/ton [38]. However, TES within the electric sector is predominantly sensible heat molten salt, which accounts for 77% of all TES [38].

2.1.0.4 Hydrogen Energy Storage

Hydrogen electrolysis involves splitting water into its respective elements, hydrogen, and oxygen, and can be done so with excess energy produced by renewables. [34]. This process takes approximately 39 KWh of electricity to produce one kg of hydrogen if it is operating at 100% efficiency [15]. The hydrogen is used as the storage medium, and oxygen is a bi-product. However, the oxygen can be used in a number of different ways, including feeding it to a sewage plant for converting microorganisms, or it can be used as a bleaching agent [53]. The hydrogen is typically stored in either high-pressure gas storage vessels or underground salt caverns. The reconversion of the hydrogen back to electricity is done using a typical combined cycle power plant. The hydrogen is burned and spins a steam turbine, then a generator converts that mechanical energy into electrical energy [53].

2.1.1 Emerging Technologies

Some emerging technologies that are not yet commercially available consist of liquid air energy storage, and gravity-based storage. Liquid-air energy storage uses excess power to compress and cool air to cryogenic temperatures. This liquid air is then stored in insulated tanks at low pressures. When power is needed, the liquid air is released, reheated by ambient temperature and expanded to power a turbine [44]. Gravity based storage uses excess power to lift material, typically rocks or concrete, and hold it has potential energy [47].

2.2 Ancillary Services

On top of performing energy arbitrage in an electricity market, LDES technologies can simultaneously participate in the Ancillary Services markets. These markets are crucial aspect of power systems, and are necessary to maintain reliability and stability of the grid. These services are a resource that system operators use at a variety of time frames to ensure a continuous power balance [26]. Regulation reserves are constantly monitoring the energy imbalances that occur when load and generation are unmatched. These reserves operate at the finest timescale of anywhere between 5-minutes and one hour [12]. Spinning reserves are the first line of defense when a significant disturbance, a loss of generation or large load step, has occurred in the system. These reserves are typically deployed as quick as 10 minutes after the disturbance [42]. Ramping reserves are deployed when longer duration events occur. Current research is analyzing the efficacy of storage devices participating in the ancillary services market. Prakash et al. [36] considered battery energy storage systems for short-term and long-term ancillary services and the associated issues. They determined that critical challenges in deploying BESS in these markets include properly sizing the system, battery degradation due to cycling, the coordination and operation of the battery energy storage systems (BESS) with other distributed energy resources (DERs).

2.2.1 Power System Operational Modeling

Power systems modeling refers to the process of representing and analyzing the operation of the electric grid to ensure reliability and economic viability. The timescale of the analysis determines how the information will be used. Analysis on the nanosecond to second scale are often studying power systems dynamics. These analysis are typically conducted to better understand the stability of the grid. Modeling that occurs on the multi-year to decadae timescale are often performing capacity expansion analysis, which are used in long-term planning studies. These studies identify the optimal, least cost, resource mixes considering policies, technological advancements and electricity demand growth [6]. Unit commitment (UC) and economic dispatch (ED) are problems that are typically solved over a year. These optimization problems are solved to determine which generating units should be turned on, and how much power they will produce to make sure that demand is met at all times such that cost is minimized [27]. Figure illustrates the different modeling techniques and associated timescales.

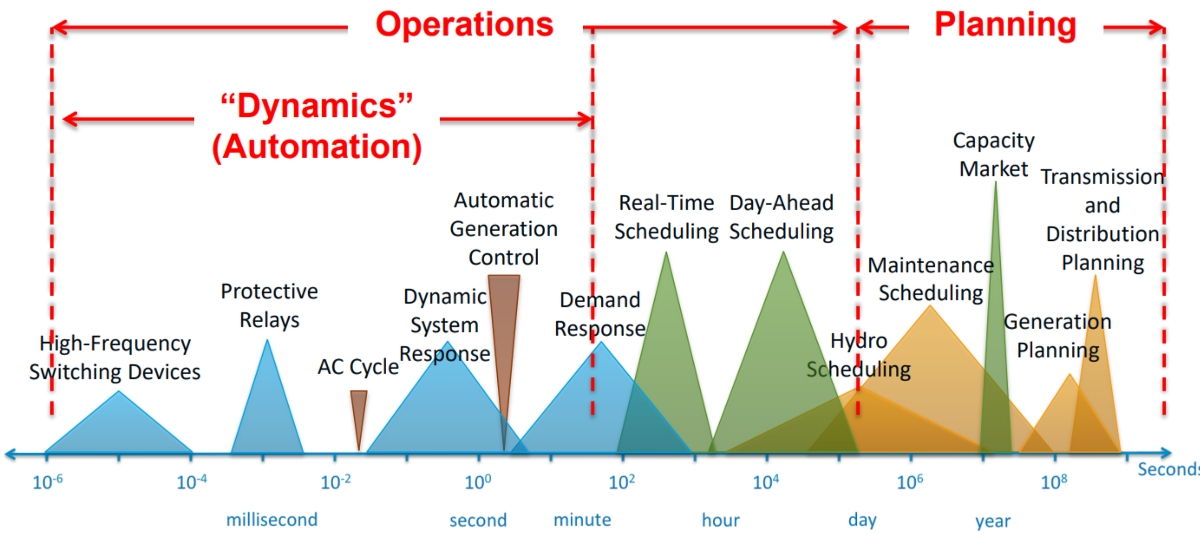

Figure 2.1: Modeling Timescales [3]

2.2.2 Unit Commitment and Economic Dispatch (UCED)

As mentioned, UCED is optimization problem, that consists of two sub-problems, used to schedule when and which generating units should be turned on and off and determine the individual power outputs of each unit. UCED is a complex problem that requires a wide range of information regarding the topology of the network, generator parameters, line parameters, and forecasts. Forecasts of price, demand, and VRE are often used to inform the model of the most economically efficient and reliable generating fleet. The first of the two sub-problem to be solved is the Unit Commitment. The UC determines which generation units should be turned on or off based on generator ramping limits, minimum and maximum down times, and minimum and maximum stable limits, and system constraints. This problem typically uses a 48 hour look ahead window, with a 24 hour operational period. The UC commits generators for the following operational period. [33]. The economic dispatch problem is solved anywhere from 5-minute to hourly intervals and determines the power output of the generation units based on short-term load and generation forecasts and system constraints. Typical ED problems are informed with a 2-4 hour look-ahead window [33].

2.2.3 LDES Arbitrage in Highly Renewable Grids

A common function of storage devices is energy arbitrage which exploits temporal price differences, buying energy from the grid when prices are low, and selling energy back to the grid when prices are high. Arbitrage is implemented by optimizing the state of charge profile of a device to exploit these price differences. Arbitrage has the additional benefit of mitigating renewable energy curtailment during times of low demand and high VRE generation. In Zhang et al. [54] the projected operation of 2,000 MW LDES in the 2050 Western Interconnect was analyzed. The study ran a UCED model using the PLEXOS software to model four different energy storage technologies. State-of-charge profiles indicated that that the storage device charges during spring when there is excess renewable energy, and begins to discharge during the summer months. A system-wide benefits analysis, measured by cost reductions in fuel and VO&M, showed that the benefits increased as storage round-trip efficiency improved.

2.2.4 Operating LDES

Maximizing the profitability of LDES is directly tied to the operational profile of the device. Short duration energy storage can provide services like voltage support, frequency response and contingency reserves, in the minute to hour time scale. LDES operates on a much larger timescale, making it a challenge to properly capture the nature of these devices. Typical operational modeling techniques focus on timescales ranging from minutes to days using look ahead periods of 24 to 48 hours, whereas LDES operates on timescales from daily to monthly. Therefore, unlike other generators found on the grid, LDES requires a longer look-ahead period than just 24 to 48 hours. The longer look-ahead period is crucial to capture price and market conditions that directly indicate how LDES should be operated. This fundamentally change the way systems with LDES should be modeled.

The process of modeling LDES requires careful consideration of the services provided, its interaction with market prices, and other components on the grid. To harness the full potential of

LDES a robust and well-rounded, and often a multi-stage, modeling technique must be employed. In response, a multitude of modeling techniques have been used to analyze the economic and technical benefit of LDES. Denholm et al. [10] analyzed the benefit of LDES from a system flexibility point of view in a highly renewable system. They determined that as systems approach 100% renewable penetrations, LDES becomes crucial in managing extended periods of low renewable generation, and providing system flexibility. Zhang et al. [54] used a two-stage production cost model to simulate the future Western Interconnect with 85% renewable penetration. They evaluated four different storage technologies with varying round-trip efficiencies analyzing total system costs, storage dispatch profiles, the generation mix, and renewable curtailment. The study found that as round-trip efficiency increases total system costs decrease.

2.2.5 Modeling Techniques

Accurately modeling the operation of LDES is an essential step in identifying the viability of integrating it onto the grid. Weitzel et al. [52] provides insight into the differences between the major modeling techniques used to model energy storage devices. The following section describe the major types of storage modeling outline by Weitzel et al., [52].

2.2.5.1 Load Model

In a load or consumer-oriented model a single or multiple loads are combined with a storage device. The objective function aims to reduce cost for the consumers by shifting load from high price times to low price times. Another objective function that falls within this domain is consumption-related objectives. These objective functions focus more specifically on how the load is being consumed. Bruni et al. [5] examined an off-grid system with renewable energy production and battery energy storage with the objective of minimizing fuel costs, and comfort deviations in terms of the temperature of the house.

2.2.5.2 Generation Model

In a generation or producer-oriented model a hybrid, storage, and renewable energy facility was examined primarily with an economic objective, then a technical objective function. Kim et al. [23] paired a wind turbine with a battery energy storage device to examine profit maximization. Kou et al. [28] also combined a wind turbine and BESS to optimize the difference between aspired and realized power levels and battery life.

2.2.5.3 Grid Model

In a grid model, the storage device is modeled as a single component in a larger system. The objective function is to minimize system-wide costs, not necessarily maximize the individual profit of the storage device. The storage device is operated such that it ensures grid and energy reliability. [28]

2.2.5.4 Market Model

The market model focuses on the behavior of the device within the grid. Broadly speaking, market models can be differentiated based on the size of the device of focus with respect to the rest of the system. Typically, power system models are developed such that a single device can not independently impact market-clearing prices [43] [2]. This is the case when using a price-taker model; the device in focus has negligible influence on market prices. Conversely, a price-maker describes a model in which the device is large enough that it does influence the market.

Storage devices can act as both price-makers and price-takers depending on what market it is bidding into. When bidding into a primary electricity market, it is more likely to act as a price-taker. The storage device responds to market prices and adjusts its operation in such a way that will maximize profit. However, when participating in smaller markets, like the ancillary services market, a storage device might operate as a price-maker. The ancillary service market includes frequency regulation, voltage stability, and contingency reserves. It is typically a smaller market, where storage devices may contribute a larger share of generation and therefore have influence over prices [43] [2].

Both price-taker and price-maker models have been used to study the influence of storage devices on a multitude of factors. Arteaga et al. [2] modeled a battery storage system as a price-taker in the bulk electricity market, and as a price-maker in the ancillary services market.

2.2.6 LDES Optimization

Regardless of the model type, modeling the operation of LDES in a greater power system is difficult and introduces new challenges. Other generation types—such as thermal, hydro, solar, wind, and short-duration storage—operate on a much shorter timescale than LDES, making them easier to model. UCED models are good at detailing system wide operations and constraints. However, these models typically use a horizon of 24 to 48 hours which is too short to capture the dynamics of LDES, but increasing the horizon is exceptionally computationally expensive. Price-taker and price-maker models are good at capturing the optimal operation of LDES, but lack detail of the greater power system. Guerra et al. [17] used a price-taker model to optimize the operation of a 2 GW LDES device. Daily state-of-charge (SOC) targets were created from the operational profile and used as a constraint in a production cost model. Using this two-stage model, they were able to capture the dynamics of the LDES and the details of the greater power system. Accurately modeling LDES is a robust and challenging area of power systems, but essential to guarantee energy reliability, economic feasibility, and grid stability.

Chapter 3

Methodology

This thesis utilized realistic forecasts and an optimization model to schedule the optimal operation of LDES devices of varying sizes. The optimal SOC profiles for these devices over an operational period was determined by solving sequential optimization problems at an interval of 24 hours. The model was run in Julia V 1.11.3 using the JuMP mathematical model [31]. The parameters and constraints of the model can be adjusted to reflect different storage technologies, however this work remained technology agnostic. Two models were developed to analyze the operations of the LDES devices, the first simulated the devices in a wholesale electricity market, and the second simulated the devices in both a wholesale electricity market and an ancillary services market. The overall objective was to maximize the profit of the storage device by exploiting temporal differences in price.

The first part of this work consisted of building the 118 Bus System in the Sienna modeling platform. Next, a UCED simulation was built and run to extract marginal price data, load data, and VRE data. Data extracted from the 118 Bus System was then used as inputs to train and use an Echo State Network (ESN) to generate a series of price forecasts. These forecasts were the used in a optimization problem to inform the model when to charge and discharge the storage device. Finally, the State of Charge (SOC) profiles, device profitability, sensitivity to forecast errors, and the overall value of modeling different devices with varying look-ahead periods was analyzed.

Model Formulation The objective function of the optimization model is to optimize the dispatch profile of the LDES for profit maximization based on realized and forecasted electricity prices. It is expressed as a mixed integer linear programming problem. It exploits price differences as an opportunity to charge and discharge the LDES. The model leverages decision and auxillary variables to encapsulate the dynamics of the storage device, including its charging and discharging profile and how it interacts with the grid. The data used in this study is provided by the 118-Bus system, which was gathered through an UCED (Unit Commitment and Economic Dispatch) problem. This data was then utilized to generate the price forecasts.

3.0.1 Rolling Horizon Optimization

The optimization model employs a rolling horizon framework where the simulations were conducted for 283 days, re-optimizing the operation of the LDES every 24 hours using a 24 hour planning period. This model would have been conducted over an entire year, but a portion of the data was used to train the Echo State Network, which is talked about more in section 3.3. The rolling horizon technique is used to capture the inter-temporal behavior of LDES. Evaluating over an extended period enables the model more make more informed decisions. Solving the optimization problem every 24 hours incorporates up-to-date information in the decision making process reducing uncertainty. The model solves the problem over the entire horizon, but only keeps decision made during the planning period, and discards any further information beyond that point. To ensure continuity across simulations with different rolling horizons, towards the end of the optimization period, the rolling shortens to only capture the 283 days being analyzed.

3.0.1.1 Decision Variables

The decision variables are parameters that are flux variables that can change whenever the model re-optimizes. In this work, these variables are the state of charge of the LDES devices, the charging and discharging variables, and the operational status of the devices at each time steps. The variables are as follows:

$e_{stored}(t)$: State of Charge (SOC) of the device at time t in [MWh]

$e_{pur}(t)$: Energy purchased from the grid at time t in [MWh]

$e_{sold}(t)$: Energy sold to the grid at time t in [MWh]

$e_c(t)$: Energy charged into storage at time t in [MWh]

$e_{dc}(t)$: Energy charged into grid at time t in [MWh]

$z_c(t)$: Binary variable specifying in charging is occurring at time $t \in [0,1]$

$z_{dc}(t)$: Binary variable specifying in discharging is occurring at time $t \in [0,1]$

Table 3.1: Decision Variables

3.0.1.2 Auxillary Variables

Auxillary variables reflect the dynamics of the system, and are representative of intermediate values. They include the revenue from selling energy to the grid and the cost of purchasing energy from the grid.

rev(t): Revenue from selling energy to grid in [$]

cost(t): Cost of purchasing energy from the grid in [$]

Table 3.2: Auxillary Variables

3.0.1.3 Parameters

The model assumes 100% charging and discharging efficiency, as well as a self-discharge rate of 0. The maximum power capacity was 100 MW. The minimum state of charge was 0, and the maximum state of charge is a function of the maximum power capacity and the discharge duration

P: Maximum Power Capacity [MW]

h: Discharge Duration [h]

E_{min}: Minimum State of Charge [MWh]

E_{max}: Maximum State of Charge [MWh]

η_{charge}: Charging Efficiency

$\eta_{\text{discharge}}$: Discharging Efficiency

η_{loss}: Self Discharge Rate

Table 3.3: Parameters

3.0.1.4 Objective Function

$$Maximize \sum_{t=1}^{T} rev(t) - cost(t) \tag{3.1}$$

The objective function formulates which quantity should be optimized in terms of decision variables. The objective function used in this work maximized the different between the revenue generation and the cost paid by charging and discharging the LDES.

3.0.1.5 Constraints

Energy Storage Bounds:

$$e_{min} \leq e_{stored}(t) \leq e_{max} \tag{3.2}$$

Charging and Discharging:

$$e_{discharge}(t) \leq z_{discharge} \times P \tag{3.3}$$

$$e_{charge}(t) \leq z_{charge} \times P \tag{3.4}$$

Equation 3.17 enforces the mutual exclusivity constraint, never allowing the device to charge and discharge at the same time. Charging and Discharging Exclusivity:

$$z_{charge}(t), z_{discharge}(t) \in \{0, 1\} \tag{3.5}$$

$$z_{charge}(t) + z_{discharge}(t) \leq 1 \tag{3.6}$$

Revenue and Cost Functions:

$$rev(t) = e_{sold}(t) \times price(t) \tag{3.7}$$

$$cost(t) = e_{pur}(t) \times price(t) \tag{3.8}$$

Charging and Discharging Efficiency:

$$e_{charge}(t) = e_{pur}(t) \times \eta_{charge} \tag{3.9}$$

$$e_{discharge}(t) = e_{sold}(t) \div \eta_{discharge} \tag{3.10}$$

State of Charge Transition:

$$e_{stored}(t+1) = e_{stored}(t) + e_{charge}(t) - e_{discharge}(t) \tag{3.11}$$

Non-Negativity:

$$e_{stored}(t), e_{charge}(t), e_{discharge}(t) \leq 0 \tag{3.12}$$

Equation 3.13 represents the energy storage constraints bounding the stored capacity at any given time to the physical limits of the device. This ensures that the physical maximum and and minimum capacity of the device are not violated.

Equations 3.14 and 3.15 constrain the amount of charging and discharging at a certain time step to the maximum power capacity of the device. At any point in time the decision variables e_{charge}, and $e_{discharge}$ can not be more than the maximum power capacity of the device. The device is constrained to charge and discharge within the bounds of its capacity. Equations 3.16 and 3.17 enforce the mutual exclusivity constraint, which guarantees that the device can not simultaneously charge and discharge. In practice, charging and discharging of any storage device are done mutually exclusively to guarantee maximal profits and system efficiency. Equations 3.18 and 3.19 are the revenue and cost functions. Revenue is a function of the amount of energy sold and the price at a given time, while cost is a function of the amount of energy bought and the price at that time.

Equations 3.20 and 3.21 represents the charge and discharge efficiencies of the devices. Equation 3.22 represents the the state of the charge of the device as a function of the current stored energy, and the charge and discharge variables. The state of charge of the following time is determined by the state of the charge of the previous time step, and the amount charged or discharged into the system. Equation 3.23 constrains the stored energy, charging and discharging variables to non-negative amounts.

3.1 Ancillary Service Model Formulation

Additional auxillary variables, decision variables and constraints are included to incorporate a simulated ancillary services market in the model. At each interval, the model chooses to participate in an hourly ancillary services market. If the model decides to participate in the market, it must hold a certain amount of energy capacity as reserve. That energy is held for the following hour as a function of the devices state-of-charge. If the model chooses to participate in the market at a particular hour, the device guarantees that at any point during that hour it could begin discharging based on the reserve requirement. This is reflected in the devices SOC for that hour.

$\mathrm{e_{as}}(t)$: Energy Sold to Ancillary Service Market (MWh) [$]

$\mathrm{z_{as}}(\mathrm{t})$: Binary Variable specifying if storage is participating in Ancillary Service Market at time $t \in [0, 1]$

Table 3.4: Ancillary Service Decision Variables

Market Participation Requirements:

$$e_{AS}(t) == z_{AS}(t) \times P \times h \times 10\% \tag{3.13}$$

$$e_{AS}(t) \geq 0.0 \tag{3.14}$$

Equations 3.24 and 3.25 reflect the requirements for participation in the A/S market. If the models chooses to participate in the market, it must hold 10% of its total energy capacity for that hour, otherwise it can not contribute a nonzero amount of energy. Revenue Functions:

$$rev_{AS}(t) = e_{AS} \times price_{AS}(t) \tag{3.15}$$

The revenue generated from participating in the A/S market is a function of the amount of energy capacity held and the A/S price at that given time. Energy Storage:

$$e_{stored}(t) \geq e_{AS}(t) \tag{3.16}$$

$$e_{AS}(t+1) \leq e_{stored}(t) \tag{3.17}$$

The energy storage constraints ensure continuity across the optimization problems. At any time, the energy stored in the device must be greater than or equal to the participation in the A/S market. The amount of energy the model chooses to participate in the following time step can not be greater than the energy stored in the previous time step. This ensures smooth energy transitions between optimization problems.

$$Maximize \sum_{t=1}^{T} rev(t) - cost(t) + rev_{AS}(t) \tag{3.18}$$

3.2 Model Limitations

This work aims to capture the optimal operation of long-duration energy storage devices, asses the implication of modeling with various time horizons and a new forecasting approach. The model is limited by key assumptions and modeling decisions that do not fully reflect the physical world. This work assumed a 100% charging and discharging, effectively ignoring losses incurred when changing the SOC. This is fundamentally not representative of the real world because all storage technologies have intrinsic and unique losses associated with charging and discharging. Additionally, this model assumed a self-discharge rate of zero, which depending on the specific technology is an important characteristic. This model also assumed a price taker formulation, assuming that the contribution of the storage devices is not significant enough to manipulate market prices. While this may be a sound assumption for storage devices participating in the wholesale electricity market, this may not be an appropriate assumption for storage devices participating in the A/S market. Including an added layer of abstraction to compensate for the effect of storage device contribution on market prices could provide a more pragmatic perspective. This model is also used to capture the operational dynamics of LDES specifically in systems with high penetrations of renewable energy. Modeling scenarios in which this isn't the case may yield incorrect or unnecessary results

3.3 118 Bus System

This work utilized data created from simulating the NREL-118 Bus System[35] to generate price forecasts. This system is an extension of the IEEE 118 Bus System, with reconfigured generation, additional technology specific operating costs, and flow limiting transmission data, and most importantly the addition of high renewable penetration. The system consists of 118 buses located in three regions connected by 175 lines and 11 two-winding transformers. There are 192 thermal generators, 43 hydro generators, and loads attached at every bus. There are 75 solar units that have total installed capacity of 3,445 MW, and 17 wind units that have a total installed capacity of 1,078 MW. The total installed capacity is 24,600 MW, and the peak load is 19,800 MW. The system was explored through a Unit Commitment and Economic Dispatch simulation with both Day Ahead and Real Time markets participating. The Sienna Modeling Platform was used to perform the analysis.

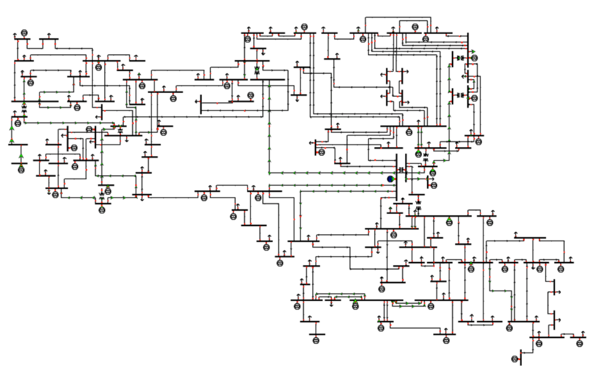

Figure 3.1: Single Line Diagram 118 Bus System

3.3.1 Time Series

The wind and solar units had a year (8670 hours) of real-time and day-ahead time series data. The data was normalized by the maximum value within the time series before it was read into Sienna to establish a time series of instantaneous capacity factors. Similarly, the load components had a year (8760 hours) of real-time and day-ahead time series data. This data was also normalized by the maximum value within the time series before it was read into Sienna. The system includes 43 hydro units, 15 of which are dispatchable and are are subject to minimum and maximum power capacity constraints, with their output determined through optimization. 28 of the hydro units are non-dispatchable, four of which have fixed loads per months. The remaining 24 non-dispatchable units have fixed hourly time-series data. The 15 dispatchable units have monthly budgets that were originally used to optimize daily hydro operation. However, since Sienna does not currently have this capability, the monthly budgets were transformed into hourly time series data by dividing the monthly budgets among all the hours in the month.

3.3.2 Unit Commitment & Economic Dispatch

The operation of a power system involves considering numerous technical aspects, such as coordinating different types of generating units, loads, and lines, while accounting for network constraints and generator ramping limits, among others. In addition, this operation must be performed in an economically efficient manner. To model a realistic power system, all of these considerations need to be reflected [7]. Running a UCED provides valuable insight into the operation of a power system including, transmission congestion, renewable energy curtailment, cost efficiency of generation, system reliability, and operating costs which can be used to determine the marginal electricity prices.

Unit Commitment (UC) is a mixed-integer linear programming (MILP) problem designed to determine the optimal fleet of generating units over a given planning horizon, ensuring supply is met while minimizing system-wide operating costs. Typically, UC is done at an interval of 24 hours, with a planning horizon of 48 hours. Generators are committed in the UC stage, ensuring that all technical and security constraints are met. The Economic Dispatch problem uses the UC commitments as constraints to decide the actual power output of each generating unit at every hour of the planning period such that supply meets demand.

The UCED problem was formulated using the Sienna modeling platform, specifically the PowerSimulation.jl (PSI) package. PSI builds a decision-making problem that calculates the optimal system operation based on forecasts of various system parameters over a given planning horizon. The UC problem uses a 24 hour interval, with hourly resolution across a 48 hour planning horizon [29]. Figure 3.2 shows these timelines.

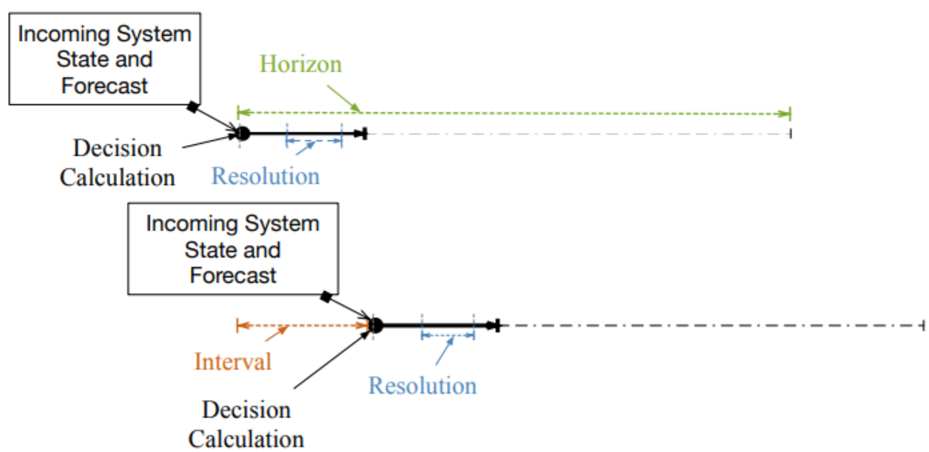

Figure 3.2: Decision Model Timeline

At every hour within the planning horizon the decision values are updated to reflect the optimal operation. The decision values calculated after the interval period are typically not implemented, and are only used to asses inter-temporal effects of certain quantities that cannot be fully analyzed within the interval. In a UCED problem, two optimization problems are run sequentially. The UC problem determines which generating units will be turned on and off, while the ED problem determines the power output of all the generating units for every hour of the planning horizon. The UC problem is analyzed using the day-ahead forecast data, while the ED problem is analyzed using the real-time data.

The UC problem is solved daily with a 48 hour planning period and a 24 hour operation period. The ED proble is solved hourly with a 2 hour planning period and an one hour operation period. The time series is transformed for these problems such that the model has a perfect horizon over the entire planning period. Sienna has a built in function that performs this transformation called the `transform-single-time-series`.

3.3.2.1 Device Models

Device models specify the behavior and constraints of specific components within the system. These device models inform the optimization models how specific components can be operated. A

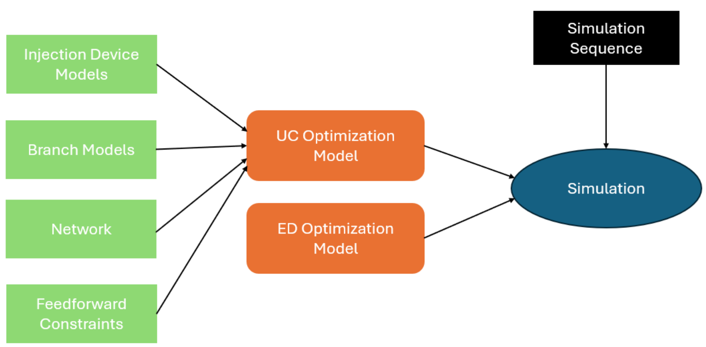

Figure 3.3: Optimization Sequence

device models can fall under any of the following categories: Injection device models, Branch models, Network models and Feedforward constraints. Any component that can withdraw or deliver power to the system needs an injection device model. Branch models are used for lines, two winding transformers and tap transformers. Network models specify how the buses and branches are constrained throughout the optimization problem. Feedforward constraints describe how information is passed between stages to capture inter-stage chronology.

A `CopperPlatePowerModel` was used as the network model in this work. This model assumes infinite transmission capacity and aggregates all components to a single node, reducing computational complexity. The lines and two winding transformers used the `Static Branch` device model

Component	Device Model Type	Device Model
Network	Network Model	CopperPlateBalanceConstraint
Line	Branch Model	Static Branch
2WTransformer	Branch Model	Static Branch
Thermal Generators	Injection Device Model	ThermalBaseUnitCommitment
Renewable Generators	Injection Device Model	RenewableFullDispatch
Hydro Generators	Injection Device Model	HydroDispatchRunofRiver
Load	Injection Device Model	StaticPowerLoad

Figure 3.4: Device Models

which uses unbounded flow and line constraints.

The thermal generator components are modeled using the `ThermalBasicUnitCommitment` model, a basic unit commitment model. This model does not represent any inter-temporal ramping or minimum on-and-off constraints. For `ThermalBasicUnitCommitment` the variables are active power, reactive power, on, start, and stop variables $(p^{th}, q^{th}, u^{th}, v^{th}, w^{th})$. The static parameters are minimum active power, maximum active power, minimum reactive power, and maximum active power
$(P^{th,max}, P^{th,min}, Q^{th,max}, Q^{th,min})$.

$$u_t^{th} P^{th,min} \leq p_t^{th} \leq P^{th,max}, \forall \in \{1, \ldots, T\} \tag{3.19}$$

$$u_t^{th} Q^{th,min} \leq q_t^{th} \leq Q^{th,max}, \forall \in \{1, \ldots, T\} \tag{3.20}$$

$$u_1^{th} = u^{th,init} + v_1^{th} - w_1^{th} \tag{3.21}$$

$$u_t^{th} = u_{t-1}^{th} + v_t^{th} - w_t^{th}, \forall \in \{2, \ldots, T\} \tag{3.22}$$

$$v_t^{th} + w_t^{th} \leq, \forall t \in \{1, \ldots, T\} \tag{3.23}$$

Equations (3.1) through (3.5) constrain the thermal units based on their static parameters and whether the device is off or on. Equations (3.1) and (3.2) state that at any point in time, the active and reactive power of the device is bounded by the minimum and maximum power limits. Equation (3.3) constrains the initial on/off status of the device based on the initial status, and the initial on and off variables. Equation (3.5) constrains the on and off variables such that they cannot both happen at the same time.

The renewable generators were modeled using the `RenewableFullDispatch` model. This model constrains the active and reactive power injections from the renewable generators to their respective time series data. The variables are the minimum active and reactive power limits of the device ($P^{re,min}, Q^{re,min}, Q^{re,max}$).

$$P^{re,min} \leq p_t^{re} \leq \text{ActivePowerTimeSeriesParamter}_{\text{t}}, \forall \in \{1, \ldots, T\} \tag{3.24}$$

$$Q^{re,min} \leq q_t^{re} \leq Q^{re,max} \forall \in \{1, \ldots, T\} \tag{3.25}$$

The loads are modeled using the `StaticPowerLoad` model which formulates non-dispatchable electric loads that extract power from the overall power balance constraints. The electric load is represented through the time series data attached to the PowerLoad components. The feedforward constraints were defined by the `SemiContinuousFeedforward` model, which was specifically applied to the thermal generator units. This constrains the `ActivePowerVariable` of the thermal units in the Economic Dispatch problem to decisions made in the Unit Commitment Problem. Equations 3.8 and 3.9 show that if in the UC stage a generator commits zero generation then the dispatch is constrained to 0. This effectively turns off the generator without having to introduce binary variables in the ED problem.

$$\text{ActivePowerRangeExpressionUB}_{\text{t}} := p_t^{th} - on_t^{th} P^{th,max} \leq 0, \forall \in \{1, \ldots, T\} \tag{3.26}$$

$$\text{ActivePowerRangeExpressionLB}_{t} := p_t^{th} - on_t^{th} P^{th,min} \geq 0, \forall \in \{1, \ldots, T\} \tag{3.27}$$

Slack variables are added to the system to account for time periods when generation either exceeds or cannot match the demand of load. A large penalty cost is added to the objective function if the slack variables are used.

It is important to note that unlike Pena et al. [35], the model did not include contingency, spinning reserves or regulation up and down reserves.

3.3.2.2 Duals

By running a UCED the marginal electricity prices can be extracted by calculating the dual problem. The duality principle suggests that an optimization problem can be analyzed from two perspectives: the primal perspective or the dual perspective. In the scope of this UCED the primal problem is the minimization of overall system costs. The lower bound of the dual problem can be calculated by relaxing a single constraint in the primal problem, which is done at every time step. By computing the duals at each time step, the cost of another MW of generation to the system can be computed. In essence, this is calculating the marginal price at every time. To compute these prices some constraints are relaxed in the optimization problem, in this case the system's active power balance constraint. This essentially transforms the optimization from the primal perspective to the dual.

At each time step, the dual variable (shadow price) is computed, which is associated with injecting an additional MW of the electricity into the system; fundamentally it is the marginal price. The dual variable can be caluclated as bus or area specific, or for the entire system. In this work, because a copper plate model was used, the system wide marginal price was determined.

3.3.2.3 UCED Results

The UCED problem was analyzed over an entire year, 8760 hours. Figures 3.5, 3.6, 3.7 display the marginal price, VRE generation and load profiles for the entire year. An upward trend in electricity prices, VRE generation, and load is observed in the summer months. Conversely, lower electricity prices and reduced load are observed in the spring and fall months. The results from this simulation are used generate forecasts, and used to optimize the scheduling of the LDES.

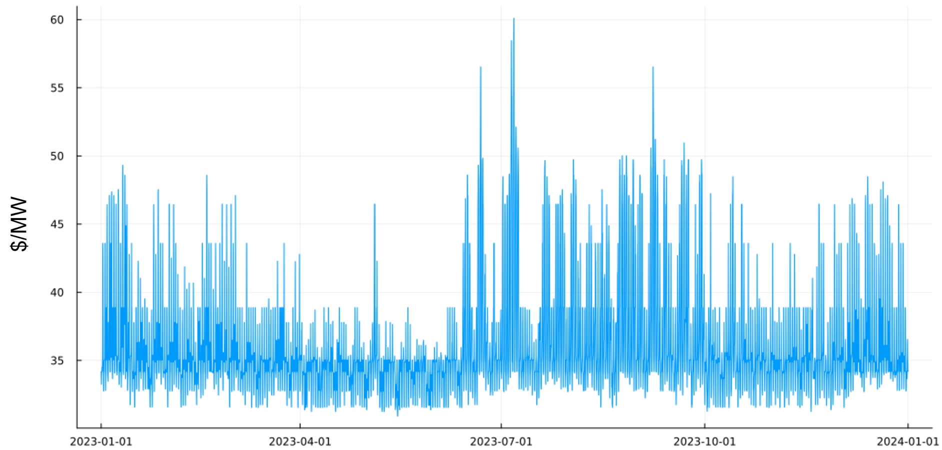

Figure 3.5: Marginal Price Profile - 118 Bus

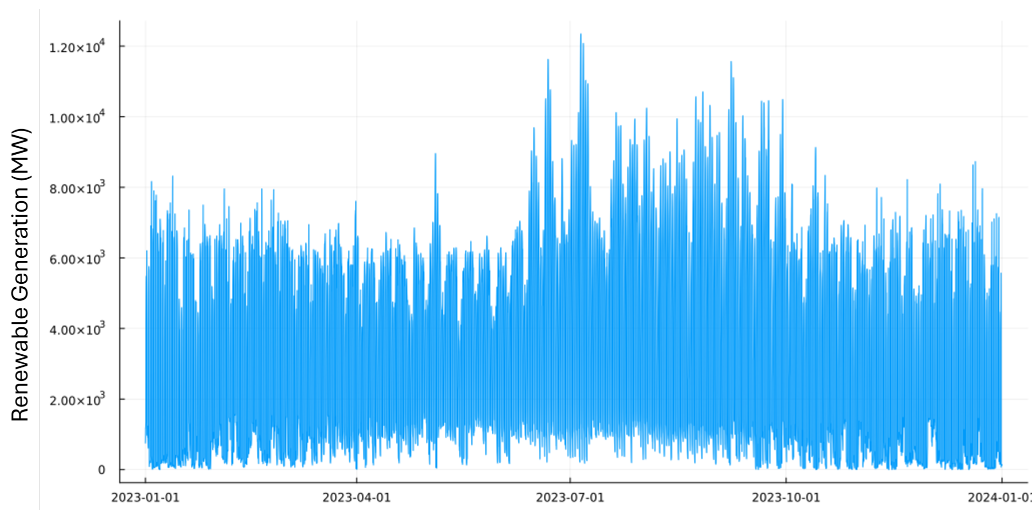

Figure 3.6: VRE Profile - 118 Bus

3.4 Forecast Generation

To accurately capture the true nature of LDES, it is essential to incorporate forecasts in the modeling process, allowing for the visualization of realistic operational profiles. This work utilized an Echo State Network (ESN), a type of recurrent neural network to generate forecasts of varying lengths at a 24 hour interval. In general, recurrent neural networks (RNNs) present a powerful approach to complex temporal problems, but can be difficult to train. Echo State Networks (ESNs) use a newer, less cumbersome approach to training and using RNNs. The complex aspect

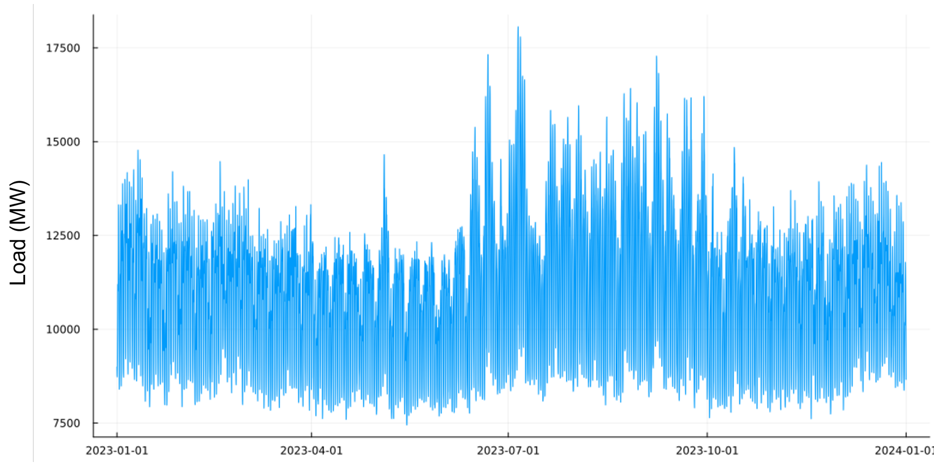

Figure 3.7: Load Profile - 118 Bus

of using an ESN is choosing the hyper-parameters such that it can be trained correctly. These parameters consist of the reservoir size, sparsity, spectral radius, input scaling, input size, and the leaking rate. In practice an ESN is given an input signal $\mathbf{u}(\mathbf{n}) \in \mathbb{R}^{\mathbf{N_u}}$ where a desired output signal $\mathbf{y}^{\mathbf{target}}(\mathbf{n}) \in \mathbb{R}^{\mathbf{N_y}}$ is known. $n = 1, ..., T$ represents discrete time, and T represents the number of data points. The input can consist of multiple sequences with varying amounts of data points. In the scope of this work, the historic price, variable renewable generation, and load profiles were used as inputs, with price as the output signal. The goal is to train a model such that the difference between the known output $\mathbf{y}^{\mathbf{target}}(\mathbf{n}) \in \mathbb{R}^{\mathbf{N_y}}$ and the output signal $\mathbf{y}(\mathbf{n}) \in \mathbb{R}^{\mathbf{N_y}}$ has minimal error.

The general method of using an ESN is to generate random reservoirs W^{in}, and W, run the ESN using a set of training data and collect the corresponding reservoir activation state $\mathrm{x}(n)$. Compute the readout weights W^{out} from the reservoir using linear regression and minimize the error between the $\mathrm{y}(n)$ and $\mathrm{y}^{\mathrm{target}}(n)$. Once the network is trained it can be used to predict output data for new input data. The structure of an ESN is depicted in Figure 3.8.

ESNs use leaky-integrated discrete time-continuous-value units which determine how much the network remembers the past. $\mathbf{x}(\mathbf{n}) \in \mathbb{R}^{\mathbf{N_x}}$ is a vector that represents the neuron activations within the reservoir. These neurons are updated according to the following functions that occur at

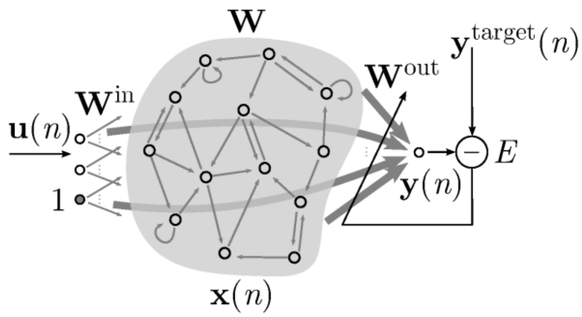

Figure 3.8: Structure of Echo State Network [32]

time steps n

$$\tilde{x}(n) = \tanh(\mathbf{W^{in}}[1; u(n)] + \mathbf{W}\mathbf{x}(n-1)) \tag{3.28}$$

$$\mathbf{x}(n) = (1-\alpha)\mathbf{x}(n-1) + \alpha\tilde{\mathbf{x}}(n) \tag{3.29}$$

$\mathbf{W} \in \mathbb{R}^{\mathbf{N_x}\times\mathbf{N_x}}$ represents the recurrent weight matrix, $\mathbf{W^{in}} \in \mathbb{R}^{\mathbf{N_x}\times(\mathbf{1}+\mathbf{N_u})}$ represents the input weight matrix. In the case that the leaking rate $\alpha \in (0, 1]$ is $\alpha = 1$ then $\tilde{\mathbf{x}}(n) \equiv \mathbf{x}(n)$.

3.4.0.1 Reservoir

The reservoir servers two main purposes, the first acting as a non-linear expansion of the input $\mathbf{u}(n)$. This transforms the input signal $\mathbf{u}(n)$ that is not linearly separable in the original space $\mathbb{R}^{N_u}$ into a linearly separable data set in $\mathbb{R}^{N_x}$ which can then be separated by $\mathbf{W}^{out}$. At the same time, the reservoir proved temporal context which provide a rich environment to obtain a desired output.

3.4.0.2 Size, Sparsity of Reservoir, and Distribution of Nonzero Elements

When using an Echo State Network a key parameter is the size of the reservoir. In gernal, the larger the reservoir, the better the performance of the ESN. This creates an easier environment for the network to find a linear combination of the input signal to predict the desired output. In the context of this work, a reservoir of 300 was used. Another parameter is the sparsity of the reservoir, which describes the number of nonzero elements in the internal weight matrix $\mathbf{W}^{in}$. This parameter has limited impact on the performance of the network. The distribution of nonzero elements of the internal weight matrix $\mathbf{W}$ has a larger impact on the performance of the network. While Gaussian distributions are commonly used, a uniform distribution was employed in this work because it is the default choice in ReservoirComputing.jl.

3.4.0.3 Spectral Radius

The spectral radius describes the maximum absolute value eigenvalue of in the reservoir connection matrix $\mathbf{W}$. The spectral radius $\rho(\mathbf{W})$ determines whether the model follows the Echo State Property.

The state of the reservoir should be uniquely defined by fading history of the input[21]

Meaning, that eventually the initial inputs should not impact the current state. The current state should only be impacted by the most recent input. This ensures that the reservoir is remembering meaningful patterns. A spectral radius that is too large can create unstable network dynamics and produce unbounded outputs. If the spectral radius is too small, this can lead to loss of nonlinearly of the internal matrix, and poor performance of timer series predictions. It is best practice to choose a spectral radius such that $\rho(\mathbf{W}) < 1$. However, spectral radii larger than 1 can be used if there are limited nonzero input $\mathbf{u}(n)$, and if the task requires a longer memory of the input. It was determined that the optimal spectral radius in the context of this work was 1.2.

3.4.0.4 Input Scaling

The input scaling determines the range from which values of Win are sample which determine how much the input $\mathbf{u}(n)$ impacts the reservoir states. The input data is also normalized to make the learning more stable. In the scope of this work one input scale is used, however it is possible to apply multiple input parameters.

3.4.0.5 Leaking Rate

The leaking rate α is the rate at which the reservoir is updated. The leaking rate should match the speed of the dynamics of the input data and the output target.

3.4.0.6 Traning the ESN & Generating Forecasts

The Julia ReservoirComputing package was used to build and then train the ESN. For the 118-Bus data the price, VRE, and load data generated from the UCED problem were used as inputs into the network, their correlation can be seen in Figure 3.9. After several attempts to produce accurate forecasts for the 118 Bus data set, the optimal parameters of the network were determined and can be seen in Table 3.5.

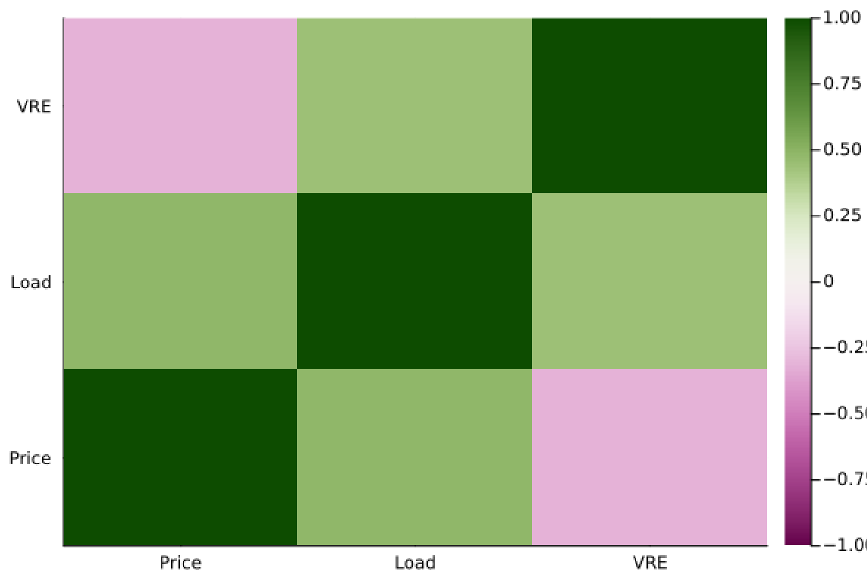

Figure 3.9: Correlation Between Price, Load and VRE

Reservoir Size	300
Sparsity	0.02667
Radius	1.2
Input Scaling	1.2
Input Size	3

Table 3.5: Echo State Network Parameter - 118 Bus Data

The input data was normalized to the maximum value within the time series, which yielded better results when training the ESN. The ESN was trained on the first 2000 hours (83 days) of the input time series. It was determined that decreasing the training length did not provide the network with rich enough data to make accurate predictions of the price profile.

Once the network was trained, the next step was to generate predictions of varying lengths at 24 hour intervals. The network was incorporated into a `for` loop such that at every 24 hours the network was retrained using the previous 2000 time steps worth of data. The network would then generate a forecast with lengths of 48 hours (2 days), 168 hours (7 days), 504 hours (21 days), or 720 hours (30 days). Figure 3.10 illustrates the training period that was used to generate the subsequent forecasts. The data left of the black dotted line is used to train the ESN, where the green line right of the black line is the forecast generated by the ESN. The ESN generates a forecast based on the desired forecast length, an input into the network.

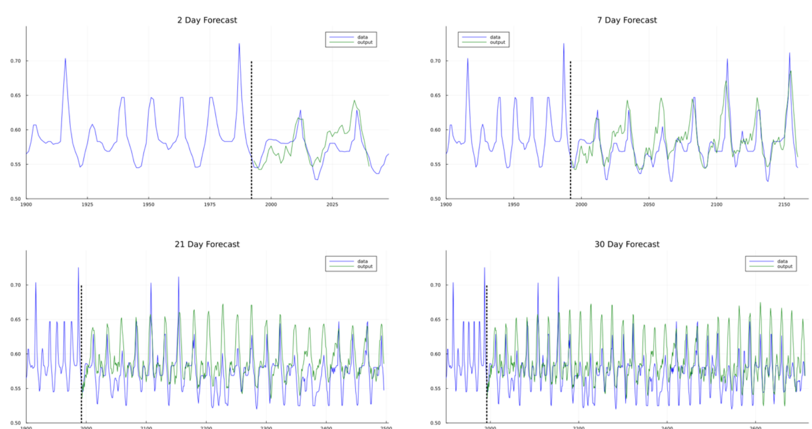

Figure 3.10: Echo State Network Training and Forecast - 118 Bus System

To asses the network in terms of predictive accuracy, the mean squared error for each hour of every forecast was computed. The error across different forecast lengths can be seen in Figures 3.11, 3.12, 3.13, and 3.14 . The cyclic pattern observed in these figures can be attributed to the ESN's difficulty to accurately predict price fluctuations, particularly during sharp increases or decreases. The steep price fluctuations correspond to the daily price spike that typically occurs in the early evening hours.

This intense price fluctuation results from a combination of factors, including a significant decline in renewable generation coinciding with a surge in demand. This phenomenon can be seen in Figure 3.15

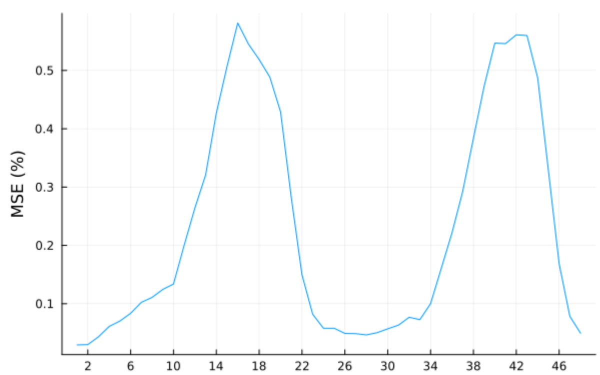

Figure 3.11: MSE 2 Day Forecast

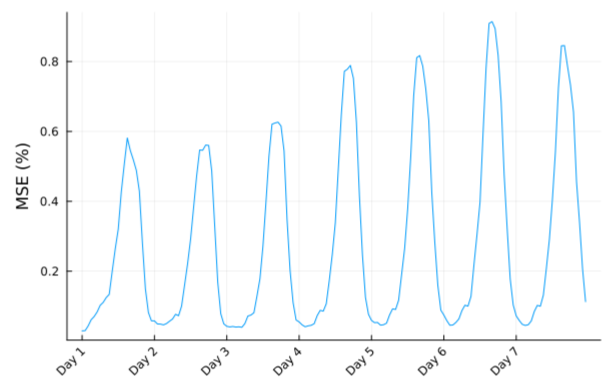

Figure 3.12: MSE 7 Day Forecast

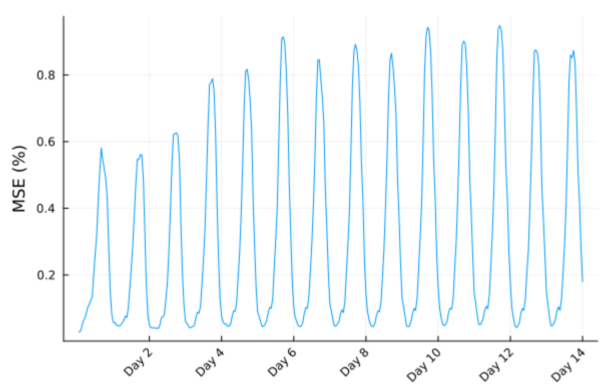

Figure 3.13: MSE 14 Day Forecast

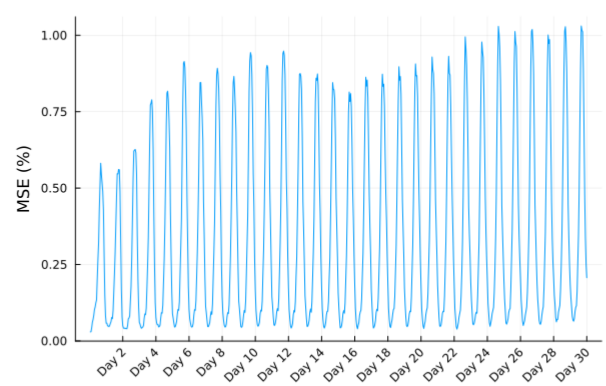

Figure 3.14: MSE 30 Day Forecast

The accuracy of these forecasts generated by the ESN is crucial for modeling the operation of the LDES.

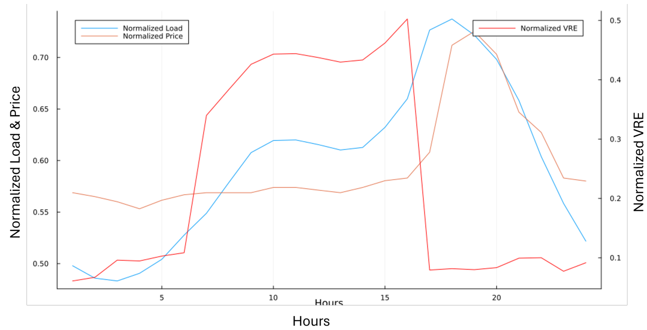

Figure 3.15: Spike in price due to an increase in load and decrease in VRE generation

3.5 Ancillary Service Market Data

The ancillary service price data used in this analysis was obtained from the Energy Reliability Council of Texas (ERCOT). This data was downloaded from the GridStatus.io platform for further processing and evaluation. The hourly-resolution data for the year depict the payment price of participating in the Spinning Reserves of the A/S market at any given hour. This data was incorporated into the model in a deterministic fashion. That is, the optimization had perfect foresight of future A/S prices. To align the A/S and electricity price data, the first 2000 data points were removed from the A/S dataset, ensuring that seasonal price trends matched across both sets.

3.5.0.1 Dynamic ESN

The price-taker model and the Echo State Network (ESN) are integrated in such a way that at each optimization interval, the ESN generates updated forecasts for the subsequent horizon. These forecasts are then used by the price-taker model to adjust its decisions or predictions accordingly, ensuring that the system dynamically adapts to new information as the optimization process progresses. At every time step, the ESN generates a forecast the length of the pre-determined horizon.

3.5.1 Solver

This thesis employs the multistage optimization problem is solved using the Xpress solver from Fico Xpress - a commercial optimization solver used for linear, mixed integer linear, convex quadratic, and convex quadratically constrained programming [14]. The model used a 0.01 MIP gap.

Chapter 4

Results

4.1 Evaluating State of Charge Profiles

Cyclic fluctuations in the state of charge are observed daily for storage with discharge durations of 12 hours of less and can be seen in Figure 4.11. These fluctuations occurs regardless of the horizon length, indicating that the optimal policy for these devices is suited best for daily charging and discharging capability. These devices exploit the intraday temporal differences in prices, charging in the middle of the day when electricity prices are low, and discharging in the evening time when electricity prices are higher. Cyclic fluctuations are also see in Figure 4.2, depicting the SOC profile for a device with 24 hours of discharge, however this cycles happen less frequently. Figure 4.3 depicts the SOC profiles simulated for a device with 48 hours of discharge. In this scenario the optimal SOC profile indicates cyclic charging and discharging, similar to that of the 12 hour device, but at less frequent intervals. From visual inspection if the simulations using a 168, 504, and 720 hour horizon capture the essence of optimal profile the best throughout the time series.

Storage devices with discharge durations of 504 to 720 hours operate following longer-term trends in prices. These devices do not experience frequent and large scale changes in state of charge, but instead gradual changes that align with extended price patterns. The optimal SOC profile for a device with 720 hours of discharge duration can be seen in Figure 4.7. The device remains relatively fully charged until approximately the 2000th interval, it subsequently decides to discharge over the course of the next 2000 optimization periods.

As the discharge duration increases, variations in the SOC profiles become more apparent across scenarios with different horizon lengths. This is most noticeably seen in scenarios where the storage device has more than 48 hours of discharge duration. The larger storage devices ($\geq$ 168 hour discharge) take advantage of longer trends in prices, namely seasonal trends discharging throughout spring and summer, and re-charging again during the fall. As the size of the storage devices grow, the scenarios with shorter horizons move further away from the optimal policy, while scenarios with longer horizon remains the closest.

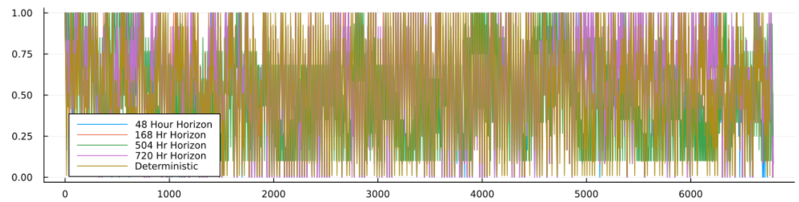

Figure 4.1: State of Charge Profiles of a device with 12 Hour Discharge Duration modeled with varying horizon lengths

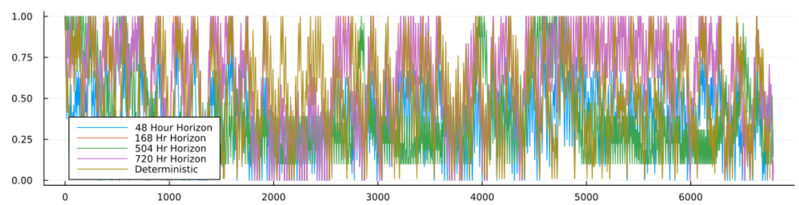

Figure 4.2: State of Charge Profiles of a device with 24 Hour Discharge Duration modeled with varying horizon lengths

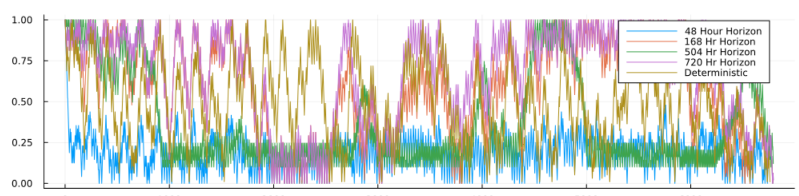

Figure 4.3: State of Charge Profiles of a device with 48 Hour Discharge Duration modeled with varying horizon lengths

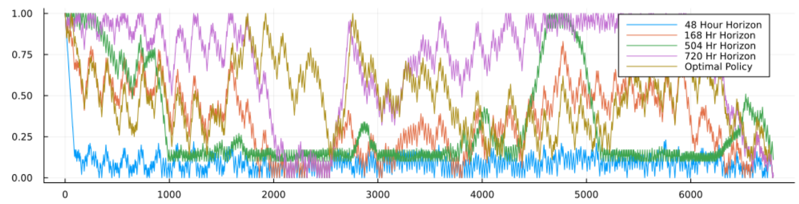

Figure 4.4: State of Charge Profiles of a device with 100 Hour Discharge Duration modeled with varying horizon lengths

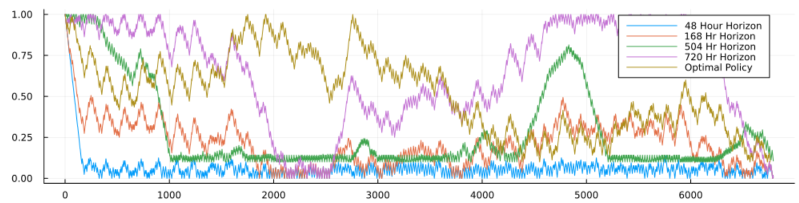

Figure 4.5: State of Charge Profiles of a device with 168 Hour Discharge Duration modeled with varying horizon lengths

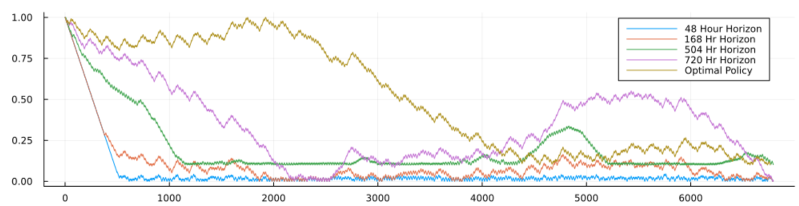

Figure 4.6: State of Charge Profiles of a device with 504 Hour Discharge Duration modeled with varying horizon lengths

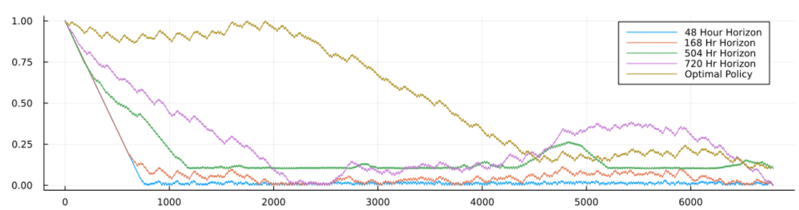

Figure 4.7: State of Charge Profiles of a device with 720 Hour Discharge Duration modeled with varying horizon lengths

4.2 Evaluating Profit Trends in Model with Forecast

The importance of horizon length can be seen in Figure 4.8 which depicts the total profit of the storage devices with respect to the rolling horizon length and discharge duration. The general trend of the heatmap shows that as discharge duration and horizon increase, profits increase, with the most profitable scenario, besides the optimal policy, being that of a storage device with 720 hours of discharge and a 720 hour horizon. However, the horizon length does have a variable impact on profitability depending on the size of the device. A device with 12 hours of discharge duration and a 48-hour horizon generates a profit of approximately $120.11 million dollars, while the same device simulated with a 720 hour horizon generates approximately $117.19 million dollars, resulting in a 2.43% decrease in profit. In this case, a longer discharge duration does not yield a greater profit like it typically should. A device with 720 hours of discharge duration and a 48 hour horizon generates approximately $373.10 million dollars, while the same device simulated with a 720 hour horizon generates $393.66 million dollars, resulting in a difference of $20.56 million dollars, approximately a 5% increase.

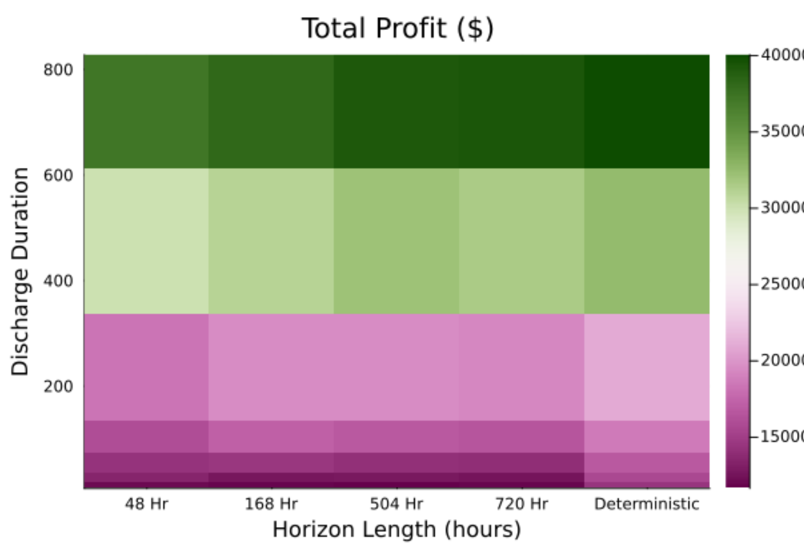

Figure 4.8: Heatmap of Profit Considering Horizon Length and Discharge Duration

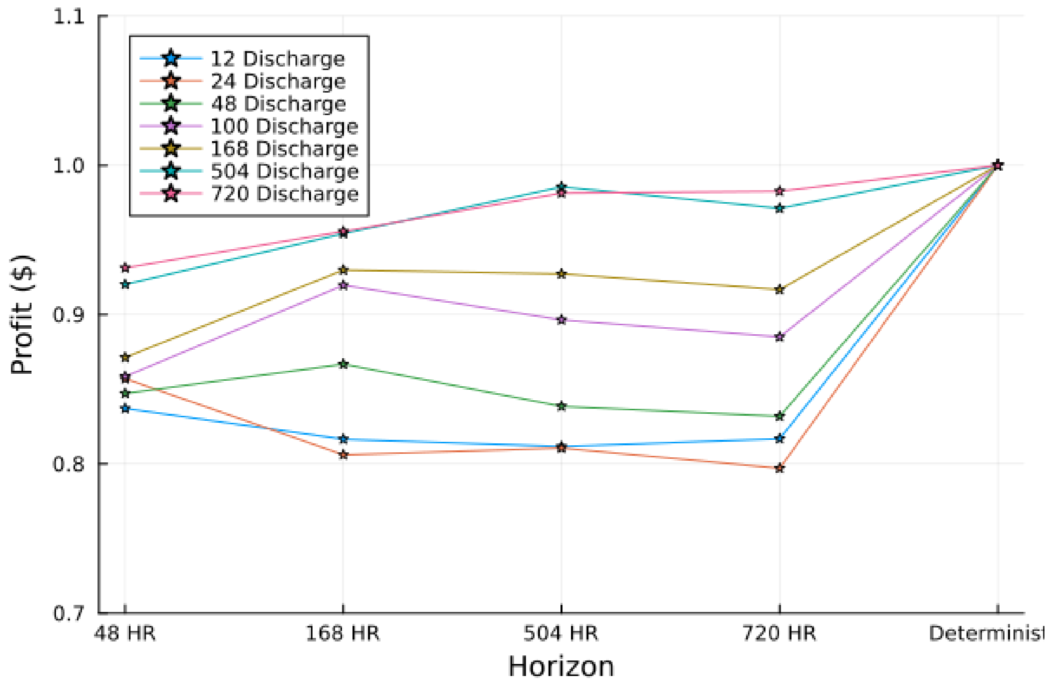

Figure 4.9: Normalized Profitability of Storage Devices of Varying Sizes Across Different Horizon Lengths.
Note: Normalized by the Deterministic Profit

4.3 Impact of Forecast Accuracy on Profitability for Different Storage Device Sizes

While, seemingly marginal, the difference between modeling with perfect forecasts versus ESN generated forecasts sheds insight onto the importance of capturing different trends in price for different storage devices. A device with 12 hours of discharge duration sees a 0.008% decrease in profit when modeled with a 48 hour horizon then with a 720 hour horizon with perfect forecasts. As previously mentioned, the same simulation using ESN-generated forecasts results in a 2.43% error. A device with a 720-hour discharge duration experiences a 5.0% increase in profits when simulated with a 48-hour horizon compared to a 720-hour horizon, which is consistent with the difference observed when using ESN-generated forecasts. Longer, ESN-generated forecasts have a more significant negative impact on profit when simulating smaller devices. The largest error in the forecast occurs during the evening spike in price, which is a crucial time for these smaller devices to exploit temporal differences. While these errors occur daily they get larger as the forecast is extended. Accurately forecasting these intraday price fluctuations is essential to capturing the full value of these smaller devices. However, it is not necessarily essential to capturing the larger devices that do not exploit these fast price trends. It is more important to capture the longer term price trends.

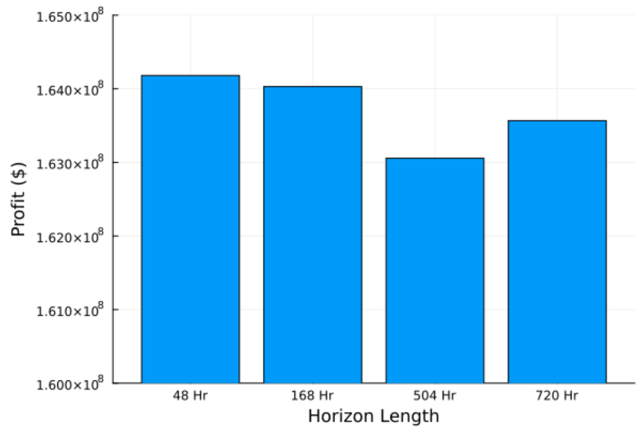

Figure 4.10: 12 Hour Discharge Duration Profit Modeled with Perfect Forecasts

4.4 Participation in the Ancillary Services Market

The participation in the ancillary service markets fundamentally changes the optimal policy of the storage devices. The model balances revenue from selling to the grid, and revenue from holding capacity to participate in the A/S market. Figures 4.11 through 4.17 display the SOC profiles for the entire 283 days. Devices with 12 hours of discharge spend a majority of their time around or above 50% capacity regardless of horizon length. These profiles closely follow the profile of the optimal policy scenario. In these scenarios, the device benefits from selling into the wholesale electricity market and participating in the A/S market. However, as the size of the device increases, and the horizon is greater than 48 hours, the device primarily participates in the A/S market.

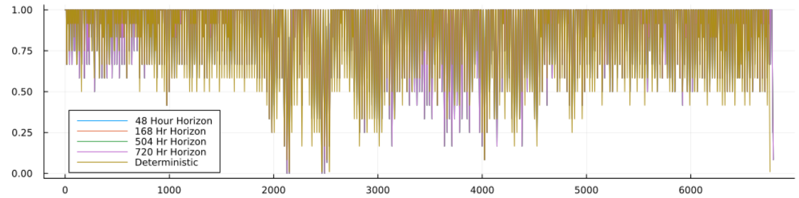

Figure 4.11: State of Charge Profiles for a 12-Hour Discharge Duration Device Modeled with Varying Horizon Lengths and Participating in the Ancillary Services Market.

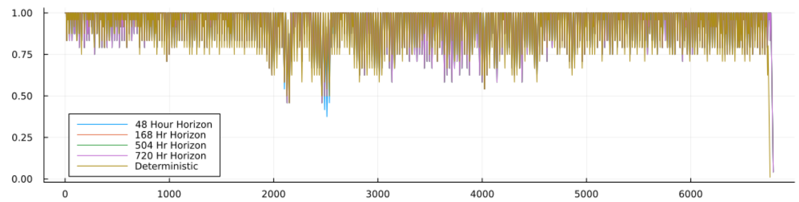

Figure 4.12: State of Charge Profiles for a 24-Hour Discharge Duration Device Modeled with Varying Horizon Lengths and Participating in the Ancillary Services Market.

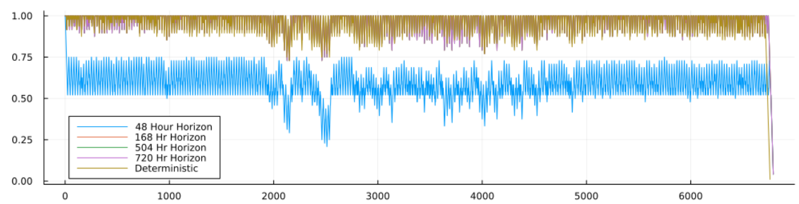

Figure 4.13: State of Charge Profiles for a 48-Hour Discharge Duration Device Modeled with Varying Horizon Lengths and Participating in the Ancillary Services Market.

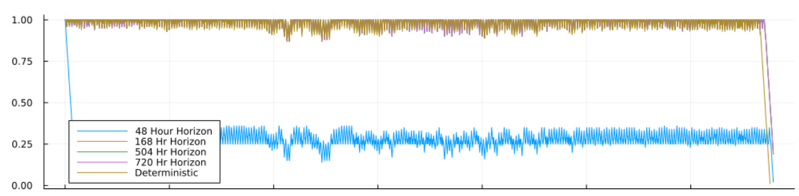

Figure 4.14: State of Charge Profiles for a 100-Hour Discharge Duration Device Modeled with Varying Horizon Lengths and Participating in the Ancillary Services Market.

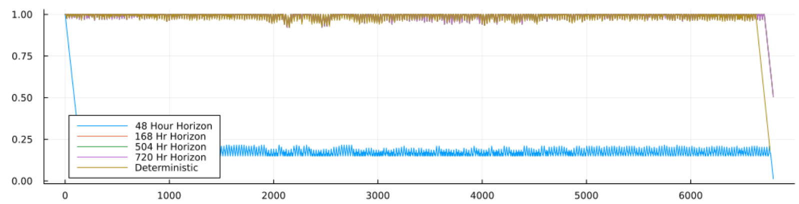

Figure 4.15: State of Charge Profiles for a 168-Hour Discharge Duration Device Modeled with Varying Horizon Lengths and Participating in the Ancillary Services Market.

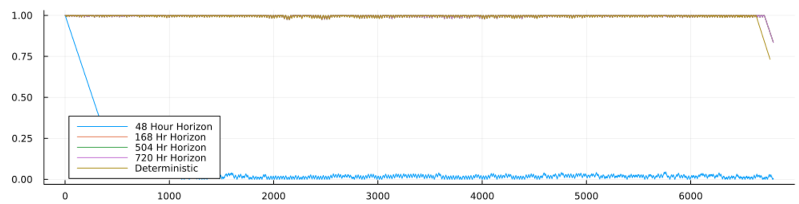

Figure 4.16: State of Charge Profiles for a 504-Hour Discharge Duration Device Modeled with Varying Horizon Lengths and Participating in the Ancillary Services Market.

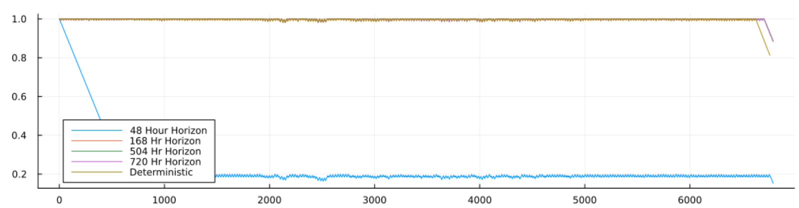

Figure 4.17: State of Charge Profiles for a 720-Hour Discharge Duration Device Modeled with Varying Horizon Lengths and Participating in the Ancillary Services Market.

4.5 Evaluating Profit Trends

Increasing the horizon length when modeling devices with discharge durations of 24 hours or less returns no gain in profit. Conversely, there is a significant increase in profit generated when modeling with a 168 hour horizon rather than a 48 hour horizon for larger devices ($\geq$ 100 hours of discharge). A nearly 90% increase in profit is generated for devices with discharge durations of 504 and 720 hours. A 76% increase is found for devices with a discharge duration of 168 hours, a 60% increase is found for devices with a 100 hour discharge duration, and a 25% increase in profitability is found for devices with a 48 hour discharge duration. Figure 4.19 displays the normalized profitability of the different sized devices over the horizon lengths.

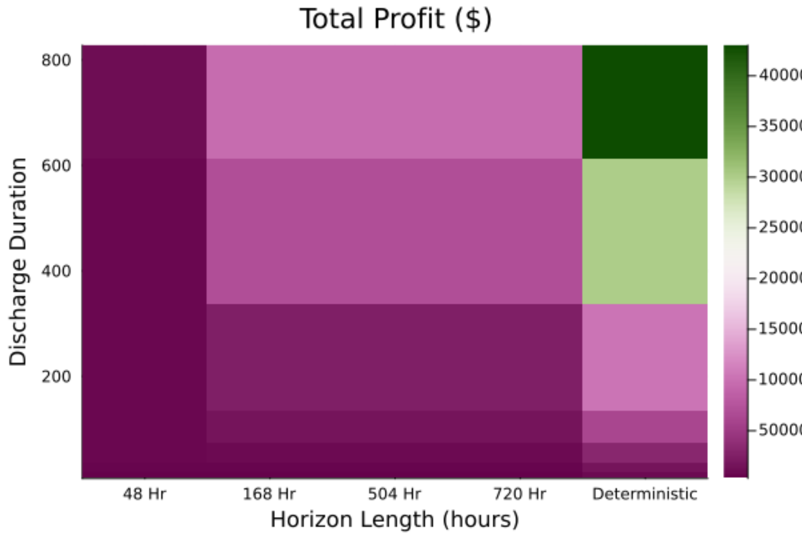

Figure 4.18: Heatmap of Profit Considering Horizon Length and Discharge Duration

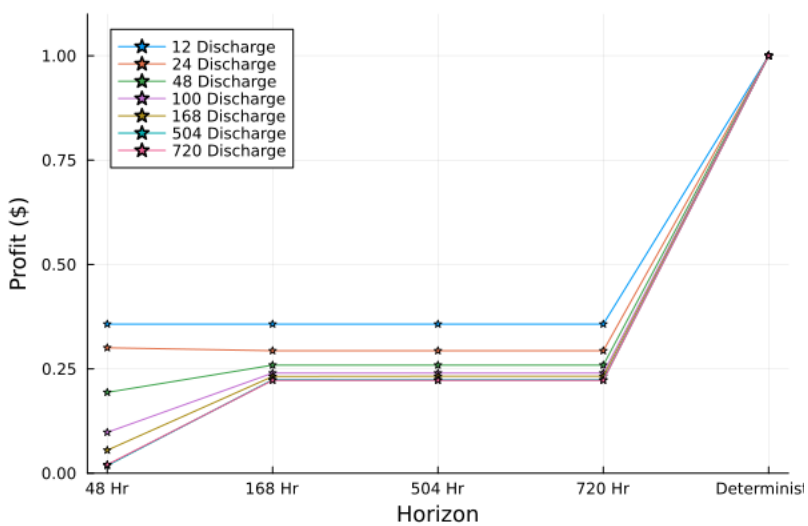

Figure 4.19: Normalized Profitability of Storage Devices of Varying Sizes Across Different Horizon Lengths.

Note: Normalized by the Deterministic Profit

Chapter 5

Conclusion

With increasing penetrations of VRE and increasingly market volotility, the incorporation of LDES has become essential to maintaining grid reliability and stabilizing price fluctuations. However the exact nature of how these devices will interact with the grid and operate remains a question for further research. This thesis intends to capture the nature of these devices modeled under different time horizons, in both a whole sale electricity market and an Ancillary Services market. As well as evaluating the efficacy of using Echo State Networks to generate forecasts that can be used in power systems modeling. Through various simulations and two different market archetypes, this thesis provides insight into the complex operation dynamics of a range of different LDES sizes. The objective of this work is to understand the potential role these devices might play in current and future power grids, and the appropriate modeling techniques necessary to fully convey their dynamics.

The Echo State Network does a good job at forecasting short term and long term price scenarios. However, it performs poorly during the daily price fluctuations due to a simultaneous drop in VRE generation. and increase in load. This issue is exacerbated when the ESN tries to predict longer term forecasts, specifically after the first 36 to 48 hours. Regardless, the ESN generates realistic price scenarios that are used to determine the optimal operation of LDES devices.

Smaller storage devices, less than 24 hours, operate strictly following daily price fluctuations and are not as influenced by longer price trends. In light of this, when modeling these devices in isolation, outside the scope of a larger power systems, longer optimization horizon are unnecessary and introduce error when using imperfect forecasts.

Larger storage devices, greater than 504 hours, are not as influenced by daily price fluctuations and instead tend to follow longer price trends. It becomes essential to model with longer horizons to represent the seasonal and monthly fluctuations in price, and less important to capture shorter-term fluctuations. The simulations indicated an increased arbitrage value for storage devices with discharge durations greater than 504 hours. Devices with discharge durations of 48 to 168 hours experience their greatest value when modeled with a 168 hour horizon. Devices with 12 to 24 hours of discharge duration were valued highest when modeled using a horizon of 48 hours.This indicates an inherent trade-off between the look-ahead horizon and the error introduced by this. It is also indicative of the ESN's ability to produce forecasts, the error incurred, and how this error impact the operation of the storage devices. While the overall error is smaller when making shorter term forecasts, the inability to perfectly capture the acute price fluctuations leads to sub-optimal operation decisions leading to an imperfect evaluation of the devices. Contrastingly, larger devices see a more optimal evaluation when modeled with longer horizon periods regardless of the increase in error. This indicates that the operational dynamics of the larger devices are not as influenced with the intraday fluctuations in price, but in the longer term price trends.

The operational dynamics of the storage devices participating in both a wholesale electricity market and an A/S market, provided insight into how these devices would operate under the influence of different price trends.

The optimal policy of the storage devices changes when permitted to participate in both the wholesale electricity and A/S market. Devices with 48 hours or more of discharge duration, modeled with horizons longer than 48 hours, operate solely within the realm of the A/S market. They don't undergo any significant charging or discharging cycles, and instead remain fully charged throughout the entire optimization period. Conversely devices of the same size, modeled with a 48 hour horizon operate in an exceptionally sub-optimal fashion. This suggests that for devices with discharge durations exceeding 24 hours, optimizing the balance between market participation and revenue requires longer horizons to effectively manage the device's operation. However this phenomenon, does not translate to devices with less than 24 hours of discharge. These devices operate in both markets simultaneously and their value is not dependent on the length of the horizon.

Chapter 6

Future Work

Building on the work of this thesis, future research can significantly deepen our understanding of the efficient management practices of these devices. Analyzing the operation of LDES technologies with the context of capital and operational expenses can provide further insight into the value of these systems. This can be implemented in this work by including additional capital and operational cost variables in the optimization function. This approach would offer for a more in depth, realistic analysis of the operation of the devices. A further analysis of proper management of LDES in both A/S markets and capacity markets can address the advantages and disadvantages of participating in one or more market environments. Findings from these studies will provide a more advanced understanding of LDES operation, which is crucial as we move toward a world of more renewables.

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