

Distributed renewable energy integration using distribution locational
marginal pricing and the food-energy-water nexus

by

Lawryn Edmonds

B.S., Kansas State University, 2017

AN ABSTRACT OF A DISSERTATION

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DOCTOR OF PHILOSOPHY

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KANSAS STATE UNIVERSITY
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Abstract

An increase in distributed energy resources (DERs), particularly non-dispatchable variable renewable energy (VRE) sources such as rooftop photovoltaic and small-scale wind turbines, brings about new challenges to distribution system operators. DERs, such as VRE sources, battery energy storage systems, distributed (conventional) generators, and responsive loads, increase the complexity of the distribution system. Therefore, system characteristics shift away from the previously passive system toward an active distribution system. With an active distribution system, there comes a need for fair and transparent pricing schemes, which reward DERs for reducing losses, voltage violations, congestion, and imbalance of lines. Further, increased energy storage capabilities and demand-responsive loads will help integrate the distributed resources by instantaneously balancing generation and demand. These balancing actions must also be rewarded.

Therefore, a distribution locational marginal price (DLMP) mechanism serving as a price signal for the economic dispatch of generation sources within the distribution system is first proposed. Defined as the marginal cost to supply the next increment of power to a specific location, this mechanism may encourage the acceptance of DERs due to the incentives arising from nodal pricing. DLMP components for energy, loss, voltage violation, and congestion for a linear approximation of the alternating current optimal power flow are leveraged in this work. The proposed method also addresses VRE uncertainty using the data-driven probability efficient point method. Numerical results show the DLMP mechanism can serve as a tool to improve distribution grid conditions by encouraging or discouraging real and reactive power consumption at specific nodes in the system. It is also demonstrated that three-phase real and reactive nodal pricing allows for better control of diverse DERs in active distribution systems. The DLMP is further used in a home energy management system application that utilizes the blockchain for secure communication.

Next, an investigation into the impact of coupling the electricity distribution and drinking water networks on the DLMP and efficient VRE integration is undergone. Water pumps serve as demand-responsive loads that follow the available VRE generation. This technique is achieved by using elevated water tanks to optimally schedule the water network operation to meet water demands while improving grid conditions. A novel linear coordinated water and energy model is formulated and validated on a coupled electrical distribution system and water network. Results show the impact of coupling water and energy networks on the cost of operation and the DLMPs. The inclusion of water tanks as alternative storage devices in the electricity distribution network are shown to moderately reduce voltage violations, line congestion, and VRE curtailments in a case with high VRE penetration.

Finally, unique demand response and storage solutions are identified within an agricultural community microgrid that considers an electricity-run green ammonia synthesis plant. The small-scale ammonia plant's operational schedule follows the available VRE generation to reduce VRE curtailment and improve grid conditions. Excess renewables in the system can be stored as chemical energy in anhydrous ammonia. When the price of electricity is extremely high, the proposed model accounts for a direct ammonia fuel cell that consumes ammonia to provide electricity back to the grid. This work proposes a linear coordinated operational model of an electricity distribution system and an electricity-run, green ammonia plant. Case studies are performed on an agricultural community microgrid. Results indicate the ammonia plant can adequately serve as a demand response resource and positively impact the DLMP. Studies showed this coupling decreased electricity costs of the ammonia plant by nearly a third, with ammonia profits increasing 17%.

This dissertation can serve as a tool for utilities implementing the DLMP market mechanism in distribution systems. It can further assist with the operation of coordinated operation of water and electricity distribution networks under uncertain VRE generation. Finally, agricultural community microgrid operators can utilize techniques proposed in this dissertation with the hope of increasing the vitality of small towns and rural communities.

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Dedication

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Preface

This dissertation, “Distributed renewable energy integration using distribution locational marginal pricing and the food-energy-water nexus,” is submitted for the degree of Doctor of Philosophy in the Mike Weigers Department of Electrical and Computer Engineering at Kansas State University. The research was conducted under the supervision of Professor Hongyu Wu.

This work is original to the best of my knowledge, except where acknowledgments and references are indicated. Most of the work has been presented in the following published peer-reviewed journals and conferences:

- M. N. Faqiry, **L. Edmonds**, H. Zhang, A. Khodaei, and H. Wu, “Transactive-Market-Based Operation of Distributed Electrical Energy Storage with Grid Constraints,” *Energies*, vol. 10, no. 11, p. 1891, Nov. 2017.
- M. N. Faqiry, **L. Edmonds**, H. Wu, and A. Pahwa, “Distribution locational marginal price-based transactive day-ahead market with variable renewable generation,” *Applied Energy* (JCR Q1, Impact Factor 9.746), vol. 259, p. 114103, Feb. 2020.
- **L. Edmonds**, B. Liu, H. Zhang, C. Scoglio, D. Gruenbacher, and H. Wu, “Blockchain-Enabled Transactive Home Energy Management Systems in Distribution Networks,” in *IEEE Kansas Power & Energy Conference*, Jul. 2020.
- **L. Edmonds**, M. N. Faqiry, H. Wu, and A. Palani, in “Three-Phase Distribution Locational Marginal Pricing to Manage Unbalanced Variable Renewable Energy,” in *IEEE Power and Energy Society General Meeting*, Aug. 2020.
- **L. Edmonds**, M. Derby, M. Hill, and H. Wu, “Coordinated Operation of Water and Electricity Distribution Networks with Variable Renewable Energy and Distribution

Locational Marginal Pricing,” *Renewable Energy* (JCR Q1, Impact Factor 8.001), vol. 177, pp. 1438-1450, Jun. 2021.

– This work was presented at the 2021 Governor’s Conference on the Future of Water in Kansas.

- **L. Edmonds**, X. Liu, and H. Wu, “Demand-Responsive Green Ammonia Plant Model and Impact on Electricity Distribution System,” in *IEEE Power and Energy Society General Meeting*, In Press, Jul. 2022.
- **L. Edmonds**, P. Pfromm, V. Amanor-Boadu, M. Hill, and H. Wu, “Green Ammonia Production-Enabled Demand Flexibility in Agricultural Community Microgrids with Distributed Renewables,” *Sustainable Energy, Grids and Networks*, Under Second Review.
- A journal paper over a larger coordinated water-energy network and the coupling’s impact on the distribution locational marginal price is in the pipeline.

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Chapter 1

Introduction

This chapter introduces the concepts researched in this dissertation. It highlights the importance and need of this research as well as provides the specific research questions and contributions of this dissertation.

1.1 Background

Renewable energy generation, such as wind and photovoltaic (PV) technologies, have drastically increased in the United States in recent years, as shown in Figure 1.1 [1]. Since 2009, the generation and capacity of all renewables in the United States have steadily increased. The facilitation of efficiently connecting variable renewable energy (VRE) resources to the grid is critical in combating climate change. Thus, providing a cleaner way to produce electricity than current methods, which mainly rely on the burning of polluting fossil fuels, such as coal and natural gas. Favorably, the United States has a plentiful resource of wind, particularly in the Midwest, which is often called the “wind belt” and is depicted in Figure 1.2 [2]. Further, many states see a significant amount of solar irradiance. In particular, states such as California, Arizona, and Nevada and have begun building large solar farms to harness this abundance of solar energy.

Such changes produce significant challenges when matching the generation to the load, for

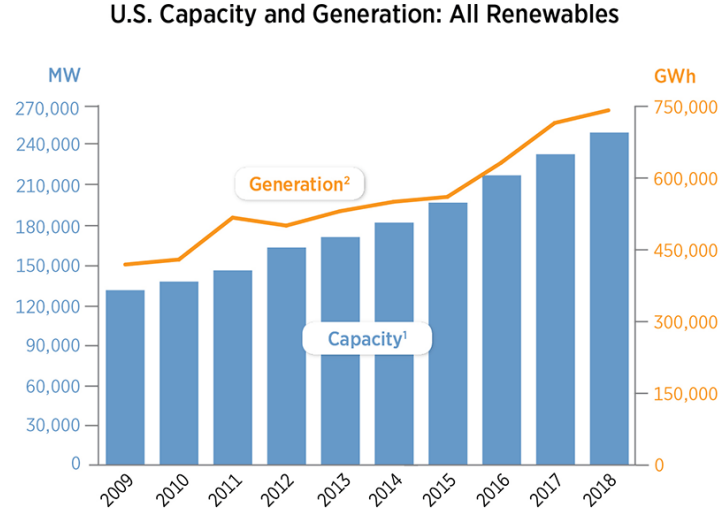


Figure 1.1: United States yearly growth in generation and capacity of all renewables. Borrowed from [1].

instance, the California Independent System Operator’s (CAISO’s) “duck curve” in Figure 1.3 [3]. With an increase in VRE, particularly solar generation, CAISO is expected to face ramping and overgeneration challenges. During solar noon, when the sun is at the highest spot in the day, solar generators risk generating more supply than demand, causing a power

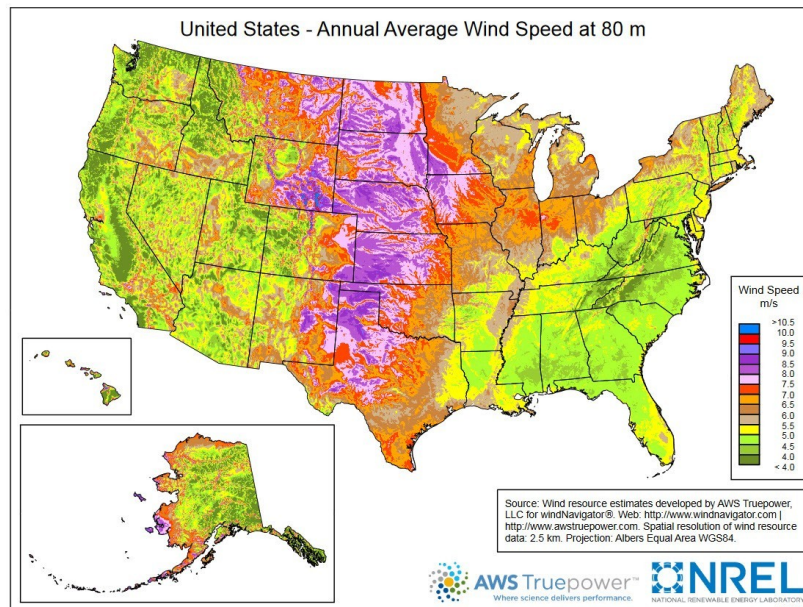


Figure 1.2: United States annual average wind speeds at 80 meters. Borrowed from [2].

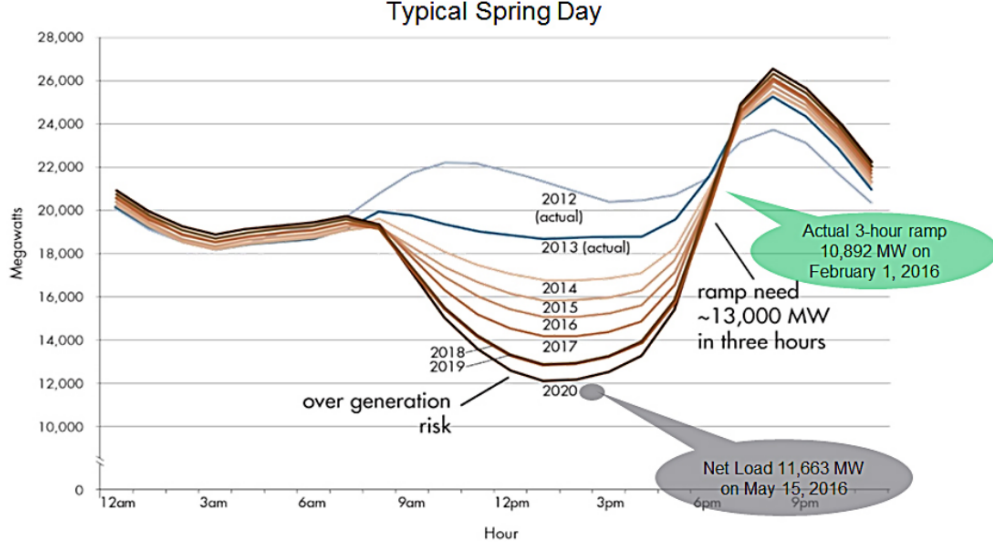


Figure 1.3: The CAISO, with an expected increase in VRE sources, experiences steep ramping needs and risk of overgeneration in the spring. Borrowed from [3].

mismatch. On the other hand, when the sun is setting, both the solar power generation decreases and the power demand increases due to less natural lighting, cooling temperatures in the winter, and more people using energy at their homes. These two factors inflict a significant ramping need from controllable generators. Existing conventional generators may not have the ramping flexibility required for the future high VRE scenario. Further, VREs have characteristics of both variability and uncertainty, meaning the power output of renewable energy technologies is not a constant value, and it is unknown exactly when the power will be available. Therefore, large amounts of VREs can cause significant challenges for electricity utilities in matching real-time generation to demand.

Further, distributed energy resources (DERs) are not adequately rewarded for their grid-serving actions. The study and implementation of transactive markets for distribution systems allow for transparent and fair pricing for actions executed in the distribution system operator's (DSO's) market. Due to differences in how various DERs function and their physical limitations, these resources must be distinctively modeled for efficient and reliable operation. In addition, distribution grid constraints such as line limits, transformer limits, and bus voltages are essential considerations in the design of the DSO's market.

Solutions commonly proposed in the literature to address challenges faced by non-

dispatchable distributed generation (wind and PV) integrated into the grid typically include the development of a distribution market [4], energy storage, and demand-response techniques [5]. This dissertation focuses on improving the grid integration of distributed renewables by using 1) a market distribution locational marginal pricing (DLMP) mechanism and 2) unique storage and demand response solutions in the food-energy-water (FEW) nexus. The remainder of this chapter briefly reviews the topics discussed in this dissertation.

1.2 Introduction to the Distribution Locational Marginal Price

The development of smart grids and the increase in DER penetration levels brings about new challenges to distribution system operators. DERs, such as variable renewable energy, battery energy storage systems (BESSs), distributed generators (DGs), and responsive loads (RLs), increase the complexity of the distribution system. Therefore, system characteristics shift away from the previously passive system toward an active distribution system. With an active distribution system, there comes a need for fair and transparent pricing schemes, which reward DERs for reducing losses, voltage violations, congestion, and imbalance of lines. Currently, utilities price electricity demands in the distribution system by using either fixed rates or time-of-use pricing for customers. Also, utilities often use net metering to buy excess energy a residential customer produces at a specified rate. Neither of these practices indicate the price of electricity in real-time. Therefore, there is a need for an appropriate pricing mechanism. One approach receiving considerable research attention is a mechanism similar to the locational marginal pricing (LMP) in the transmission system, referred to as the distribution locational marginal price.

DLMP is defined as the marginal cost to supply the next increment of power to a specific location. It may serve as a price signal for the economic dispatch of generation sources within the distribution system. Incentives arising from nodal pricing may encourage the acceptance of DERs in the distribution system and enable the chance for greater revenue of utilities due

to reduced losses, voltage violations, and line congestion.

The LMP formulation in the transmission system, which utilizes a direct current optimal power flow (DCOPF) model, cannot be directly used in the distribution system as the resistance to reactance (r/x) ratio is higher than in the transmission system. Therefore, the results do not reflect the true nodal prices in the distribution system [6]. It remains challenging to use full alternating current optimal power flow (ACOPF) as its nonlinear nature does not allow for an efficient way to decompose DLMP into its components, i.e., energy, loss, voltage, and congestion, which are crucial for transactive energy market-based operation of the distribution system. Therefore, linearized ACOPF, considering system topology and constraints, is used to calculate DLMP and its components and has been shown to provide comparable prices to true ACOPF [6]. Linearized ACOPF also immensely reduces the computational complexity of attaining DLMPs.

Along with the idea of nodal distribution pricing, there is a drive for reactive power pricing with the new age of the smart distribution grid. Currently, reactive power is not priced; it is just monitored or penalized if a customer, typically industrial, has a power factor outside of a given range. If reactive power pricing were enabled in the distribution system, it could incentivize reducing reactive power demand and improve power factors.

Unlike the transmission system, the distribution system is somewhat unbalanced. Therefore, there is also a motivation for three-phase nodal pricing. To mitigate imbalances across phases, some utilities monitor the imbalance and manually direct load to other phases after large imbalances occur. Currently, automatic balancing of the system is not practiced. One motive for this research is to use an economic price signal to eliminate the imbalance of power on phases in real-time while utilizing the maximum amount of VRE possible.

Finally, as actual VRE outputs rarely match their forecasted values, an existing method to address uncertainty is adopted in this work. The novel, data-driven probability efficient point (PEP) method is used to find the expected VRE generation at specific confidence levels based on a large amount of historical data. The deterministic output from the PEP method is then used to balance the system's generation and demand. The PEP method offers the DSO a tool in managing VRE uncertainty.

1.2.1 Introduction to the DLMP Application in HEMS

The DLMP can be used as a price signal to encourage or discourage energy consumption in a distribution system. One area that could benefit from this price signal is residential and industrial customers seeking a reduction in electricity costs. In commercial and residential buildings, energy consumption accounts for more than 70% of total electricity usage, profoundly impacting the power grid’s operation. Approximately 100 million single-family homes in the United States account for 36% of the electricity load and often determine the peak system load, especially on hot summer days when residential air conditioning use is high [7].

Future smart cities equipped with smart home energy management systems (HEMSs) have the potential to play a pivotal role in reducing global energy consumption while maintaining economic, reliable, and secure power grid operation. A HEMS is a smart home automatic control system that can optimally control residential appliances to serve multiple objectives of residential customers (e.g., electricity cost minimization, peak load minimization) while maintaining the customer’s thermal comfort in the presence of uncertain weather and electricity consumption [8–10].

From the perspective of the utility, widely distributed HEMSs in residential areas can serve as demand response (DR) providers, which shift loads to non-peak hours and minimize voltage violations and line congestion [8, 11]. From the perspective of homeowners, HEMSs are developed to optimize forward-looking schedules for a residential home’s appliances, such as a heating, ventilation, and air-conditioning system, refrigerators, water heaters, rooftop solar, energy storage, lighting, and electric vehicles. Although HEMS devices reduce customer electricity costs, cyber-attacks and privacy concerns may lead to reduced customer engagement in DR programs [12].

The realization of HEMS requires wireless communication via Zigbee or Wi-Fi, which can be hacked, eavesdropped on, and compromised, providing intruders additional ways to invade homeowners’ privacy. In transactive distribution systems with a high penetration of HEMSs [7], homeowners are required to submit load forecasts and potentially price bids to the

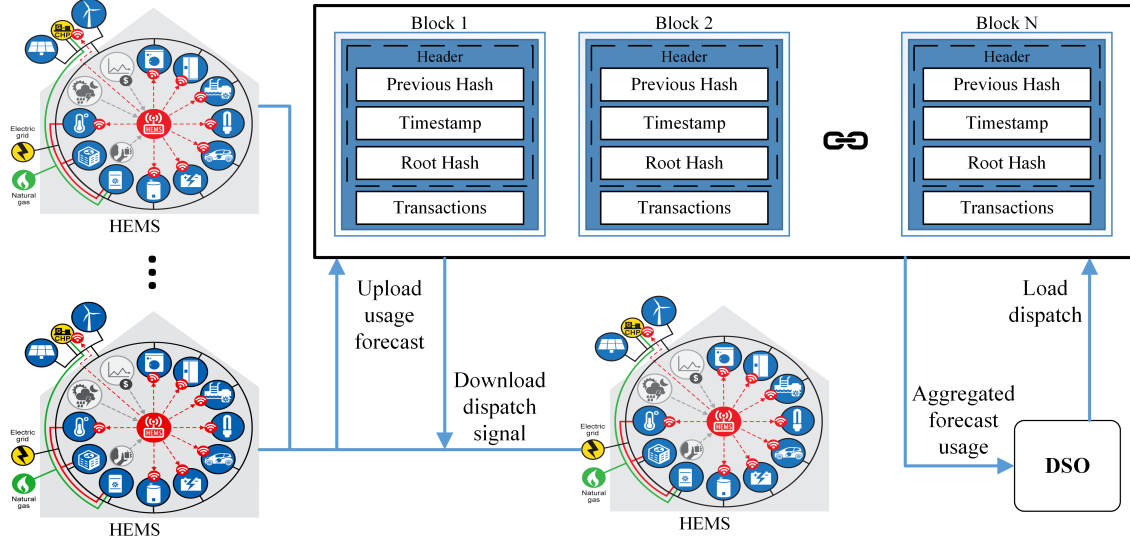


Figure 1.4: Blockchain interaction with HEMS. In the first stage, users upload load forecasts. Then, users download the dispatch signal in the second stage. Published in [18].

distribution system operator for power balancing purposes [13]. The electricity consumption data are sensitive information that can infer a user's habits and lifestyle [14, 15]. The privacy leak and potential misuse of user-provided data could cause loss of a homeowner's physical property and additional susceptibility to cyber-attack. The submitted load forecast provides an attack surface for malicious intruders to predict whether a HEMS user is home or not.

Furthermore, a long-term eavesdrop will increase the chances of a correct prediction, which makes HEMS users vulnerable to a sneaky attack. Therefore, a smart contract within a private blockchain is proposed to keep customers' information confidential. Blockchains are distributed ledgers that are tamper-evident and tamper-resistant [16, 17]. Transactional data are saved to the blockchain in an ever-growing record list, called blocks. Each block also contains a timestamp and a hash related to the previous block. A blockchain-based smart contract refers to the code that is automatically executed when specific actions occur in the blockchain [17]. Figure 1.4 depicts how the blockchain will be used to provide secure data transfer between residential homes and the DSO.

1.3 Introduction to the Water-Energy Nexus

Water and electricity networks are two critical infrastructures in today's society. Though typically operated independently, these infrastructures are profoundly interdependent. For example, in 2015, 41% of the water withdrawn in the United States was sent to electrical power plants mainly for cooling purposes, with 3% of this water being consumed [19]. On the other hand, water pumps require electrical energy to pump water to customers, water treatment centers, and for use in the agriculture industry [20]. The agriculture sector is responsible for 43% of the total water withdrawn in North America [21]. Further, about 80% of municipal water costs are for electricity, and municipal water networks consume around 3-4% of the United States' energy and as much as 13% when including residential water energy usage [22]. Anticipated increases in water scarcity, variability, and uncertainty within the water network, particularly during extreme events, can lead to vulnerabilities in the United States' energy network [20].

Researchers and governmental entities alike have long studied the synergy between water and electricity networks. For example, authors in References [23] and [24] present long-term integrated planning problems for water and electricity systems in the New England region in the United States and China, respectively. On the other hand, optimal operation of combined water and energy networks are considered in many works, such as [25] and [26]. Various other published articles define and study the water-energy nexus, dating back to the 1990s [27].

However, changes over recent years have caused water and electricity utilities to improve efficiencies through cooperation. For example, severe drought can lead to limited water availability and constrained operation of power plants. In 2012, Hurricane Sandy caused significant operational problems when vital water infrastructure lost power [28]. Policy developments, technological advances, and increased population growth are additional reasons for water and electricity utilities to improve efficiencies through cooperation. Further, with the rise in water demands [29] and prices, as water prices in the United States increased nearly 40% from 2008 to 2016 [30], water utilities must begin to look at ways to reduce their

operational costs and electricity usage. Additionally, VRE sources have increased in urban electrical distribution networks. Such changes produce significant challenges when matching the generation to the load.

As stated previously, solutions provided in the literature for mismatches in power generation and load are demand response techniques and the use of energy storage resources [5]. Storage options include battery storage, concentrating solar power combined with thermal energy storage [31], and utility-scale pumped storage hydro [32, 33]. These storage projects can have substantial capital costs [34]; therefore, cheaper energy storage ideas are needed. A less costly avenue for energy storage could be through gravitational potential energy storage in existing water tanks.

To address these challenges, this dissertation proposes a framework for urban water and energy networks to cooperate by reducing peak electricity loads and VRE curtailments through flexibility in the water pump power consumption. For example, electrical utility operators can shift pump demand by using water tanks as storage devices. The water network subsequently provides a service to the electricity network and must be rewarded.

One way to accurately reward active resources in the distribution system is by buying and selling energy at the true cost of electricity at a node, namely, the distribution locational marginal price. The DLMP is the marginal cost to serve the next unit of power at a distribution network node. It is comparable to the locational marginal price of the transmission network. The DLMP mechanism embedded into future distribution energy markets is a useful tool in integrating various types of distributed energy resources into the existing electricity distribution network by incentivizing ancillary services. Further, DLMPs indicate the health of the network as they are higher when the distribution system sees operational issues, e.g., congestion on lines and voltages violations at nodes. This DLMP increase is due to a cost-causation pricing mechanism to the node that provokes these operational issues. The DLMP mechanism itself serves as a financial incentive.

1.4 Introduction to the Food-Energy-Water Nexus

Modern power distribution systems have seen increased renewable energy (RE) penetrations in recent years. With characteristics of variability and uncertainty, these resources pose challenges for the aging power grid that was not originally engineered to operate in this manner [35]. Mismatched power load and generation has always been problematic. One of the significant operational challenges of RE penetration is the mismatch that occurs due to the uncertain and variable generation output from RE sources, along with the increasing unpredictability of customer demands due to an increased penetration of distributed energy resources, such as small-scale wind and rooftop PV technologies. Imbalances can lead to load shedding, curtailed power generation, or the operation of base load generators when it is not economical or necessary [36]. Solutions to this challenge typically include an increase of energy storage resources and or demand response techniques [5]. If excess renewable energy generation is present in the system, energy can be stored and used later, so it does not go to waste. On the other hand, if there is insufficient generation in the system to match the load, flexible loads allow the energy demand to follow the potentially fast-changing (on the order of minutes/hours) generation supply. Further, authors in [37] indicate sufficient operating reserve, through energy storage, demand response, and flexible generators, reduces the cost of integrating variable renewables into power grids.

Current energy storage options, particularly conventional battery energy storage, face degradation of energy capacity over charging and discharging cycles, short storage times, and thermal runaway. Therefore, long-term (more than one day) energy storage solutions should be explored. Ammonia can be consumed by a direct ammonia fuel cell (DAFC) to provide energy to the grid in times of need, which can serve as another method to address the variability of renewable energy resources. Therefore, the cooperation between electricity distribution systems and green ammonia plants offers a unique solution to grid integration of renewable resources.

Therefore, a framework for a rural agricultural community microgrid is proposed in this dissertation to alleviate the aforementioned challenges. Community microgrids benefit both

the community and the grid and have characteristics of 1) spanning a large area and benefiting many customers, 2) can be owned by a utility, and 3) lowering system costs by deploying DERs at optimal locations. In contrast, traditional microgrids are owned by individual customers and typically only benefit that single customer or a few surrounding customers and do very little for the grid [38]. The cooperation between a rural energy system and an ammonia synthesis plant reduces peak electricity loads and allows chemical energy storage in the form of ammonia to mitigate renewable generation curtailment. Utility operators can shift ammonia plant electricity demands to best serve the utility so long as the desired amount of ammonia is produced by the end of a given time frame. In return, the ammonia plant must be rewarded for providing these services to the electricity system.

Transacting energy at the true cost of electricity at a node is one method to accurately reward active resources in the distribution grid. A technique that achieves this is the distribution location marginal price mechanism, which is the marginal cost to supply the next increment of power to a node. This method is similar to the locational marginal pricing mechanism practiced in the electric transmission market today. With characteristics of fair, transparent, and cost-causation prices, this mechanism is very desirable for future distribution markets integrating various distributed energy resources [39]. A financial incentive for ancillary services to ease operational issues such as voltage violations and congestion on lines comes from the integration of this mechanism, as DLMPs are higher when these issues arise in the system.

Ammonia is the focus of this work primarily due to its importance to agriculture. Bio-available nitrogen is essential for all life and is central to the food-energy-water nexus. Manufactured, nitrogen-rich ammonia (NH_3) and derivatives like urea are used to fertilize crops. The use of ammonia fertilizers is responsible for about 40% of the global food production today [40, 41]. It has been proven that ammonia used as fertilizer can substantially increase crop yields for the same input of water [40]. Many farmers use the anhydrous ammonia produced by the plant considered in this work for crop fertilizer, and ammonia production consumes 30-50% of the energy used for crop production [40]. Consequently, an ammonia plant serving as a flexible demand to the distribution grid can provide a commodity that

can be used locally. Further, the global transport of ammonia is well established. Existing infrastructure allows for bulk ammonia to be transported by pipeline, road, rail, and ship [42]. Finally, the use of ammonia as an energy vector (for hydrogen) is receiving considerable attention [43–46], suggesting the existence of a viable market for energy stored as ammonia.

Today, most large-scale ammonia producers do not rely on substantial amounts of electricity for ammonia synthesis. Typically, natural gas or coal is used as the fuel and or hydrogen source for ammonia production, and NH_3 is condensed using the century-old Haber-Bosch process. This procedure is referred to as “brown” ammonia. However, in the procedure studied in this work, the ammonia is produced by deriving hydrogen (H_2) from water, through the energy-intensive water electrolysis procedure, along with sourcing nitrogen (N_2) through an air separation unit. The N_2 and H_2 , called syngas, are then fed into the existing Haber-Bosch catalyst to create NH_3 . If the electricity used to power this process is generated from renewable resources, the output is referred to as “green” ammonia. Figure 1.5 outlines the procedure for ammonia synthesis considered in this work. Ammonia produced using fossil fuels produces an estimated 670 million metric tons of fossil carbon dioxide (CO_2) emissions per year [47]. Green ammonia used as fertilizer can help lower the dependence of food on fossil fuels while aiding in the decarbonization of ammonia production.

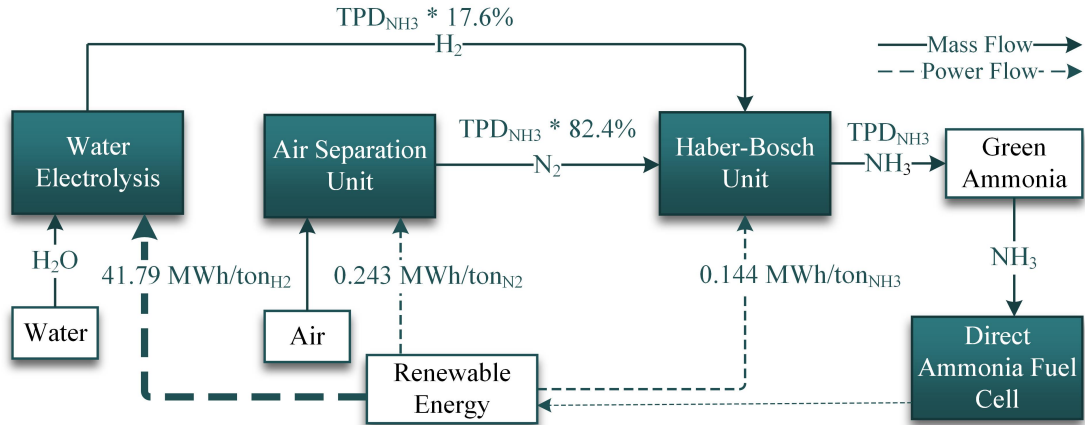


Figure 1.5: Proposed green ammonia plant procedure. Arrow width indicates relative size of energy transfer. Power consumption rates provided here are discussed in Section 5.3.1. (TPD=tons per day) To be published in [48].

Using the true cost of electricity through the DLMP mechanism can also be beneficial for

the adoption of green ammonia. There may be times of very low DLMP values throughout the day, and the ammonia plant can take advantage of this by consuming electricity during these times.

1.5 Research Motivations

Modern power distribution systems have seen an increase in variable renewable energy penetration in recent years. The existing power grid was not originally designed to operate with such resources due to their variability, uncertainty, and potential to create reverse power flows, among other challenges. One of the most significant challenges arising from large VRE penetration is mismatched power and load generation. This mismatch is further impacted by the expected increase in customer-owned distributed energy resources, which decreases the accuracy of predicting residential loads. Fast-acting demand response techniques and energy storage solutions assist with instantaneous power mismatch.

This work proposes various techniques to enhance grid interconnection of devices with uncertain outputs by providing 1) an accurate pricing mechanism framework, 2) VRE uncertainty handling using an existing technique, 3) unique energy storage options, and 4) demand response capabilities within the interdependent FEW nexus. Figure 1.6 graphically depicts the main goals of this dissertation. The basis of this work relies on a market mechanism to accurately reward active resources in the distribution network, namely, distribution locational marginal price. This work is modeled after the well-established LMP mechanism used in the transmission system today. This work further looks at the interdependencies within the vital FEW nexus to provide storage and demand response solutions to mitigate power imbalances brought about by the expected large penetration of VRE sources in the distribution grid. The following research questions are therefore established.

Research Question 1: Can the distribution locational marginal price market mechanism facilitate the integration of distributed renewable energy resources by providing an accurate reward at the true cost of electricity?

Research Question 2: Can operational flexibilities and unique energy storage solutions be

found within the interdependent food-energy-water nexus to improve the capability of the distribution grid integrating variable renewable energy resources?

Research Question 3: What is the impact on the distribution locational marginal price and overall health of an electricity distribution system that includes demand-responsive loads and energy storage techniques?

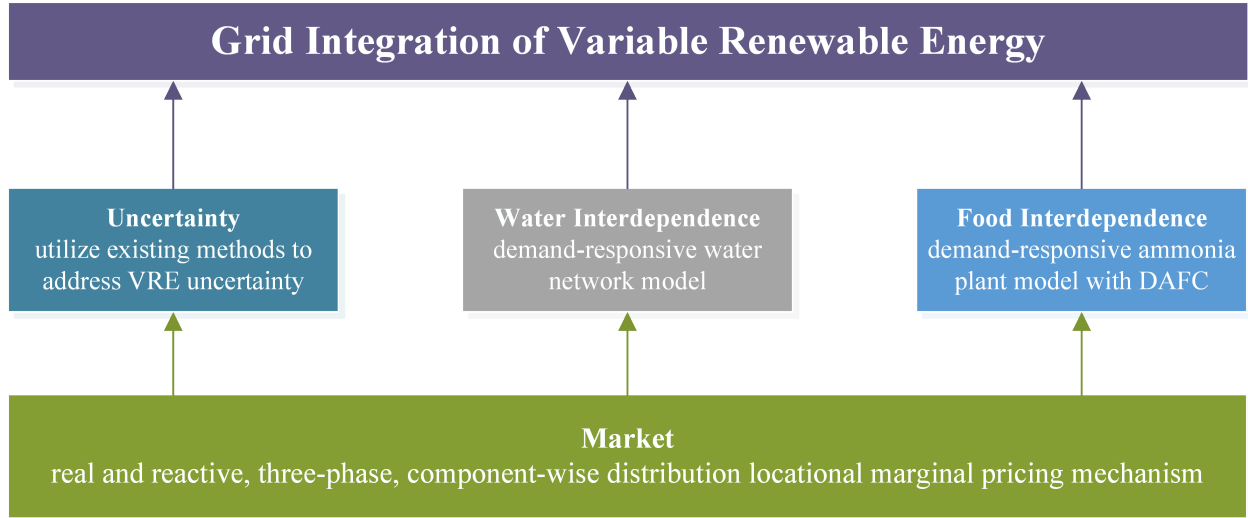


Figure 1.6: Proposed methods to enhance grid integration of distributed VRE resources with DLMP as the foundation of this work.

1.6 Research Contributions

This work is unique in that it looks to the food-energy-water nexus for solutions to the challenge of generation and load imbalance when there is a large penetration of variable renewable energy in the electricity distribution grid. This dissertation aims to highlight alternate storage technologies within the FEW nexus that can enhance VRE integration to the grid. Interconnections between these sectors also provide a platform for demand response techniques, which can further increase the capability of the power grid to accommodate large amounts of VRE sources. The basis of this work is the DLMP mechanism, which provides the true cost of supplying electricity at each node. The objectives, contributions, and research outcomes of this dissertation are outlined below.

Objective 1: A real and reactive, three-phase, and component-wise DLMP model is established and tested on a realistic distribution network that includes VREs, DGs, RLs, BESSs, and VRE uncertainty.

- To economically schedule DERs (including stochastic VRE), a transactive, DLMP-based day-ahead market (DAM) model is proposed. Building upon recent work in [6], two additional DLMP components (voltage violation and congestion) are derived using a linearized ACOPF model.
- The VRE uncertainty is managed using a novel, data-driven PEP model based on historical VRE generation data while no probability distribution function is assumed. The output of the PEP method is used in the proposed transactive DAM as a deterministic value of VRE generation.
- The significance of the real and reactive, three-phase, component-wise pricing in the proposed transactive model is revealed while analyzing the VRE penetration's influence on the DLMP components. Novel findings on negative real and reactive DLMP components under high VRE penetration are also discussed.

These contributions are discussed in Chapter 3 and in the following articles:

M. N. Faqiry, L. Edmonds, H. Zhang, A. Khodaei, and H. Wu, "Transactive-Market-Based Operation of Distributed Electrical Energy Storage with Grid Constraints," *Energies*, vol. 10, no. 11, p. 1891, Nov. 2017 [49].

M. N. Faqiry, L. Edmonds, H. Wu, and A. Pahwa, "Distribution locational marginal price-based transactive day-ahead market with variable renewable generation," *Applied Energy* (JCR Q1, Impact Factor 9.746), vol. 259, p. 114103, Feb. 2020 [50].

L. Edmonds, M. N. Faqiry, H. Wu, and A. Palani, "Three-Phase Distribution Locational Marginal Pricing to Manage Unbalanced Variable Renewable Energy," in *IEEE Power and Energy Society General Meeting*, Aug. 2020 [51].

L. Edmonds, B. Liu, H. Zhang, C. Scoglio, D. Gruenbacher, and H. Wu, “Blockchain-Enabled Transactive Home Energy Management Systems in Distribution Networks,” in *IEEE Kansas Power & Energy Conference*, Jul. 2020 [18].

Objective 2: The effect of the water and electricity network coordination in a future distribution market considering DLMPs is investigated for the first time.

- A mixed-integer linear programming (MILP) model of coordinated water and electricity distribution networks using a combined convex relaxation and 2D piece-wise linearization techniques while considering VRE stochasticity and DLMP in the model is proposed.
- The effect of the water and electricity network coordination in a future distribution market considering DLMPs is shown. An exploration into the capability of reducing voltage violations and line congestion in the electricity distribution network is conducted.
- To investigate the impact a larger coupled water-energy network has on the DLMP, a bigger network model with additional pumps and tanks is devised. The computational impact of increasing water network size is outlined.

These contributions are discussed in Chapter 4 and in the following article:

L. Edmonds, M. Derby, M. Hill, and H. Wu, “Coordinated Operation of Water and Electricity Distribution Networks with Variable Renewable Energy and Distribution Locational Marginal Pricing,” *Renewable Energy* (JCR Q1, Impact Factor 8.001), vol. 177, pp. 1438-1450, Jun. 2021 [52].

Objective 3: Similarly, unique operational flexibilities and energy storage techniques within the FEW nexus are investigated, along with the impact of this coupling on the DLMP.

- A novel MILP model for coordinated operation of an electricity distribution system and ammonia plant while considering DLMP in the model is proposed. Constraints for a small-scale, green ammonia plant are modeled for the first time in this work.
- For the first time, the effect of the ammonia plant and electricity system coordination in a future distribution market considering a high penetration of renewable energy and DLMPs is shown. The capability of the ammonia plant in reducing line congestion and voltage violations in the electricity distribution system is examined.
- To investigate the resiliency of an agricultural community microgrid, an emergency case is considered. A case where wind turbines are shut down for safety purposes and only critical loads are met is performed. The impact of a direct ammonia fuel cell serving the community in times of need is explored.

These contributions are discussed in Chapter 5 and in the following articles:

L. Edmonds, X. Liu, and H. Wu, “Demand-Responsive Green Ammonia Plant Model and Impact on Electricity Distribution System,” in *IEEE Power and Energy Society General Meeting*, In Press, Jul. 2022 [53].

L. Edmonds, P. Pfromm, V. Amanor-Boadu, M. Hill, and H. Wu, “Green Ammonia Production-Enabled Demand Flexibility in Agricultural Community Microgrids with Distributed Renewables,” *Sustainable Energy, Grids and Networks*, Under Second Review [48].

In conclusion, this work proposes the utilization of four techniques to enhance VRE integration into the distribution grid. First, the DLMP market mechanism is proposed to accurately reward active resources in the distribution network. Next, unique storage techniques and operational flexibilities are explored, first within the water-energy nexus (WEN) alone and then within the FEW nexus. These techniques offer solutions to the power imbalance issues large penetrations of VRE can cause in electricity distribution networks. Finally, VRE uncertainty is handled using an existing technique called the PEP method.

1.7 Organization of this Dissertation

This dissertation is organized as follows. Chapter 1 introduced the concepts in this work, including the background, research questions, and contributions of this dissertation. Chapter 2 outlines the existing challenges in this area and provides a review of related literature. In Chapter 3, a linear electricity distribution model is provided, along with a three-phase, real and reactive, component-wise decomposition of the DLMP. Also, an application where the DLMP price signal is communicated to a home energy management system using the secure blockchain technology is explored. In Chapter 4, coupling of interdependent water and energy models is proposed, and the impact of this coupling on the DLMP is investigated. Similarly, the coupling between a green ammonia plant and electricity distribution model with consideration of a fuel cell, and its impact on the DLMP, is outlined in Chapter 5. Finally, Chapter 6 presents key conclusions of this work and suggests avenues for future research.

Chapter 2

Challenges and Related Work

This chapter highlights the gaps in existing research as well as provides a state-of-the-art literature review on the topics covered in this dissertation.

2.1 Distribution Locational Marginal Price

Several papers investigate distribution locational marginal price (DLMP) market models for the distribution system using either a direct current optimal power flow (DCOPF) model or a modified alternating current optimal power flow (ACOPF) model. Authors in [54–57] study DCOPF-based DLMP model formulations. However, in [6], Yuan et al. prove using a DCOPF model to formulate DLMP produces significant errors due to the lower x/r ratio in the distribution system compared to the transmission system, where DCOPF models are used to calculate the locational marginal price (LMP). Furthermore, DCOPF models lack the inherent features to include real and reactive power losses, voltage violations, and reactive power pricing, which are imperative for transactive distribution markets.

Recent studies that model a modified or approximation of ACOPF when formulating the DLMP mechanism, and determine one or more of its components, are presented in [6, 58, 59]. Energy and loss components are derived in [6] while excluding voltage violation and congestion components, responsive loads (RLs), and variable renewable energy (VRE)

uncertainty. A day-ahead market (DAM) model considering the management of congestion and voltage support is proposed in [58]. This is achieved with a mixed-integer second-order cone program to model the ACOPF. This study does not include battery energy storage system (BESS) units with temporal constraints, VREs, or RLs. Similarly, utilizing a first-order approximation of the alternating current power flow manifold model derived in [60], authors in [59] propose a trust-region-based method to find the DLMP and its constituents. This study outperforms [6] but neglects to incorporate BESS and stochastic VRE that can cause reverse power flows, leading to negative real and reactive DLMPs.

Further, to address VRE uncertainty, there are multiple noteworthy optimization methods in the literature, such as chance-constrained optimization (CCO) [61], robust optimization (RO) [62], interval optimization (IO) [63], and stochastic optimization (SO) [64]. A recent review can be found in Reference [65]. In this work, the stochastic generation of VREs is modeled as a chance-constrained model, in which the minimum amount of VRE generation at a certain confidence level is obtained. To fully leverage a large amount of historical VRE datasets without assuming an explicit probability distribution, a data-driven probability efficient point (PEP) method, mathematically defined in Section 3.3.2, to solve the chance-constrained model is adopted. The PEP, also referred to as the $\mathbf{p}$ -efficient point or $\mathbf{pLEP}$, was introduced by Prékopa in the 1990s [66]. This method requires no knowledge of the underlying probability distribution function (PDF) of the uncertainty as it depends only on historical VRE data. Authors in [67] extend the PEP method in [66] to a mixed-integer linear programming (MILP) model that can be efficiently solved with commercial solvers. The PEP method has been successfully and extensively used to solve chance-constrained stochastic programming problems in many areas of study, such as stock market portfolio selection [68], fiber optic production planning [69], and disaster evacuation modeling [70]. A similar method to deal with uncertainty while not assuming a single PDF is described in [71], where a unit commitment model is optimized based on multiple PDFs, which has been shown to be distributionally robust.

Additionally, three-phase DLMP has recently gained significant research attention [58, 72–78]; however, few papers combine real and reactive, component-wise (i.e., energy,

loss, voltage violation, and congestion) DLMPs of a three-phase unbalanced system while considering multiple DER types. While [58] provides component-wise real and reactive DLMPs, the effect of the unbalanced load and generation case on the DLMP is not considered. Authors in [72] use direct regulation methods (through the use of soft open points) and real power component-wise DLMP signals to solve the congestion management problem in three-phase systems but do not consider reactive power DLMPs. Also, this work neglects VRE, RL, and BESS models. Although the authors in [76] model distributed generators (DGs), RLs, and VRE sources, there is no breakdown of the individual DLMP components or reactive power pricing. While [74] and [75], model three-phase real and reactive power pricing, there is no component-wise DLMP decomposition. Authors in [73] use state estimation to observe a three-phase unbalanced system with DGs and BESSs. While they break down the DLMP into energy, loss, and congestion components, they ignore the voltage component and reactive power pricing. Authors in [77] provide a component-wise, real and reactive DLMP market model but ignore VRE, RL, and BESS models. A three-phase ACOPF DLMP model considering DERs and RLs is provided in [78]. Table 2.1 summarizes contributions of recently published work associated with DLMPs. To this end, existing formulations in the literature lack the inherent features needed to model loss, voltage violations, and reactive power pricing. These factors are essential for a transactive distribution market.

Table 2.1: Three-phase DLMP reference contribution summary.

Reference	Three-Phase	Component-wise	Q Pricing	VRE Model
Bai et al. [58]		✓	✓	
Zhao et al. [72]	✓	✓		
Wei et al. [76]	✓			✓
Alsaleh, Liu et al. [74], [75]	✓		✓	
Meng et al. [73]	✓			
Hanif et al. [77]	✓	✓	✓	
Liu et al. [78]	✓			
Our work [51]	✓	✓	✓	✓

2.1.1 DLMP Application in HEMS

As home energy management system (HEMS) research is so new, an investigation into the data security is rarely found in the literature. Authors in [79] indicate the importance of data security within HEMS but do not address solutions for the issue. The advantage blockchain has over other security methods is that it does not need a trusted third party. Authors in [80, 81], to name a couple, propose the use of blockchain to preserve the privacy of homeowners when aggregating real-time smart meter data but do not extend their model to a HEMS case. However, forecasted data is potentially more important to protect rather than real-time data, as one can use the forecasted data to more accurately predict future user behavior. Researchers in [82] investigate blockchain’s use in smart homes in the context of Internet of Things (IoT). To the best of my knowledge, security practices for day-ahead or hour-ahead forecasted load data in a HEMS framework have not been investigated.

Blockchain was initially designed as a distributed, peer-to-peer database in 2008 [83]. The motivation for blockchain was to trade electronic cash without a financial institution’s or third-party’s assistance. Therefore, financial transactions between two parties are not based on trust but rather cryptographic proof. Traditionally, transactions are recorded in the blockchain using a proof-of-work consensus mechanism, which is computationally impractical to change if the majority of nodes are honest. Miners solve complicated verification tests before publishing the block to the blockchain. The number that solves this test is called the nonce. A unique hash value is created to define all the information in a block. A single change in the block creates an entirely different hash. This hash value includes the previous block’s hash, so the blocks are linked in a cryptographic hash tree stored in each block. The system’s state is updated when nodes reach consensus on previously published blocks. The most popular use of blockchain is Bitcoin, a cryptocurrency service [83].

Public and private keys can further protect the data in the blockchain. Public and private keys create an avenue by which users can interact using encryption and decryption techniques. Public keys ensure users are addressable in the blockchain, while private keys enable the user to be seldom identified. Privacy can still be maintained by keeping public

keys anonymous. Private keys are used as a digital signature when a user approves data to be recorded in the blockchain. Others then use the user’s public key to verify the information before adding it to the blockchain. Also, information can be privately shared using the receiver’s public key to encrypt the data. The receiver can then decrypt the data using its private key.

Private or permissioned blockchains can add another level of privacy as only verified users are allowed access to the blockchain. As public blockchains allow user access without verifying trustworthiness, complex and computationally-intensive consensus mechanisms, i.e., proof-of-work, are required to ensure a trusted environment. Compared to the lightweight mechanisms typically used in a trusted, private blockchain, such as proof-of-authority, these are energy-intensive and slow.

A smart contract is an automated computer code publicly embedded in the blockchain forever. These are publicly viewable and, therefore, transparent agreements that are guaranteed to execute automatically when certain conditions occur within the blockchain or the contract’s functions are called. Intended initially for trustless financial markets, blockchain and smart contract research has expanded into various other applications and recently expanded into electrical power applications [84, 85].

2.2 Water-Energy Nexus

Several methods for day-ahead scheduling of water pumps based on electricity prices have been proposed in the literature [86–92]. Works [86–89, 91, 92] consider drinking water pumps, while [90] considers both freshwater and wastewater pumps in their model. Further, authors in Reference [86] propose a mixed-integer second-order cone program to solve the water supply network using a fixed price scheme. The alternating direction method of multipliers (ADMM) is used to provide suboptimal solutions to the water network’s biconvex objective function that minimizes the cost of electricity used to power the pumps. An electricity network and the corresponding constraints are not considered. A second pump scheduling method considers a coupled water and electricity network with physical constraints for both

in Reference [87]. The result is a nonconvex, quadratically-constrained quadratic problem using feasible point pursuit-successive convex approximation methods to solve. Then, a distributed ADMM-based algorithm is used to update water and energy variables in an alternating fashion. Outputs from DERs and electricity prices are considered as fixed values.

Two recently published papers [88, 89] are most relevant to this work. First, Oikonomou et al., using an MILP model, consider optimizing water pump and tank schedules with respect to a fixed electricity price while maximizing the profit to the water network for providing services, such as demand response and frequency regulation, to the electricity transmission network [88]. A sensitivity analysis of the number of tanks in a water distribution network was also pursued in this work. Then, Oikonomou and Parvania provided an MILP model of the coupled water and transmission network and constraints in Reference [89], where the impact on the LMP was further investigated. A case where the transmission system operator optimizes water network flexibility was considered. However, the model does not consider water valves, VRE units, and stochasticity.

In contrast to the transmission system, the electricity distribution network is characterized by a lower x/r ratio and a radial topology. Smaller than their transmission counterparts, peak loads of typical distribution network feeders range from 0.6-28.5 MW, and typical lengths range from 1.1-32.6 miles [93]. Further, DERs, voltage limits, power losses, etc., are prominent in the electricity distribution network and need to be taken into account. Therefore, Oikonomou and Parvania, in Reference [90] also considered a coupled water and energy distribution-level model, where fixed hourly price tariffs are applied to the water network. In this mixed-integer quadratically constrained programming model, the water treatment facility is also treated as a flexible load. Again, stochasticity and valves are not considered in this model. In a similar paper that considers the optimal operation of water-energy microgrids, Moazeni and Khazaei develop an MILP model that is compared against a mixed-integer nonlinear programming model in Reference [91]. Although this work includes DERs and bidding in a distribution network, valves and the stochasticity of the VRE units are ignored. However, Wang et al. in Reference [92], propose a robust operation of the water-energy nexus where uncertainties in wind generation outputs are considered. The

authors consider a transmission-level multi-energy system.

These approaches are not suitable to the present problem because a coupled model must be considered to capture the impacts one network has on the other. Further, it is important to consider the variability of renewable resources because their forecasts do not always match their actual power output. Finally, fixed energy prices do not reflect the impact actions in the water network have on the true cost of electricity. There has been little work in the literature on combined water and electricity distribution networks that consider VRE uncertainty. Furthermore, the impact of the coordination of the water network on the DLMP is still unknown. This dissertation aims to fill this gap by studying the optimal operation of interdependent electricity water distribution networks under VRE uncertainty.

Table 2.2 compares recently published work in this area to the contributions of this work. Novel to this area of study, an integrated MILP water and electricity distribution model that handles the uncertainty of VRE resources using the PEP method is proposed in this dissertation. Also considered is the inclusion of valves in the proposed water model. More importantly, a study of how actions in the water network impact the DLMP and the physical condition of the electricity network are included in this work.

Table 2.2: Water-energy nexus reference contribution summary.

Reference	Merged Water-Energy Network	VRE Uncertainty	Distribution Network	VRE	DLMP
Fooladivanda et al. [86]					
Zamzam et al. [87]	✓		✓	✓	
Oikonomou et al. [88], [89]		✓			
Oikonomou and Parvania [90]	✓		✓		
Moazeni and Khazaei [91]	✓		✓	✓	
Wang et al. [92]	✓	✓(RO)		✓	
Our work [52]	✓	✓(PEP)	✓	✓	✓

2.3 Food-Energy-Water Nexus

Electricity-run green ammonia plants are not a new concept, with the first research published in this area in the 1960s. Pioneering work published in 1977 proposes the concept of storing wind energy in the form of hydrogen [94], but the process has only recently approached economic feasibility. With the increase in low-cost renewable energy technologies being added to the grid, electricity prices have decreased in recent years [95], making more environmentally friendly ammonia production feasible. Yet, the economics for synthesizing brown ammonia still slightly outperform the method proposed in this work. With the energy demand of green ammonia and brown (natural gas) ammonia being 7.7 MWh/ton_{NH₃} [96] and 32.75 MBTU/ton_{NH₃} (9.6 MWh/ton_{NH₃}) [97], and at the ten year (2010-2019) annual average cost of natural gas at \$3.3021/MBTU [98], electricity prices will have to drop from current levels of about \$0.1353/kWh in the United States in 2020 [99] to below \$0.014/kWh for the traditional method of synthesizing ammonia using natural gas to be less economical. The economics for green ammonia improve with penalties or taxes for releasing carbon monoxide and carbon dioxide into the atmosphere or incentives or premiums for green products. Independently, the price of electricity is expected to fall in the coming years. This price of electricity may be achievable within 10-15 years as renewable generation and battery storage increase. Less reliance on traditional power plants, which have comparatively higher operation and maintenance costs, will also contribute to a decline in the price of electricity. These trends favor lower electricity prices and greater economic competitiveness of green ammonia.

To illustrate the rapid changes taking place, consider that the energy demand of green ammonia has recently reduced from around 10.4 MWh/ton_{NH₃} to 7.7 MWh/ton_{NH₃} (the value used above) due to a breakthrough in the commercialization of a solid oxide electrolysis cell in the water electrolysis procedure [96].

In part because of the rapid changes, the energy management of green ammonia plants has not been well researched to this date, to the best of my knowledge. Further, the impact of energy flexibility from green ammonia plants and direct ammonia fuel cells on the DLMP

is yet to be explored.

There are many tangentially related papers within the realm of electrification of ammonia production. A recent, comprehensive review of the production, distribution, and storage of nitrogen-based alternative fuels, including green ammonia, is provided in [100]. Further, authors in [42] and [101] provide reviews of ammonia applications for power as well as the many factors that arise therefrom. This area gained significant attention in the late 2010s with substantial work that investigates electrolytic hydrogen synthesis [102], green ammonia synthesis or power-to-ammonia (P2A) [103–108], and power-to-ammonia-to-power (P2A2P) technology [109]. Authors in [110] provide a process analysis of renewable-powered ammonia production, focusing on solar power. However, these works mainly focus on the feasibility of these processes rather than the coupling between the ammonia and electricity sectors.

More specifically, many distantly related papers consider the planning of these two systems. For example, an ADMM algorithm is used in [111] to solve a co-planning model to optimize wind generation and ammonia plant(s) siting and configuration as well as electricity transmission system expansion with respect to total investment and operational costs. While this work considers power balance constraints and direct current (DC) power flow modeling, real-time or day-ahead scheduling of the two systems is beyond the scope of this work. Additionally, authors in [112] consider joint planning of hydrogen production and electricity systems to enable high levels of variable renewable energy resources and energy system decarbonization. This work also analyzes the marginal cost of electricity under different hydrogen demand scenarios.

Further, under a similar concept to the research proposed in this work, authors in [113] consider flexibility within an integrated natural gas and electricity transmission system, including hydrogen production via electrolysis and steam methane reforming. A day-ahead scheduling model considering transmission grid and gas network constraints is provided. Authors in [114] consider hydrogen (from electrolysis) production flexibility in transmission grids with variable renewable energy sources and consider DC power flow and balance constraints. Additionally, [115] and [116] consider electrolytic hydrogen synthesis while considering transmission grid constraints, while [116] considers locational electricity pricing. It is important

to consider this transmission-level interaction, but the models cited above do not focus on distribution systems, especially future distribution systems with diverse distributed energy resources.

Complementary to this research, authors in [117] propose a multi-energy (electrical, ammonia, and thermal energy carriers) thermo-electrochemical model with thermal and power balancing constraints. Still, physical grid constraints were not considered. The proposed methodology was tested on a laboratory-level, small-scale microgrid. A comparison of various storage techniques, including P2A, traditional battery storage, and power-to-gas (P2G) applications, such as rapid response electrolysis for methane (CH_4) and hydrogen (H_2) is described. Authors in [118] evaluate the thermodynamic performance and energy efficiency of solar-powered intermittency mitigation through clean ammonia synthesis and direct ammonia fuel cells. The formulation developed in [119] is used to optimally schedule wind-powered ammonia generation with respect to least-cost annual operations. Authors in [120] provide a combined capacity planning and scheduling of green ammonia production. Though the aforementioned works consider ammonia as a storage medium for excess renewable generation and power balance constraints, they do not consider physical grid constraints. Therefore, the impact of this procedure on the grid and the DLMP appears to be a fruitful area of inquiry.

Chapter 3

Electricity Distribution System Model and Distribution Locational Marginal Price Formulation¹

This chapter provides a linear electricity distribution model and formulates a distribution locational marginal pricing (DLMP) mechanism. The model and mechanism are further tested for validity and used in a potential future application.

3.1 Background

The electricity distribution system model equations and the DLMP decomposition are formulated in the following sections. First, a simplified model is developed and tested. Next, the model is expanded to include power losses. The DLMP components are derived based on this model. Further, variable renewable energy (VRE) uncertainty is accounted for using the data-driven probability efficient point (PEP) method. This model is tested, and case studies demonstrate the significance of component-wise pricing. The model is further extended to account for unbalanced three-phase distribution systems, and a case study showing the

¹This chapter is a combination of slightly modified versions of our published articles [18, 49–51].

importance of three-phase DLMPs is provided. Finally, the unbalanced three-phase model, and the DLMP price signals, are used as a basis for a home energy management system (HEMS) application utilizing the blockchain.

3.2 Simplified Electricity Distribution System Model

A balanced three-phase, lossless electricity distribution system is first considered. Simplified DistFlow equations, which are extensively used in the literature [121–125], have been adopted here. The nodes are indexed from 1 to N , where N is the total number of nodes. As shown in Figure 3.1, line i is the line connecting the upstream node, $u(i)$, and the set of downstream nodes, $d\{i\}$, to node i . All variables related to line i are subscripted by index $i \in N$, for phase $\phi \in \Phi$, and time $t \in \mathcal{T}$.

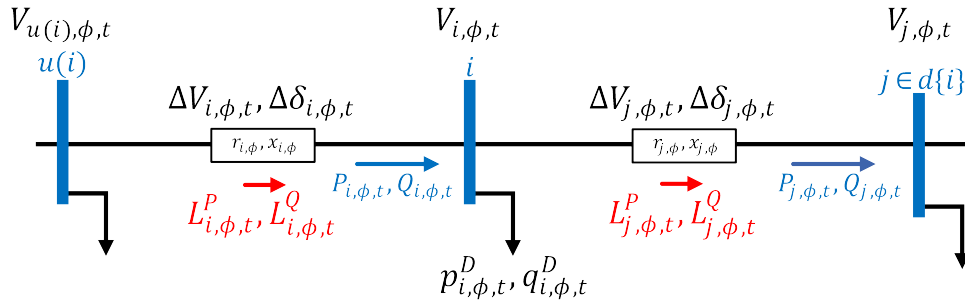


Figure 3.1: Distribution branch with line i connecting bus $u(i)$ to node i .

3.2.1 Objective Function

The objective function value, defined in (3.1), is captured in C^E . Objective function components, $\mathcal{O}(p_{i,\phi,t})$ and $\mathcal{O}(q_{i,\phi,t})$, are functions of real and reactive power and will be explicitly defined in each section of research in this dissertation.

$$C^E = \mathcal{O}(p_{i,\phi,t}) + \mathcal{O}(q_{i,\phi,t}) \quad (3.1)$$

3.2.2 Distribution Power Balance

Constraints (3.2)-(3.3) model the total system real and reactive power balance. The real and reactive power net node injections $(p_{i,\phi,t}, q_{i,\phi,t})$ are modeled in (3.4)-(3.5). Each node must see a balance in real and reactive power demand $(p_{i,\phi,t}^{Dem}, q_{i,\phi,t}^{Dem})$ and generation $(p_{i,\phi,t}^{Gen}, q_{i,\phi,t}^{Gen})$.

$$\sum_{i,\phi} p_{i,\phi,t} = 0 \quad (3.2)$$

$$\sum_{i,\phi} q_{i,\phi,t} = 0 \quad (3.3)$$

$$p_{i,\phi,t} = \sum_{Dem} p_{i,\phi,t}^{Dem} - \sum_{Gen} p_{i,\phi,t}^{Gen} \quad (3.4)$$

$$q_{i,\phi,t} = \sum_{Dem} q_{i,\phi,t}^{Dem} - \sum_{Gen} q_{i,\phi,t}^{Gen} \quad (3.5)$$

3.2.3 Distribution Power Flow

Defined in (3.6) and (3.7), the real and reactive power flows are represented by variables $P_{i,\phi,t}$ and $Q_{i,\phi,t}$. Per unit (pu) nodal voltage, $V_{i,\phi,t}$, is defined in (3.8) in reference to the substation voltage, $V_{1,\phi,t}$. Here, r_i and x_i represent the resistance and reactance belonging to line i .

$$P_{i,\phi,t} = \sum_k P_{k,\phi,t} + p_{i,\phi,t} \quad (3.6)$$

$$Q_{i,\phi,t} = \sum_k Q_{k,\phi,t} + q_{i,\phi,t} \quad (3.7)$$

$$V_{i+1,\phi,t} = V_{i,\phi,t} - (r_{i+1} \cdot P_{i+1,\phi,t} + x_{i+1} \cdot Q_{i+1,\phi,t}) V_{1,\phi,t}^{-1} \quad (3.8)$$

3.2.4 System Constraints

Voltage and line limit bounds are enforced by constraints (3.9) and (3.10), respectively. Here, ϵ is a small value, normally 5%, and $\bar{S}_{i,\phi}$ is the maximum megavolt-ampere (MVA) line limit. The initially convex, quadratic apparent power flow limit, $|P_{i,\phi,t}|^2 + |Q_{i,\phi,t}|^2 \leq \bar{S}_{i,\phi}^2$, is linearly

approximated in (3.10). Obtained from *Convex Optimization of Power Systems* [126], this equation models the outer approximation of the system power flow.

$$1 - \epsilon \leq V_{i,\phi,t} \leq 1 + \epsilon \quad (3.9)$$

$$|P_{i,\phi,t}| + |Q_{i,\phi,t}| \leq \sqrt{2} \cdot \bar{S}_{i,\phi} \quad (3.10)$$

3.2.5 DER Constraints

A conventional distributed generator (DG) with segments is considered. The small-scale DG does not face ramping constraints. In (3.11), the sum of the segment generation, $p_{i,w,\phi,t}^G$, should equal the total generation output, $p_{i,\phi,t}^G$. The segment generation has to lie within the given bounds $[0, \bar{P}_{i,w,\phi}^G]$ in (3.12), and the total real power generation has to satisfy the bounds $[\underline{P}_{i,\phi}^G, \bar{P}_{i,\phi}^G]$ in (3.13). If the DG is not considered to consume reactive power, the lower bound for the reactive power output, $q_{i,\phi,t}^G$, is zero. Otherwise, the reactive power output of the DG must lie within a fraction, $\pm\kappa_i^G$, of the real power output (3.14). Similarly, (3.15) requires the segment load, $p_{i,w,\phi,t}^D$, to sum to the full load, $p_{i,\phi,t}^D$, which must lie within the given bounds $[0, \bar{P}_{i,w,\phi}^D]$ in (3.16). The lower and upper total power demand limits $[\underline{P}_{i,\phi}^D, \bar{P}_{i,\phi}^D]$ in (3.17) must also be maintained.

Equation (3.18) determines the allocated real demand, $p_{i,\phi,t}^D$, from the requested demand, $\bar{p}_{i,\phi,t}^D$. If considered in the model, the difference between these values is captured in $s_{i,\phi,t}^D$ and is penalized in the objective function at the value of lost load. Equation (3.19) limits the positive load shedding value to a fraction, σ^D , of the requested demand. Equation (3.20) sets the reactive power demand, $q_{i,\phi,t}^D$, to a fraction (κ_i^D) of the real power demand.

Similar to the power demand, the renewable energy resources are able to be curtailed to achieve feasibility. Equation (3.21) determines the dispatched real renewable energy generation, $p_{i,\phi,t}^R$, from the expected generation, $\bar{p}_{i,\phi,t}^R$. The difference is captured in $s_{i,\phi,t}^R$ and can be penalized in the objective function to discourage renewable energy curtailment. The positive curtailment is limited to a value less than the expected generation (3.22). If power electronics allow reactive power to be generated and consumed by the renewable energy gen-

erators, the reactive generation, $q_{i,\phi,t}^R$, is held within $\pm\kappa^R$ of the dispatched real renewable energy generation, as in (3.23).

$$p_{i,\phi,t}^G = \sum_w p_{i,w,\phi,t}^G \quad (3.11)$$

$$0 \leq p_{i,w,\phi,t}^G \leq \bar{P}_{i,w,\phi}^G \quad (3.12)$$

$$\underline{P}_{i,\phi}^G \leq p_{i,\phi,t}^G \leq \bar{P}_{i,\phi}^G \quad (3.13)$$

$$0 / -\kappa_i^G \cdot p_{i,\phi,t}^G \leq q_{i,\phi,t}^G \leq \kappa_i^G \cdot p_{i,\phi,t}^G \quad (3.14)$$

$$p_{i,\phi,t}^D = \sum_w p_{i,w,\phi,t}^D \quad (3.15)$$

$$0 \leq p_{i,w,\phi,t}^D \leq \bar{P}_{i,w,\phi}^D \quad (3.16)$$

$$\underline{P}_{i,\phi}^D \leq p_{i,\phi,t}^D \leq \bar{P}_{i,\phi}^D \quad (3.17)$$

$$p_{i,\phi,t}^D = \bar{p}_{i,\phi,t}^D - s_{i,\phi,t}^D \quad (3.18)$$

$$0 \leq s_{i,\phi,t}^D \leq \sigma^D \cdot \bar{p}_{i,\phi,t}^D \quad (3.19)$$

$$q_{i,\phi,t}^D = \kappa_i^D \cdot p_{i,\phi,t}^D \quad (3.20)$$

$$p_{i,\phi,t}^R = \bar{p}_{i,\phi,t}^R - s_{i,\phi,t}^R \quad (3.21)$$

$$0 \leq s_{i,\phi,t}^R \leq \bar{p}_{i,\phi,t}^R \quad (3.22)$$

$$0 / -\kappa_i^R \cdot p_{i,\phi,t}^R \leq q_{i,\phi,t}^R \leq \kappa_i^R \cdot p_{i,\phi,t}^R \quad (3.23)$$

Also considered in this work is battery energy storage systems (BESSs). The BESS unit's state of charge (SOC), $c_{i,\phi,t}^B$, is modeled in Equation (3.24). Energy is dissipated from a BESS unit through self-discharge ("leakage"), or during charging and discharging. These effects are accounted for using the respective scaling coefficients, $\gamma_{i,\phi,t}$, $\check{\gamma}_{i,\phi,t}$, and $\hat{\gamma}_{i,\phi,t}$, which lie on the interval $(0,1]$. The BESS unit's SOC depends on the SOC of the previous timeslot $(t-1)$ and the charging ($\check{p}_{i,\phi,t}^B$) or discharging ($\hat{p}_{i,\phi,t}^B$) action the BESS makes between timeslots (Δt) .

$$c_{i,\phi,t}^B = \gamma_{i,\phi,t} \cdot c_{i,\phi,t-1}^B - \Delta t \left(\hat{\gamma}_{i,\phi,t} \cdot \hat{p}_{i,\phi,t}^B - \frac{\check{p}_{i,\phi,t}^B}{\check{\gamma}_{i,\phi,t}} \right) \quad (3.24)$$

The SOC of the BESS has to stay within a minimum ($\underline{C}_{i,\phi}$) and maximum ($\overline{C}_{i,\phi}$) SOC, as in (3.25). In Equation (3.26), the net grid injection into the BESS unit ($p_{i,\phi,t}^B$) is modeled as the difference in grid power injection $\check{p}_{i,\phi,t}^B$ and extraction $\hat{p}_{i,\phi,t}^B$. The BESS injection and extraction are both bound by the BESS rate of charging ($\underline{B}_{i,\phi}$) or discharging ($\overline{B}_{i,\phi}$) when the unit is scheduled, as in (3.27) and (3.28). The BESS unit is prohibited from charging and discharging at the same time through the use of two binary variables $\check{z}_{i,\phi,t}$ and $\hat{z}_{i,\phi,t}$. The reactive power of the battery, $q_{i,\phi,t}^B$, must lie between zero or $-\kappa^B$ and $+\kappa^B$ of the real power BESS extraction, as in (3.29).

$$\underline{C}_{i,\phi} \leq c_{i,\phi,t}^B \leq \overline{C}_{i,\phi} \quad (3.25)$$

$$p_{i,\phi,t}^B = \check{p}_{i,\phi,t}^B - \hat{p}_{i,\phi,t}^B \quad (3.26)$$

$$\underline{B}_{i,\phi} \cdot \check{z}_{i,\phi,t} \leq \check{p}_{i,\phi,t}^B \leq \overline{B}_{i,\phi} \cdot \check{z}_{i,\phi,t} \quad (3.27)$$

$$\underline{B}_{i,\phi} \cdot \hat{z}_{i,\phi,t} \leq \hat{p}_{i,\phi,t}^B \leq \overline{B}_{i,\phi} \cdot \hat{z}_{i,\phi,t} \quad (3.28)$$

$$0 / -\kappa_i^B \cdot p_{i,\phi,t}^B \leq q_{i,\phi,t}^B \leq \kappa_i^B \cdot p_{i,\phi,t}^B \quad (3.29)$$

Frequent charging and discharging of the BESS unit decreases its lifetime [127–129]. Therefore, a restriction on high number of charging and discharging cycles is imposed by including a minimum number of charging and discharging hours using additional mixed-integer constraints, as defined in (3.30)-(3.42).

$$0 \leq \hat{z}c_{i,\phi,t} \leq \mathcal{T} \cdot \hat{z}_{i,\phi,t} \quad (3.30)$$

$$(\mathcal{T} + 1)\hat{z}_{i,\phi,t} - \mathcal{T} \leq \hat{z}c_{i,\phi,t} - \hat{z}c_{i,\phi,t-1} \leq 1 \quad (3.31)$$

$$\hat{z}c_{i,\phi,t} \geq \hat{M}_{i,\phi} \cdot \hat{z}\hat{\mathbf{n}}_{i,\phi,t+1} \quad (3.32)$$

$$\hat{z}_{i,\phi,t} - \hat{z}_{i,\phi,t-1} = \hat{z}\hat{\mathbf{m}}_{i,\phi,t} - \hat{z}\hat{\mathbf{n}}_{i,\phi,t} \quad (3.33)$$

$$0 \leq \check{z}c_{i,\phi,t} \leq \mathcal{T} \cdot \check{z}_{i,\phi,t} \quad (3.34)$$

$$(\mathcal{T} + 1)\check{z}_{i,\phi,t} - \mathcal{T} \leq \check{z}c_{i,\phi,t} - \check{z}c_{i,\phi,t-1} \leq 1 \quad (3.35)$$

$$\check{z}c_{i,\phi,t} \geq \check{M}_{i,\phi} \cdot \check{z}\check{\mathbf{n}}_{i,\phi,t+1} \quad (3.36)$$

$$\check{z}_{i,\phi,t} - \check{z}_{i,\phi,t-1} = \check{z}\check{\mathbf{n}}_{i,\phi,t} - \check{z}\check{\mathbf{m}}_{i,\phi,t} \quad (3.37)$$

$$\check{z}_{i,\phi,t} + \hat{z}_{i,\phi,t} \leq 1 \quad (3.38)$$

$$\hat{z}\hat{\mathbf{m}}_{i,\phi,t} + \hat{z}\hat{\mathbf{n}}_{i,\phi,t} \leq 1 \quad (3.39)$$

$$\check{z}\check{\mathbf{n}}_{i,\phi,t} + \check{z}\check{\mathbf{m}}_{i,\phi,t} \leq 1 \quad (3.40)$$

$$\hat{z}\hat{\mathbf{m}}_{i,\phi,t} + \check{z}\check{\mathbf{m}}_{i,\phi,t} \leq 1 \quad (3.41)$$

$$\hat{z}\hat{\mathbf{n}}_{i,\phi,t} + \check{z}\check{\mathbf{n}}_{i,\phi,t} \leq 1 \quad (3.42)$$

Equation (3.30) ensures the discharging counter, $\hat{z}c_{i,\phi,t}$, is nonnegative and does not exceed the scheduling horizon limit, determined by $\mathcal{T}$. The discharging counter is increased by one if the unit is discharging, as modeled in (3.31). The discharging counter must be higher than the minimum number of consecutive discharging hours of the BESS unit, $\hat{M}_{i,\phi}$, as in (3.32). This is achieved by use of a not discharging indicator, $\hat{z}\hat{\mathbf{n}}_{i,\phi,t}$. Constraint (3.32) also ensures the counter is higher than the minimum number of consecutive discharging hours when the unit stops discharging, indicated by the not discharging indicator at unity ‘1’. When the discharging state, $\hat{z}_{i,\phi,t}$, changes value, Equation (3.33) captures this change in the discharging, $\hat{z}\hat{\mathbf{m}}_{i,\phi,t}$, and not discharging, $\hat{z}\hat{\mathbf{n}}_{i,\phi,t}$, indicators. Similar explanations for Equations (3.34)–(3.37) hold for the charging aspect of the BESS. The integer charging

counter, $\check{z}c_{i,\phi,t}$, is bound by the scheduling horizon in (3.34), is increased by one if the unit is charging in (3.35), and is used in (3.36) to achieve the minimum requirement for the number of consecutive charging hours, $\check{M}_{i,\phi}$. Equation (3.37) captures the change in charging status (indicated by $\check{z}_{i,\phi,t}$) using the charging and not charging indicators, $\check{z}\check{m}_{i,\phi,t}$ and $\check{z}\check{n}_{i,\phi,t}$, respectively. Further, the BESS is unable to charge and discharge at the same time, as in (3.38), and Equations (3.39)-(3.42) ensure the (not) charging and (not) discharging indicators are not activated at the same time. This BESS model allows the DSO to properly limit the unit's frequency of charging and discharging cycles, thus preventing BESS degradation over time.

3.2.6 Simplified Distribution Model Case Study

Simulation results corroborate the concepts presented in Sections 3.2.1-3.2.5. These results are published in [49]. In this simplified model, $\mathcal{O}(p_{i,\phi,t})$ and $\mathcal{O}(q_{i,\phi,t})$ in (3.1) are defined as in (3.43) and (3.44). Subscript ϕ is omitted as this model is assumed to be balanced three-phase. The objective function maximizes the social welfare of the system.

$$\mathcal{O}(p_{i,\phi,t}) = \sum_{i,q,t} c_{i,q,t}^{G,P} \cdot p_{i,q,t}^G + \sum_{i,t} \hat{c}_{i,t}^{B,P} \cdot \hat{p}_{i,t}^B - \sum_{i,t} \check{c}_{i,t}^{B,P} \cdot \check{p}_{i,t}^B - \sum_{i,w>1,t} c_{i,w,t}^D \cdot p_{i,w,t}^D \quad (3.43)$$

$$\mathcal{O}(q_{i,\phi,t}) = 0 \quad (3.44)$$

Here, DGs bid at $c_{i,q,t}^{G,P}$ for real power, where subscript q indicates the segment energy and bid block using a piecewise bidding method to approximate the fuel cost of the DGs. The real power segments supplied by the generators are indicated by $p_{i,q,t}^G$. Note, the reactive power of the DG ($q_{i,t}^G$) is held to $+\kappa^G$ of the real power. The BESS units bid at a cost of $\hat{c}_{i,t}^{B,P}$ for extraction of power from the battery and $\check{c}_{i,t}^{B,P}$ for injection of power into the battery, where $\hat{c}_{i,t}^{B,P} \geq \check{c}_{i,t}^{B,P}$ to create a positive revenue. Variables $\hat{p}_{i,t}^B$ and $\check{p}_{i,t}^B$ indicate the real power the BESS unit consumes or supplies, respectively. Not included in the objective function, the reactive power of the BESS ($q_{i,t}^B$) is held to $\pm\kappa^B$ of the real power. The load aggregators (LAs) combine their customer's demands and divide them into bidding blocks

for each timeslot. Each block includes an amount of power as well as a monetary bid the LA is willing to pay for that power. However, the first segment of the LA is considered as only an energy amount without a price bid due to the assumption that not all customers served by the LA are price-responsive. This energy value represents the forecasted base load of the system, which must be served by the distribution system operator (DSO). Therefore, $c_{i,w,t}^D$, where $w \geq 1$ represents the real power price bids, and $p_{i,w,t}^D$ represents the real power demand met by the system. Further, curtailment of the power demand is not permitted in this model, i.e., $\sigma^D = 0$ in Equation (3.19). The renewable energy (RE) resources are zero-marginal-cost units, i.e., bid at \$0/MWh, and are therefore not present in the objective function. However, the reactive power output of the RE units is held to $+\kappa^R$ of the real power output. Reactive power pricing is not considered in the optimization of this model, as in (3.44).

Further, in this simplified model, Dem and Gen in (3.4) and (3.5) include real and reactive power demands $(p_{i,\phi,t}^D, q_{i,\phi,t}^D)$ and power supplied from distributed, conventional generators $(p_{i,\phi,t}^G, q_{i,\phi,t}^G)$, BESSs $(p_{i,\phi,t}^B, q_{i,\phi,t}^B)$, and forecasted renewable energy sources (RESs) $(p_{i,\phi,t}^R, q_{i,\phi,t}^R)$, respectively.

Finally, the simplified power flow problem is considered as $\mathbf{P}_1$ and is defined as:

$\mathbf{P}_1$: min(3.1)

subject to: (3.2)-(3.20), and (3.23)-(3.42)

Case studies are performed on a modified Institute of Electrical and Electronics Engineers (IEEE) 13-bus system with a high penetration of DERs, as depicted in Figure 3.2. The proposed mixed-integer linear programming (MILP) formulation is implemented in the General Algebraic Model System (GAMS) utilizing the CPLEX solver [130]. The system load is increased by 30%.

The bid of the wholesale market is a typical 24 hour winter LMP from [131]. The LMP varies from \$15/MWh to about \$42/MWh. The renewable energy source's generation is considered fixed and cleared at the DLMP due to its non-dispatchable nature. The BESS's charging and discharging bids are \$20/MWh and \$25/MWh, respectively, and were chosen

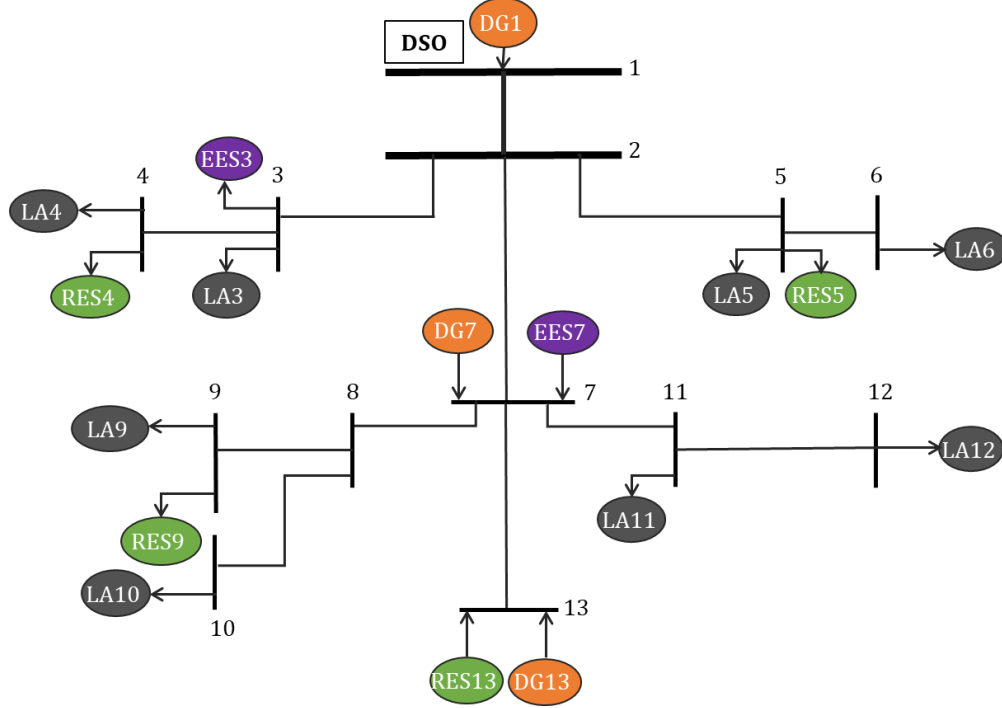


Figure 3.2: Radial IEEE 13-bus distribution system with different types of distributed energy resources on each bus. (Acronym EES here stands for electrical energy storage and has been replaced with BESS in the text.) Published in [49].

to show the schedules of the BESS units clearly. However, a realistic levelized cost of storage value should be used based on the unit's type. The calculation of this value includes many factors, such as the capital cost, operation and maintenance costs, installation costs, investment tax credits, battery degradation, and others [132]. The DGs bid in three blocks, except DG1, i.e., the substation node, which is considered to bid only one block of 10 MW at the LMP. A monetary bid and the maximum amount of power that the DG can supply at that bid are included in each block.

Injections from DERs and the wholesale market vary with the LMP. The DG's output increases as the LMP increases, and thus, the wholesale market injection decreases. Figure 3.3 illustrates this occurrence, including DLMPs at Buses 1, 7, and 13 and the DGs at Buses 7 and 13. Recall the Lagrange multiplier of the power balance constraint determines the DLMP, which is the marginal cost of serving the next unit of power at each bus. Therefore, as DLMP 7 and 13 are identical, serving the next MWh at each of these buses is equivalent in this case.

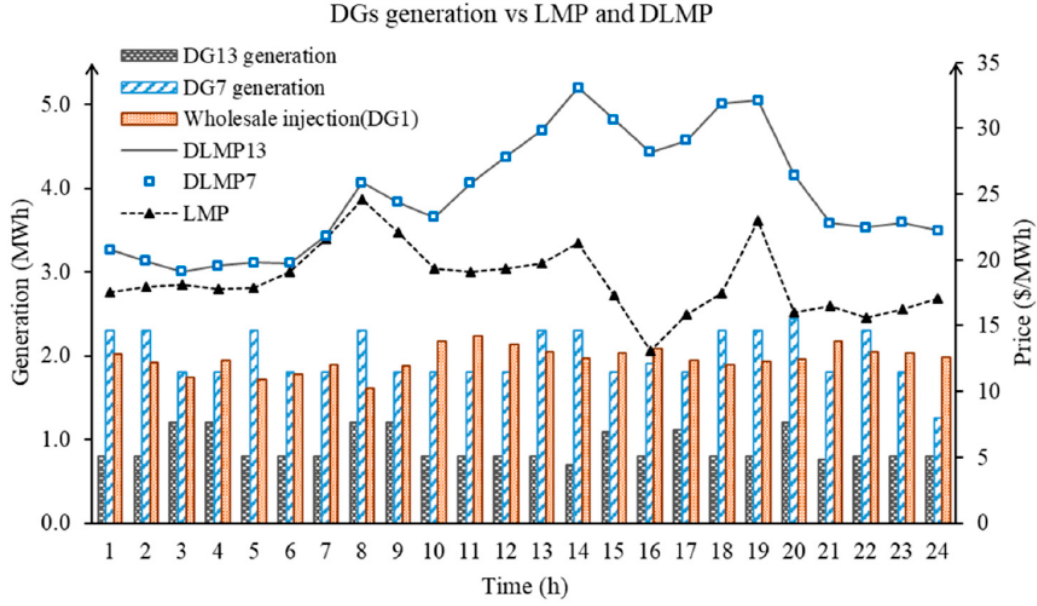


Figure 3.3: Wholesale injection at LMP versus DG7 and DG13's schedules and DLMPs. Published in [49].

To show an in-depth look at the outcome of a LA's segment-wise bidding structure, Figure 3.4 depicts LA6's second block bid and its resulting schedule compared to the DLMP at Bus 6. Recall the LA's first block, i.e., the base load, will be served in all timeslots at the

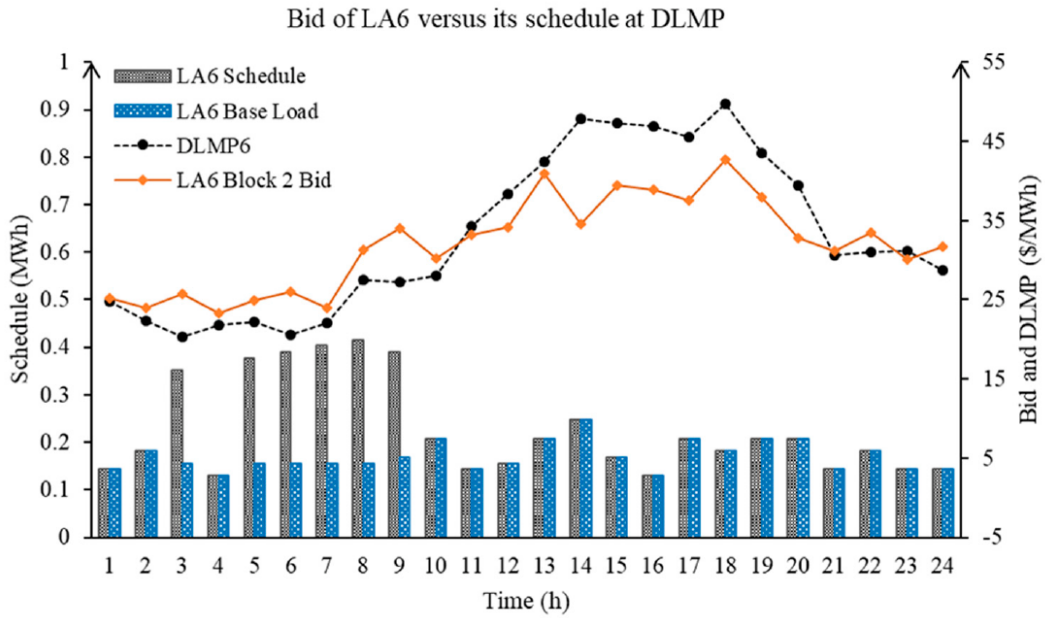


Figure 3.4: LA6 bid versus DLMP at Bus 6 and its schedule. Published in [49].

DLMP. It is verified that the power demand of the LA will go beyond the first block only when the segment-wise bids are lower than the DLMP at that bus. Otherwise, only the first block will be served by the DSO.

The DLMPs of the BESS units' buses also determine the charging and discharging schedule. The schedule for the BESS unit at Bus 3 with respect to the DLMP at Bus 3 is illustrated in Figure 3.5, where the horizontal lines indicate the injection and extraction bids. The bars show the BESS SOC while the shaded region indicates the BESS's charging (negative) and discharging (positive). In general, the BESS charges when the DLMP is low and discharges when the DLMP is high or above the extraction bid. Despite the DLMP being higher than the injection bid in Hours 9-11, the BESS is charging during this period. It is efficient to charge the BESS when the DLMP is lower and sell in times the DLMP is much higher, Timeslots 12-20, for example. In this case, the BESS also faces minimum charging or discharging periods of three hours, which impacts this schedule. Further, due to the initial SOC of 0.1 MWh and maximum charging rate of 0.05 MW/h, BESS3 would not be able to completely charge to 0.5 MWh until Hour 8.

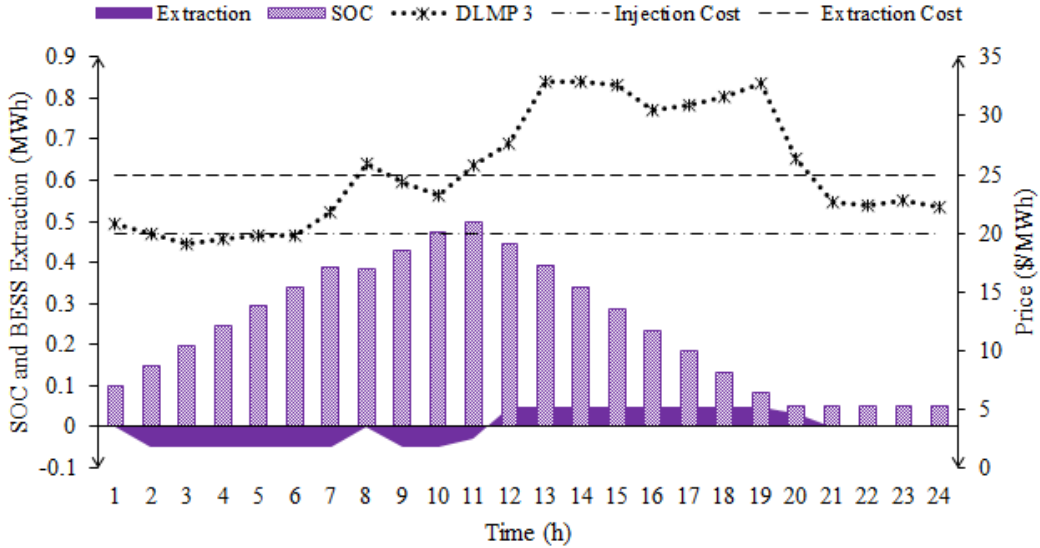


Figure 3.5: BESS3's schedule is dependent upon the DLMP at Bus 3. Published in [49].

3.3 Electricity Distribution System Model with Loss

To more accurately represent an electricity distribution system, a model for real and reactive power losses is derived. Originally nonlinear in nature, unique techniques are used to linearize the power loss equations as defined in Section 3.3.1. Additionally, considering that wind and solar predictions do not match actual power outputs, a probability efficient point method is adopted, as defined in Section 3.3.2, to handle the VRE uncertainty. Further, the DLMP is composed into energy, loss, voltage, and congestion components in Section 3.3.3 to better understand what causes DLMP behaviors in the system. Finally, this model is tested and validated in Section 3.3.4.

Here, the substation node or the point of common coupling (PCC) is indexed as 0, and the rest of the nodes are ordered from 1 to N , where N is the total number of nodes/lines. By excluding the root (substation) node, the same index is applied to both the lines and nodes. Indexing this way in a radial distribution system proved to simplify the modeling and presentation of the power flow model and sensitivity analysis.

3.3.1 Power Losses

The linearized power flow method in [6] is adopted and modified to establish the relationship between real and reactive power injections, line losses, and nodal voltages. First considered is the relationship between the voltage and power injections, which leads to the relationship with real and reactive power losses. Using the indexing described above, the linearized power flow is rewritten according to voltage drops and angle differences. Interested readers can refer to [6] for more details. According to Figure 3.1, the power flow equations for line i can be written as (3.45). Subscripts ϕ and t are dropped for clarity. Here, L_i^P and L_i^Q are real and reactive power losses, and $\Delta\delta_i$ represents the voltage angle for node i .

$$(P_i + L_i^P) + j(Q_i + L_i^Q) = \frac{V_{u(i)}^2 - V_{u(i)}V_i\cos(\Delta\delta_i) - jV_{u(i)}V_i\sin(\Delta\delta_i)}{r_i + jx_i} \quad (3.45)$$

Equation (3.45) is first expanded to real and imaginary components, as in (3.46) and

(3.47).

$$(P_i + L_i^P) = \frac{\mathbf{r}_i \cdot [V_{u(i)}(V_{u(i)} - V_i \cos(\Delta\delta_i))]}{\mathbf{r}_i^2 + \mathbf{x}_i^2} + \frac{\mathbf{x}_i \cdot (V_{u(i)} V_i \sin(\Delta\delta_i))}{\mathbf{r}_i^2 + \mathbf{x}_i^2} \quad (3.46)$$

$$(Q_i + L_i^Q) = -\frac{\mathbf{r}_i \cdot (V_{u(i)} V_i \sin(\Delta\delta_i))}{\mathbf{r}_i^2 + \mathbf{x}_i^2} + \frac{\mathbf{x}_i \cdot [V_{u(i)}(V_{u(i)} - V_i \cos(\Delta\delta_i))]}{\mathbf{r}_i^2 + \mathbf{x}_i^2} \quad (3.47)$$

Assuming $\Delta\delta_i \approx 0$ and $|V_{u(i)}| = |V_i| = 1$ pu (allowing $\sin(\Delta\delta_i) = \Delta\delta_i$ and $\cos(\Delta\delta_i) = 1$) the following equations, (3.48) and (3.49), are derived.

$$P_i + L_i^P \approx \frac{\mathbf{r}_i}{\mathbf{r}_i^2 + \mathbf{x}_i^2} \cdot (V_{u(i)} - V_i) + \frac{\mathbf{x}_i}{\mathbf{r}_i^2 + \mathbf{x}_i^2} \cdot (\Delta\delta_i) \quad (3.48)$$

$$Q_i + L_i^Q \approx \frac{\mathbf{r}_i}{\mathbf{r}_i^2 + \mathbf{x}_i^2} \cdot (\Delta\delta_i) + \frac{\mathbf{x}_i}{\mathbf{r}_i^2 + \mathbf{x}_i^2} \cdot (V_{u(i)} - V_i) \quad (3.49)$$

By letting, $\Delta V_i = (V_{u(i)} - V_i)$, $Z_i^r = \frac{\mathbf{r}_i}{\mathbf{r}_i^2 + \mathbf{x}_i^2}$, and $Z_i^x = \frac{\mathbf{x}_i}{\mathbf{r}_i^2 + \mathbf{x}_i^2}$, (3.48) and (3.49) can be written in terms of ΔV_i and $\Delta\delta_i$, as in (3.50) and (3.51).

$$P_i + L_i^P = Z_i^r \cdot \Delta V_i + Z_i^x \cdot \Delta\delta_i \quad (3.50)$$

$$Q_i + L_i^Q = Z_i^x \cdot \Delta V_i - Z_i^r \cdot \Delta\delta_i \quad (3.51)$$

In (3.50) and (3.51), the voltage drop ΔV_i and the voltage angle difference $\Delta\delta_i$ in line i determines the power flow and loss in line i serving node i . Equation (3.52) states this in vector-matrix form.

$$\begin{bmatrix} \mathbf{P} + \mathbf{L}^P \\ \mathbf{Q} + \mathbf{L}^Q \end{bmatrix} = \mathbf{Z} \cdot \begin{bmatrix} \Delta \mathbf{V} \\ \Delta \boldsymbol{\delta} \end{bmatrix} \quad (3.52)$$

Here, $\mathbf{Z} = \begin{bmatrix} \mathbf{Z}^r & \mathbf{Z}^x \\ \mathbf{Z}^x & -\mathbf{Z}^r \end{bmatrix}$ where $\mathbf{Z}^r = \begin{bmatrix} Z_1^r & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & Z_N^r \end{bmatrix}$ and $\mathbf{Z}^x = \begin{bmatrix} Z_1^x & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & Z_N^x \end{bmatrix}$ are diagonal matrices. According to the way lines and nodes are indexed, N shows the number of nodes as well as the number of lines in a radial network. Therefore, $(P, L^P, Q, L^Q, \Delta V_i, \Delta\delta_i) \in \mathbb{R}^N$, $\mathbf{Z} \in \mathbb{R}^{(2N \times 2N)}$ and $(\mathbf{Z}^r, \mathbf{Z}^x) \in \mathbb{R}^{(N \times N)}$. Since $\mathbf{Z}$ is a square invertible matrix, $\Delta \mathbf{V}$ and $\Delta \boldsymbol{\delta}$ are given by the

linear relationship in (3.53).

$$\begin{bmatrix} \Delta \mathbf{V} \\ \Delta \boldsymbol{\delta} \end{bmatrix} = \mathbf{Z}^{-1} \cdot \begin{bmatrix} \mathbf{P} + \mathbf{L}^P \\ \mathbf{Q} + \mathbf{L}^Q \end{bmatrix} \quad (3.53)$$

The substation voltage magnitude minus the total voltage drop from the substation ($\mathbf{V}_0$) to node i gives the voltage magnitude at node i , mathematically written in (3.54).

$$\mathbf{V} = \mathbf{V}_0 - \boldsymbol{\mathcal{U}} \cdot \Delta \mathbf{V} \quad (3.54)$$

Here, $\boldsymbol{\mathcal{U}} \in \mathbb{R}^{(N \times N)}$ is the upstream node-to-line incidence matrix between node i and line j and is defined in (3.55). Therefore, $\boldsymbol{\mathcal{U}}(i)$ is the set of lines connecting node i to the substation node.

$$[\boldsymbol{\mathcal{U}}]_{ij} = \begin{cases} 1 & \text{if } j \in \boldsymbol{\mathcal{U}}(i) \\ 0 & \text{otherwise} \end{cases} \quad (3.55)$$

By replacing $\Delta \mathbf{V}$ from (3.53) and letting $\mathbf{Z}_V = \mathbf{Z}^{-1}(1 : N, 1 : 2N)$, Equation (3.54) can be rewritten as in (3.56). Here, $(\mathbf{V}, \mathbf{V}_0) \in \mathbb{R}^N$ and $\mathbf{V}_0 = [V_0 \dots V_0]^T$.

$$\mathbf{V} = \mathbf{V}_0 - \boldsymbol{\mathcal{U}} \mathbf{Z}_V \begin{bmatrix} \mathbf{P} + \mathbf{L}^P \\ \mathbf{Q} + \mathbf{L}^Q \end{bmatrix} \quad (3.56)$$

The magnitudes of node voltages are given in terms of line power flows, line losses, and network structure in reference to the substation node voltage in (3.56). Therefore, the node voltage magnitude can ultimately be written as a function of power injections (p_i, q_i), line losses (L_i^P, L_i^Q), and other network parameters. As the i^{th} element of the right-hand side of (3.56), $P_i + L_i^P$ and $Q_i + L_i^Q$ can be written as in (3.57) and (3.58) according to the notation

defined in Figure 3.1.

$$P_i + L_i^P = p_i + \sum_{k \in d\{i\}} (P_k + L_k^P) + L_i^P \quad (3.57)$$

$$Q_i + L_i^Q = q_i + \sum_{k \in d\{i\}} (Q_k + L_k^Q) + L_i^Q \quad (3.58)$$

Equations (3.57) and (3.58) are rewritten in vector-matrix form in (3.59) and (3.60).

$$\mathbf{P} + \mathbf{L}^P = \mathcal{D}(\mathbf{p} + \mathbf{L}^P) \quad (3.59)$$

$$\mathbf{Q} + \mathbf{L}^Q = \mathcal{D}(\mathbf{q} + \mathbf{L}^Q) \quad (3.60)$$

Where, $\mathcal{D} \in \mathbb{R}^{(N \times N)}$ is the downstream node-to-node (and line-to-line) incidence matrix from node i to node j including self (diagonal elements) as defined in (3.61).

$$[\mathcal{D}]_{ij} = \begin{cases} 1 & \text{if } j \in \mathcal{D}(i) \text{ or } i = j \\ 0 & \text{otherwise} \end{cases} \quad (3.61)$$

By substituting (3.59) and (3.60) into (3.56), and with some modifications, Equation (3.62) is derived.

$$\mathbf{V} = \mathbf{V}_0 - \mathcal{U} \mathbf{Z}_V \begin{bmatrix} \mathcal{D} & \mathbf{0} \\ \mathbf{0} & \mathcal{D} \end{bmatrix} \begin{bmatrix} \mathbf{p} + \mathbf{L}^P \\ \mathbf{q} + \mathbf{L}^Q \end{bmatrix} \quad (3.62)$$

Allowing $\mathcal{M} = [\mathcal{M}_p \mathcal{M}_q] = \mathcal{U} \mathbf{Z}_V \begin{bmatrix} \mathcal{D} & \mathbf{0} \\ \mathbf{0} & \mathcal{D} \end{bmatrix}$, (3.62) is rewritten as (3.63). Here, $(\mathcal{M}_p, \mathcal{M}_q) \in \mathbb{R}^{(N \times N)}$ are network-related matrices associated with real and reactive power injections and losses. In reference to the substation voltage $\mathbf{V}_0$, (3.63) computes the nodal voltages $\mathbf{V}$.

$$\mathbf{V} = \mathbf{V}_0 - \mathcal{M}_p(\mathbf{p} + \mathbf{L}^P) - \mathcal{M}_q(\mathbf{q} + \mathbf{L}^Q) \quad (3.63)$$

The real and reactive power losses L_i^P and L_i^Q are defined in (3.64), and approximated

according to (3.65) and (3.66), respectively. Adapted from [6], the losses are linearized using a first-order Taylor series approximation by omitting the second and higher-order terms. The variables $(\mathbf{p}^*$ and $\mathbf{q}^*)$ denote an exogenously obtained feasible power flow solution and are used as the center point of the Taylor series approximation.

$$\left\{ L_i^P, L_i^Q \right\} = \left\{ r_i \frac{P_i^2 + Q_i^2}{V_i^2}, x_i \frac{P_i^2 + Q_i^2}{V_i^2} \right\} \quad (3.64)$$

$$\mathbf{L}^P(\mathbf{p}, \mathbf{q}) \approx \mathbf{L}^P(\mathbf{p}^*, \mathbf{q}^*) + \sum_i \frac{\partial \mathbf{L}^P}{\partial p_i} (p_i - p_i^*) + \sum_i \frac{\partial \mathbf{L}^P}{\partial q_i} (q_i - q_i^*) \quad (3.65)$$

$$\mathbf{L}^Q(\mathbf{p}, \mathbf{q}) \approx \mathbf{L}^Q(\mathbf{p}^*, \mathbf{q}^*) + \sum_i \frac{\partial \mathbf{L}^Q}{\partial p_i} (p_i - p_i^*) + \sum_i \frac{\partial \mathbf{L}^Q}{\partial q_i} (q_i - q_i^*) \quad (3.66)$$

From the above formulations, the following final equations are obtained and used for power balance, power flow, voltage, and loss. Constrains (3.67)-(3.68) model the total system real and reactive power balance. Here $L_{i,\phi,t}^P$ and $L_{i,\phi,t}^Q$ are the linearized real and reactive power losses. Defined in (3.69) and (3.70), the real and reactive power flow are represented by variables $P_{i,\phi,t}$ and $Q_{i,\phi,t}$. Nodal voltage, $V_{i,\phi,t}$, is defined in (3.71) in reference to the substation voltage, $V_{0,\phi,t}$. This equation is used in setting the voltage constraints in (3.9). As shown, system parameters $\mathcal{M}_{i,\phi,j}^P$ and $\mathcal{M}_{i,\phi,j}^Q$ are comprised of upstream and downstream incidence matrices and line resistance and reactance diagonal matrices. Also shown, originally quadratic relations of the real and reactive power flow, line impedance, and nodal voltage, real and reactive power losses are approximated using a first-order Taylor series approximation around an exogenously obtained feasible point [6].

$$p_{0,\phi,t} + \sum_i (p_{i,\phi,t} + L_{i,\phi,t}^P) = 0 \quad (3.67)$$

$$q_{0,\phi,t} + \sum_i (q_{i,\phi,t} + L_{i,\phi,t}^Q) = 0 \quad (3.68)$$

$$P_{i,\phi,t} = p_{i,\phi,t} + \sum_{k \in d\{i\}} (p_{k,\phi,t} + L_{k,\phi,t}^P) \quad (3.69)$$

$$Q_{i,\phi,t} = q_{i,\phi,t} + \sum_{k \in d\{i\}} (q_{k,\phi,t} + L_{k,\phi,t}^Q) \quad (3.70)$$

$$V_{i,\phi,t} = V_{0,\phi,t} - \sum_{k \in N} \mathcal{M}_{i,\phi,k}^P \cdot (p_{k,\phi,t} + L_{k,\phi,t}^P) - \sum_{k \in N} \mathcal{M}_{i,\phi,k}^Q \cdot (q_{k,\phi,t} + L_{k,\phi,t}^Q) \quad (3.71)$$

3.3.2 Probability Efficient Point

The PEP method is used to address stochastic VRE generation. The output of this method determines the expected VRE output, $\bar{p}_{i,\phi,t}^R$, which is included in Gen in Equation (3.4). The advantage of the PEP method over other methods (e.g., stochastic optimization) is that it does not require the assumption of an underlying (joint) probability distribution function of stochastic parameter(s). This is useful in problems like the one considered in which a large volume of historical datasets of the stochastic parameters is available, but getting an explicit joint probability distribution function is challenging. The data-driven PEP method that solves VRE generation efficient points using historical data at a certain probability level is described as follows.

Let $\mathbb{S}$ denote the set of historical realizations of the stochastic vector $\tilde{\mathbf{d}} = (\mathbf{d}_1, \dots, \mathbf{d}_n, \dots, \mathbf{d}_R)$ for R VRE sites. The s^{th} sample of the historical realizations of $\tilde{\mathbf{d}}$, is denoted as $\mathbf{d}_{\mathbf{s}} = (\mathbf{d}_{\mathbf{s},1}, \dots, \mathbf{d}_{\mathbf{s},n}, \dots, \mathbf{d}_{\mathbf{s},R})$, where $\mathbf{s} \in \mathbb{S}$. The probability of each scenario, $\mathbf{s}$, is denoted as $\mathbb{p}_{\mathbf{s}}$. The MILP in (3.72)-(3.76) solves the PEP, as determined in [50, 67].

$$\min_{\mathbf{v}_1^\beta, \dots, \mathbf{v}_R^\beta} \sum_{n=1}^R \mathbb{V}_n^\beta \quad (3.72)$$

Subject to:

$$\sum_{\mathbf{s} \in \mathcal{S}} \mathbb{P}_{\mathbf{s}} \zeta_{\mathbf{s}} \geq \beta \quad (3.73)$$

$$\mathbf{v}_n^\beta \geq \mathbf{d}_{\mathbf{s},n} \zeta_{\mathbf{s}}, \quad n = 1, \dots, R, \mathbf{s} \in \mathcal{S} \quad (3.74)$$

$$\zeta_{\mathbf{s}} \in \{0, 1\}^{|\mathcal{S}|} \quad (3.75)$$

$$\mathbf{v}_n^\beta \in \mathbb{R}_+, \quad n = 1, \dots, R \quad (3.76)$$

The element-wise sum of the PEP vector, $\mathbf{v}^\beta$, guarantees a minimal solution (3.72). The total probability of a set of samples must at least be equal to the probability level, β , and is satisfied in constraint (3.73). Equation (3.74) guarantees each element of the solution ($\mathbf{v}_n^\beta \in \mathbf{v}^\beta$) must be greater than or equal to the corresponding sample in the historical data set ($\mathbf{d}_{\mathbf{s},n} \in \mathbf{d}_{\mathbf{s}}$) of “selected” samples. This is achieved by using binary variable $\zeta_{\mathbf{s}}$ (3.75), which is one if all constraints $\mathbf{v}_n^\beta \geq \mathbf{d}_{\mathbf{s},n}$, $n = 1, \dots, R$, are met in the $\mathbf{s}^{th}$ sample, and zero otherwise. The realized solutions must be real, positive values ($\mathbb{R}_+$) as in (3.76). Constraints (3.73) and (3.74) ensure $\mathbf{v}^\beta$ satisfies the requirement of a set of scenarios whose aggregate probability is at least equal to the enforced probability level β .

Once the probability efficient point of the VRE generation at probability level β is represented by $\mathbf{v}^\beta$, stochastic value $\bar{p}_{i,\phi,t}^R$ included in Gen in Equation (3.4) will be replaced by the deterministic value $\mathbf{v}_n^\beta$. The PEP model can easily be extended to address uncertainties in electrical load forecasts. However, these components are assumed to be accurately forecasted with a small percent error as opposed to the VRE generation. Therefore, uncertainties associated with electricity demands are not considered.

3.3.3 Component-Wise DLMP Decomposition

As shown in (3.77) and (3.78), real and reactive energy ($\Omega_{\phi,t}^{EP}, \Omega_{\phi,t}^{EQ}$), loss ($\Omega_{i,\phi,t}^{LP}, \Omega_{i,\phi,t}^{LQ}$), voltage violation ($\Omega_{i,\phi,t}^{VP}, \Omega_{i,\phi,t}^{VQ}$), and congestion ($\Omega_{i,\phi,t}^{CP}, \Omega_{i,\phi,t}^{CQ}$) components are summed to the total real and reactive DLMP ($\Omega_{i,\phi,t}^P, \Omega_{i,\phi,t}^Q$). This component-wise DLMP formulation is

published in [50].

$$\Omega_{i,\phi,t}^P = \Omega_{\phi,t}^{E_P} + \Omega_{i,\phi,t}^{L_P} + \Omega_{i,\phi,t}^{V_P} + \Omega_{i,\phi,t}^{C_P} \quad (3.77)$$

$$\Omega_{i,\phi,t}^Q = \Omega_{\phi,t}^{E_Q} + \Omega_{i,\phi,t}^{L_Q} + \Omega_{i,\phi,t}^{V_Q} + \Omega_{i,\phi,t}^{C_Q} \quad (3.78)$$

$$\Omega_{i,\phi,t}^{L_P} = \Omega_{\phi,t}^{E_P} \sum_{j \in N} \frac{\partial L_{j,\phi,t}^P}{\partial p_{i,\phi,t}} + \Omega_{\phi,t}^{E_Q} \sum_{j \in N} \frac{\partial L_{j,\phi,t}^Q}{\partial p_{i,\phi,t}} \quad (3.79)$$

$$\Omega_{i,\phi,t}^{L_Q} = \Omega_{\phi,t}^{E_Q} \sum_{j \in N} \frac{\partial L_{j,\phi,t}^Q}{\partial q_{i,\phi,t}} + \Omega_{\phi,t}^{E_P} \sum_{j \in N} \frac{\partial L_{j,\phi,t}^P}{\partial q_{i,\phi,t}} \quad (3.80)$$

$$\Omega_{i,\phi,t}^{V_P} = \sum_{i'} (v_{i',\phi,t}^{\min} - v_{i',\phi,t}^{\max}) \frac{\partial V_{i',\phi,t}}{\partial p_{i,\phi,t}} \quad (3.81)$$

$$\Omega_{i,\phi,t}^{V_Q} = \sum_{i'} (v_{i',\phi,t}^{\min} - v_{i',\phi,t}^{\max}) \frac{\partial V_{i',\phi,t}}{\partial q_{i,\phi,t}} \quad (3.82)$$

$$\Omega_{i,\phi,t}^{C_P} = \sum_{j \in u\{i\}} \rho_{i,\phi,t}^1 \frac{\partial S_{j,\phi,t}}{\partial p_{i,\phi,t}} \quad (3.83)$$

$$\Omega_{i,\phi,t}^{C_Q} = \sum_{j \in u\{i\}} \rho_{i,\phi,t}^2 \frac{\partial S_{j,\phi,t}}{\partial q_{i,\phi,t}} \quad (3.84)$$

The real and reactive energy components of the DLMP are determined by the shadow prices of (3.67) and (3.68). If the substation node is providing the next marginal unit of power, these values are equal to the LMP (λ_t^{p0} , λ_t^{q0}) at the substation node. Real and reactive loss components are determined by loss sensitivities with respect to nodal power injections, as summarized in (3.79) and (3.80) and detailed in Equations (3.85)-(3.92). By considering a constant voltage at node i in (3.64), the sensitivities of real and reactive power losses on line j to real and reactive power injections at node i are derived in (3.85)-(3.88).

$$\frac{\partial L_{j,\phi,t}^P}{\partial p_{i,\phi,t}} = \left(2P_{j,\phi,t} \frac{\partial P_{j,\phi,t}}{\partial p_{i,\phi,t}} + 2Q_{j,\phi,t} \frac{\partial Q_{j,\phi,t}}{\partial p_{i,\phi,t}} \right) \cdot \frac{r_{j,\phi}}{V_{i,\phi,t}^2} \quad (3.85)$$

$$\frac{\partial L_{j,\phi,t}^P}{\partial q_{i,\phi,t}} = \left(2P_{j,\phi,t} \frac{\partial P_{j,\phi,t}}{\partial q_{i,\phi,t}} + 2Q_{j,\phi,t} \frac{\partial Q_{j,\phi,t}}{\partial q_{i,\phi,t}} \right) \cdot \frac{r_{j,\phi}}{V_{i,\phi,t}^2} \quad (3.86)$$

$$\frac{\partial L_{j,\phi,t}^Q}{\partial p_{i,\phi,t}} = \left(2P_{j,\phi,t} \frac{\partial P_{j,\phi,t}}{\partial p_{i,\phi,t}} + 2Q_{j,\phi,t} \frac{\partial Q_{j,\phi,t}}{\partial p_{i,\phi,t}} \right) \cdot \frac{x_{j,\phi}}{V_{i,\phi,t}^2} \quad (3.87)$$

$$\frac{\partial L_{j,\phi,t}^Q}{\partial q_{i,\phi,t}} = \left(2P_{j,\phi,t} \frac{\partial P_{j,\phi,t}}{\partial q_{i,\phi,t}} + 2Q_{j,\phi,t} \frac{\partial Q_{j,\phi,t}}{\partial q_{i,\phi,t}} \right) \cdot \frac{x_{j,\phi}}{V_{i,\phi,t}^2} \quad (3.88)$$

The line flow sensitivities in (3.89)-(3.92) are derived using further simplification from Equations (3.57) and (3.58). By using Equations (3.89)-(3.92) in Equations (3.85)-(3.88) and solving recursively, the loss sensitivities used for the loss DLMP components are computed.

$$\frac{\partial P_{j,\phi,t}}{\partial p_{i,\phi,t}} = \mathcal{D}(j, i) + \sum_{k \in d(j)} \mathcal{D}(j, k) \frac{\partial L_{k,\phi,t}^P}{\partial p_{i,\phi,t}} \quad (3.89)$$

$$\frac{\partial P_{j,\phi,t}}{\partial q_{i,\phi,t}} = \sum_{k \in d(j)} \mathcal{D}(j, k) \frac{\partial L_{k,\phi,t}^P}{\partial q_{i,\phi,t}} \quad (3.90)$$

$$\frac{\partial Q_{j,\phi,t}}{\partial p_{i,\phi,t}} = \sum_{k \in d(j)} \mathcal{D}(j, k) \frac{\partial L_{k,\phi,t}^Q}{\partial p_{i,\phi,t}} \quad (3.91)$$

$$\frac{\partial Q_{j,\phi,t}}{\partial q_{i,\phi,t}} = \mathcal{D}(j, i) + \sum_{k \in d(j)} \mathcal{D}(j, k) \frac{\partial L_{k,\phi,t}^Q}{\partial q_{i,\phi,t}} \quad (3.92)$$

Similarly, voltage components are determined by voltage sensitivities to nodal power injections, and are computed in Equations (3.93) and (3.94) where $\frac{\partial V_i}{\partial p_i}$ and $\frac{\partial V_i}{\partial q_i}$ according to Equation (3.63) are found. The shadow prices of (3.9) on all nodes i' that meet a lower or upper voltage limit are captured in $v_{i',\phi,t}^{min}$ and $v_{i',\phi,t}^{max}$. Together with Equations (3.93) and (3.94), these shadow prices are used to compute the voltage violations component, as indicated in (3.81) and (3.82).

$$\frac{\partial V_{i,\phi,t}}{\partial p_{i',\phi,t}} = -\mathcal{M}_p(i, i') - \sum_{k=1}^N \mathcal{M}_p(i, k) \cdot \frac{\partial L_{k,\phi,t}^P}{\partial p_{i',\phi,t}} - \sum_{k=1}^N \mathcal{M}_q(i, k) \cdot \frac{\partial L_{k,\phi,t}^Q}{\partial p_{i',\phi,t}} \quad (3.93)$$

$$\frac{\partial V_{i,\phi,t}}{\partial q_{i',\phi,t}} = -\mathcal{M}_q(i, i') - \sum_{k=1}^N \mathcal{M}_q(i, k) \cdot \frac{\partial L_{k,\phi,t}^Q}{\partial q_{i',\phi,t}} - \sum_{k=1}^N \mathcal{M}_p(i, k) \cdot \frac{\partial L_{k,\phi,t}^P}{\partial q_{i',\phi,t}} \quad (3.94)$$

Finally, congestion components are determined by lines' apparent power flow sensitivities with respect to nodal power injections, defined in (3.95) and (3.96). The combinations of the four Lagrange multipliers that come from expanding the absolute values in (3.10) to a linear form are captured in $\rho_{i,\phi,t}^1$ and $\rho_{i,\phi,t}^2$ and are used in (3.83) and (3.84). The four separate constraints give $\pm P_i \pm Q_i \leq \sqrt{2} \bar{S}_i$ with shadow prices $\{\rho_{++}, \rho_{--}, \rho_{+-}, \rho_{-+}\}$. Here, $\rho_{(p,q),1} = \rho_{++} - \rho_{--} + \rho_{+-} - \rho_{-+}$, and $\rho_{(p,q),2} = \rho_{++} - \rho_{--} - \rho_{+-} + \rho_{-+}$. The combination of real and reactive power injections is captured in $S_{j,\phi,t}$. The congestion prices are computed by replacing (3.89)-(3.92) in (3.95) and (3.96).

$$\sum_{j \in u\{i\}} \rho_{j,\phi,t} \frac{\partial S_{j,\phi,t}}{\partial p_{i,\phi,t}} = \sum_{j=1}^N \mathbf{u}(i, j) \cdot \rho_{p,1}(j) \cdot \frac{\partial P_{j,\phi,t}}{\partial p_{i,\phi,t}} + \sum_{j=1}^N \mathbf{u}(i, j) \cdot \rho_{p,2}(j) \cdot \frac{\partial Q_{j,\phi,t}}{\partial p_{i,\phi,t}} \quad (3.95)$$

$$\sum_{j \in u\{i\}} \rho_{j,\phi,t} \frac{\partial S_{j,\phi,t}}{\partial q_{i,\phi,t}} = \sum_{j=1}^N \mathbf{u}(i, j) \cdot \rho_{q,2}(j) \cdot \frac{\partial Q_{j,\phi,t}}{\partial q_{i,\phi,t}} + \sum_{j=1}^N \mathbf{u}(i, j) \cdot \rho_{p,1}(j) \cdot \frac{\partial P_{j,\phi,t}}{\partial q_{i,\phi,t}} \quad (3.96)$$

3.3.4 Component-Wise DLMP Case Study

A case study was conducted to verify and test the methods and models proposed in Sections 3.3.1-3.3.3. These results are published in [50]. In this model, $\mathcal{O}(p_{i,\phi,t})$ and $\mathcal{O}(q_{i,\phi,t})$ are defined as in (3.97) and (3.98). Subscript ϕ is dropped here as this model is balanced three-phase. The objective function maximizes the social welfare in the proposed system.

$$\begin{aligned}\mathcal{O}(p_{i,\phi,t}) = & \sum_t \lambda_t^{p_0} \cdot p_{0,t} + \sum_{i,w,t} c_{i,w,t}^{G,P} \cdot p_{i,w,t}^G + \sum_{i,t} \hat{c}_{i,t}^{B,P} \cdot \hat{p}_{i,t}^B - \sum_{i,t} \check{c}_{i,t}^{B,P} \cdot \check{p}_{i,t}^B \\ & - \sum_{i,w>1,t} c_{i,w,t}^{D,P} \cdot p_{i,w,t}^D + \sum_{i,w,t} \xi_{i,t}^D \cdot s_{i,w,t}^D + \sum_{i,t} \xi_{i,t}^R \cdot s_{i,t}^R\end{aligned}\quad (3.97)$$

$$\mathcal{O}(q_{i,\phi,t}) = \sum_t \lambda_t^{q_0} \cdot q_{0,t} + \sum_{i,w,t} c_{i,w,t}^{G,Q} \cdot q_{i,w,t}^G - \sum_{i,w>1,t} c_{i,w,t}^{D,Q} \cdot q_{i,w,t}^D \quad (3.98)$$

Here, $\lambda_t^{p_0}$ and $\lambda_t^{q_0}$ are the real and reactive LMP prices at the substation node, and $p_{0,t}$ and $q_{0,t}$ are the real and reactive net power injections at the substation node. If these net power injections are negative, the DSO buys real or reactive power from the distribution system at the respective LMP. DGs bid at a cost of $c_{i,w,t}^{G,P}$ for real power and $c_{i,w,t}^{G,Q}$ for reactive power, where subscript w indicates the segment energy and bid block using a piecewise bidding method to approximate the supply cost of DGs. Variables $p_{i,w,t}^G$ and $q_{i,w,t}^G$ indicate the real and reactive segment power the generators supply. These values must lie within their respective segment constraints and sum to their total output $p_{i,t}^G$ and $q_{i,t}^G$, as in (3.11). The reactive power output of the DG must lie within a fraction, $\pm\kappa^G$, of the real power output, as in (3.14). The BESS units bid at a cost of $\hat{c}_{i,t}^{B,P}$ for extraction of power from the battery and $\check{c}_{i,t}^{B,P}$ for injection of power into the battery. Variables $\hat{p}_{i,t}^B$ and $\check{p}_{i,t}^B$ indicate the power the BESS unit consumes or supplies, respectively. Reactive power from the BESS is held to $\pm\kappa^B$ of the real power. Although not present in the objective function, the reactive power of the renewable energy sources ($q_{i,t}^R$) are held to $\pm\kappa^R$ of the real power ($p_{i,t}^R$). Here, bids for demand are placed at $c_{i,w,t}^{D,P}$, where $w \geq 1$ represents the real power price bids, and $p_{i,w,t}^D$ represents the real power demand which is met by the system. Therefore, the fifth term in $\mathcal{O}_p(x_t)$ is modeled for $w > 1$ to consider only the demand segments that place bids, as the first segment is a must-serve load. As similar explanation holds for reactive power demand bids, $c_{i,w,t}^{D,Q}$, and segments, $q_{i,w,t}^D$. The final two terms in (3.97) indicate the value of lost load (ξ^D) or renewable generation (ξ^R) times the sum of the real power demand shed ($s_{i,t}^D$) or the VRE unit's curtailment ($s_{i,t}^R$), which are utilized to achieve feasibility.

Further, in this model, Dem and Gen in (3.4) and (3.5) include real and reactive power demands and power supplied from DGs, BESSs, and variable renewable energy sources ($\bar{p}_{i,t}^R$) determined by the PEP method in Section 3.3.2.

Finally, the power flow problem with losses is considered as $\mathbf{P}_2$ and is defined as:

$\mathbf{P}_2$: min(3.1)

subject to: (3.4)-(3.5), (3.9)-(3.42), and (3.65)-(3.71)

A modified Pacific Gas & Electric (PG&E) 69-node system, shown in Figure 3.6, is utilized to simulate the proposed MILP models in the GAMS/CPLEX environment [130]. The nodal power demands are split into three segments of 50%, 25%, and 25%. The first segment is fixed as a must-serve load, while the remaining two segments (the price-responsive loads) place monetary bids in randomly generated ranges of [13.8, 28.1] and [10.3, 26.5] \$/MWh for real power. Reactive power bids at 30% of these amounts. The BESS bid at \$25/MWh for extraction and \$20/MWh for injection, and the zero-marginal-cost VREs bid at \$0/MWh. The substation node sees a typical-day LMP in the range of [16.45, 42.14] \$/MWh. Western Wind and Solar Integration Study (WWSIS) historical data sets [133] for wind and PV generation at four different sites are used to implement the PEP method and obtain the VRE generation at different confidence levels. VRE units within close proximity are considered identical and assigned the same historical data set.

Scenarios I-IV are simulated in this study to show the effect of VRE penetration on the component-wise DLMP. Scenarios I and II face a 200% system load while Scenarios III and IV see 100% system load. Scenarios I-IV experience 0% ($K=0$), 50% ($K=1$), 100% ($K=2$), and 200% ($K=4$) VRE output penetration at a confidence level of $\beta=0.75$, where K is a scaling factor of the VRE output. The results of this study are depicted in Figure 3.7, where the left and right columns represent the real and reactive power outcomes, respectively, at Node 60, where the majority of the system's load is located. The four DLMP components are represented with bars, while the sum of the components, the total real and reactive DLMP ($\Omega_{i,t}^P, \Omega_{i,t}^Q$), is the dotted red line and the real and reactive LMP at the substation node ($\lambda_t^{p0}, \lambda_t^{q0}$) is the starred green line. Represented by the purple bar, the energy component of the

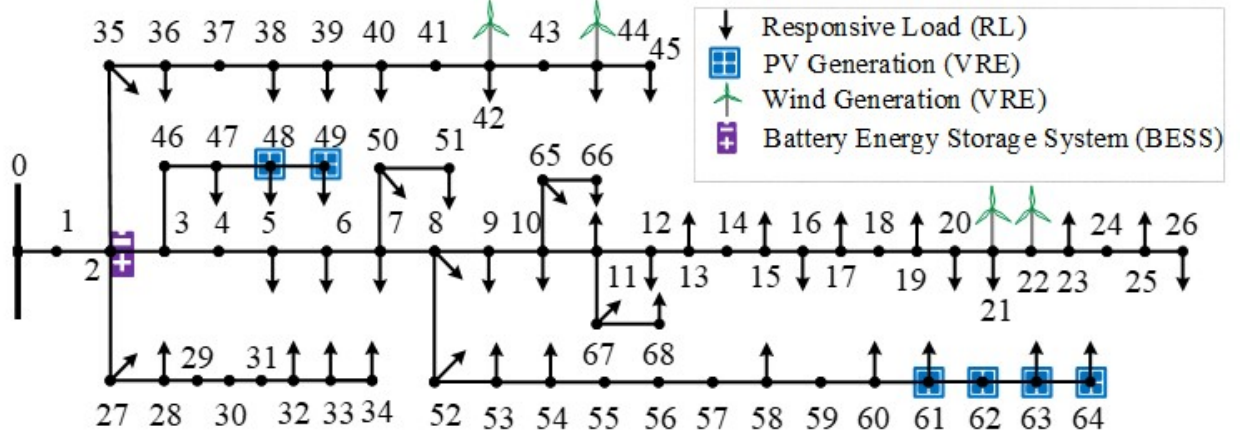


Figure 3.6: Modified PG&E 69-node system with diverse DERs. Published in [50].

DLMP ($\Omega_t^{EP}, \Omega_t^{EQ}$) is given by the Lagrange multiplier of Equations (3.67) and (3.68) and is equivalent to the LMP of the substation node if the marginal unit serving the next increment of load (MWh, MVARh) comes from the wholesale market. The amount of megavolt-ampere reactive (MVARs) served in an hour is notated as MVARh.

In Scenario I, voltage ($\Omega_{60,t}^{VP}, \Omega_{60,t}^{VQ}$) and congestion components ($\Omega_{60,t}^{CP}, \Omega_{60,t}^{CQ}$) of the DLMP appear on Node 60 during Timeslots 16-18 due to a voltage violation at Node 64 and congestion at Line 2, which occur due to high demands. These cost-causation values are incurred to Node 60 for its participation in increasing the voltage violation and power flow congestion for other nodes and lines in the system. Injection at any node causes unavoidable transference losses over the lines, therefore loss components ($\Omega_{i,t}^{LP}, \Omega_{i,t}^{LQ}$) appear in every timeslot. In this scenario, the marginal unit happens to be the substation node, as indicated by the energy components (given by the supply-demand curve's equilibrium point) and LMP overlapping.

In Scenario II, VRE units are added ($K=1$ and $\beta=0.75$), as in Figure 3.6. The voltage violation and congestion prices present in Scenario I in Hours 16-18 are completely removed. The addition of the zero-marginal-cost VREs support the grid by reducing the power flow on Line 1 and other lines and decreasing voltage drops across all nodes. This is achieved by serving the large demands at Node 60 by the nearby VREs at Nodes 61-64 and, thus, resolves the issues occurring in Scenario I. Further, the LMP does not coincide with the

energy price in Timeslots 10-12. Therefore, the distributed energy resources completely serve the system's total real power demand. No real power is consumed from the substation during this timeframe. Reiterated, the settlement of the equilibrium price was determined by a bid lower than the LMP; therefore, the substation no longer serves as the marginal unit in these hours. However, this is not the case for the reactive power energy components ($\Omega_{60,t}^Q$) and the reactive power LMP at the substation node ($\lambda_t^{q_0}$). This is because the reactive power outputs of the VRE units are constrained to $\pm\kappa^R=30\%$ of their real power outputs through the use of inverters. Due to the lack of available reactive power from the distributed resources, reactive power must be withdrawn from the substation node in this case, resulting in equal reactive power LMPs and energy components.

As more VRE penetration ($K=2$ and $\beta = 0.75$) is activated in Scenario III, no congestion or voltage violations occur. However, negative energy and loss components appear during Timeslots 10-12. Here, VRE units are curtailed at a generation curtailment cost of $\xi^R=\$100/\text{MWh}$ to achieve system feasibility. Therefore, Node 60 is paid at ξ^R to consume real power and for causing losses, i.e., $\Omega_{60,t}^{LP}=-\$4.085/\text{MWh}$. Contrarily, reactive energy and loss DLMP components are all positive, except in Timeslots 10-12, where the reactive loss component is negative. This is because the reactive power of the VRE is not curtailed at a penalty in the objective power, as is the case for the real power. Rather the reactive power is held within a flexible range ($\pm\kappa^R$) of the actual real power output, which is based on the capability of the inverter. Further, the reactive power demand of the system is higher than what the DERs are capable of producing, and the substation is the marginal unit for the reactive power demand. Notice, reactive power consumption increases real power losses according to Equations (3.65) and (3.86). Therefore, the reactive power at Node 60 in Timeslots 10-12 is incentivized around $-\$3.40/\text{MVARh}$ to consume reactive power (increase real power losses) to decrease VRE curtailment and the associated costs. To the best of my knowledge, such interesting details between real and reactive component-wise pricing have never been demonstrated.

Due to the high VRE penetration ($K=4$ and $\beta=0.75$) in Scenario IV, large reverse power flows cause several nodes to violate their upper voltage limit, causing negative real and

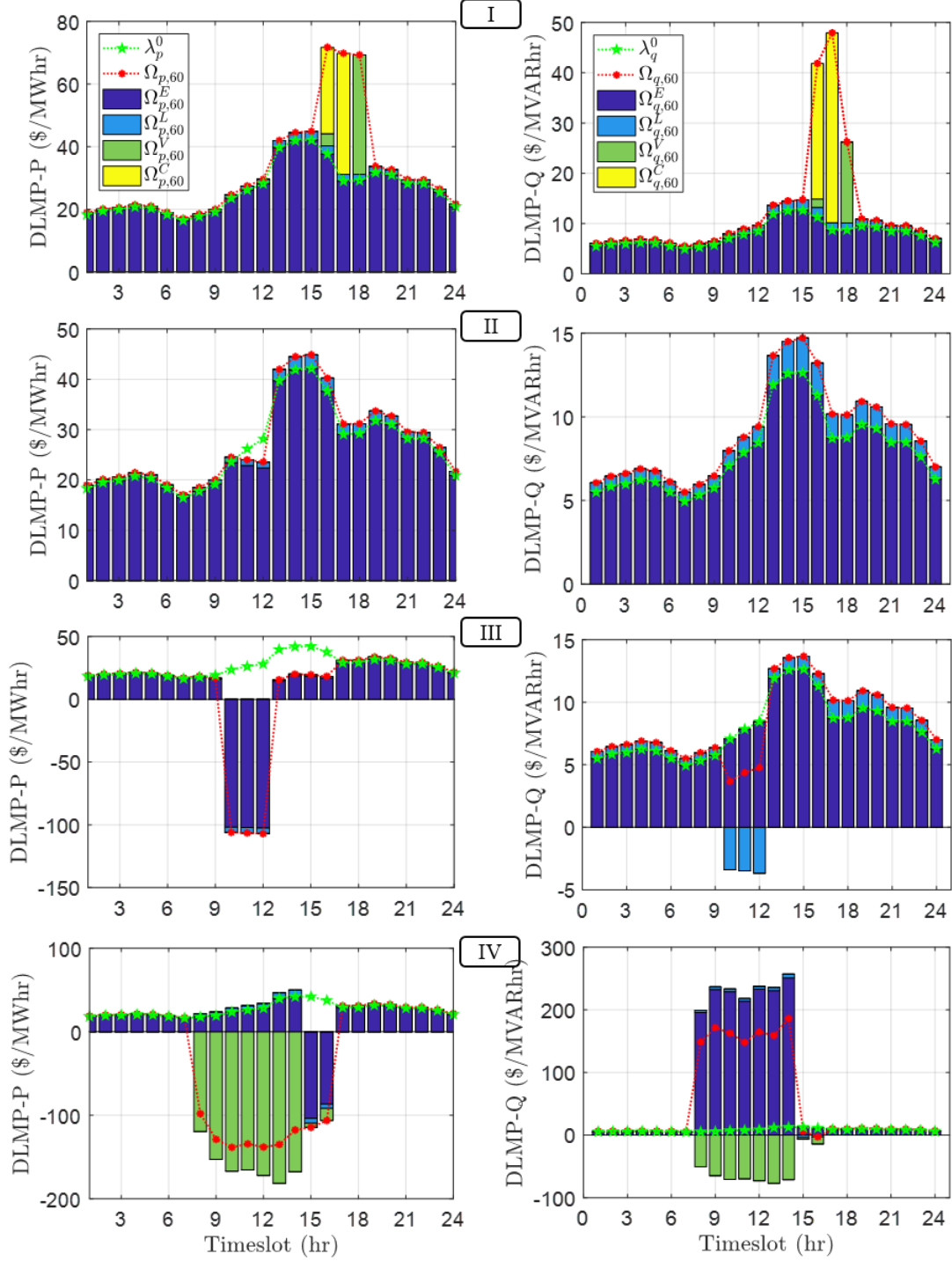


Figure 3.7: Node 60's real and reactive DLMPs (DLMP-P, DLMP-Q) ($\Omega_{60,t}^P = \Omega_{p,60}$, $\Omega_{60,t}^Q = \Omega_{q,60}$), their components, energy ($\Omega_t^{EP} = \Omega_p^E$, $\Omega_t^{EQ} = \Omega_q^E$), loss ($\Omega_{60,t}^{LP} = \Omega_p^L$, $\Omega_{60,t}^{LQ} = \Omega_q^L$), voltage violation ($\Omega_{60,t}^{VP} = \Omega_p^V$, $\Omega_{60,t}^{VQ} = \Omega_q^V$), and congestion ($\Omega_{60,t}^{CP} = \Omega_p^C$, $\Omega_{60,t}^{CQ} = \Omega_q^C$), and LMPs ($\lambda_t^{p0} = \lambda_p^0$, $\lambda_t^{q0} = \lambda_q^0$) in Scenarios I-IV. Published in [50].

reactive voltage components $\Omega_{60,t}^{V_P}$ and $\Omega_{60,t}^{V_Q}$. Node 60 is encouraged to consume during Hours 8-14, as it is the largest sink in the system. Therefore, its consumption maintains a lower system voltage and avoids further VRE curtailment during Timeslots 15-16. However, the total reactive power DLMP ($\Omega_{60,t}^Q$) is still a large positive value, despite the negative voltage components ($\Omega_{60,t}^{V_Q}$). This indicates that while the real power DLMP is negative, the reactive power DLMP may not be negative as well. Therefore, the net DLMP ($\Omega_{i,t}^P + \Omega_{i,t}^Q$) could be positive or negative, depending on the system's reactive power demand and supply capabilities. These conclusions support the need for reactive power pricing in distribution systems.

Finally, the proposed MILP model is compared to the full-ACOPF results from the open-source MATPOWER solver to validate the power flow results under peak load conditions. As shown in Figure 3.8, the errors prove to be acceptable. At 130% of the load level, the maximum errors in the line flow and losses are 1.34% and 4.26%, while the voltage error of the node farthest from the substation is less than 0.04%.

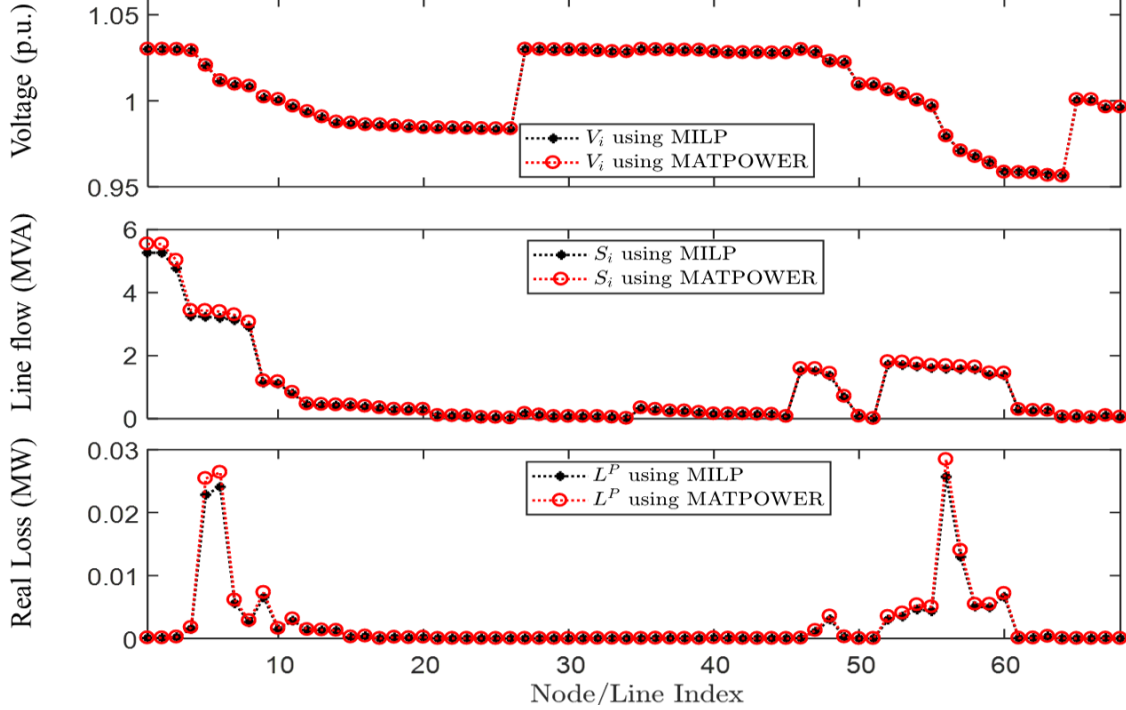


Figure 3.8: Power flow comparison of the proposed method to ACOPF. Published in [50].

3.4 Three-Phase Unbalanced Model

Considering that most electricity distribution systems are three-phase systems and the amount of load (and distributed generation) on each phase does not match across all phases, the model is extended to account for unbalanced systems in Section 3.4.1. This model is tested and validated in Section 3.4.2

3.4.1 Balance Equations

The real and reactive power imbalance between phases at the substation node are restricted by (3.99) and (3.100) within a small percentage, $\Delta\phi_p$ and $\Delta\phi_q$, respectively. These constraints distinguish this model from the balanced model in Section 3.3.

$$|p_{i,\phi,t} - p_{i,\phi',t}| = \Delta\phi_p \quad \forall \phi \in \Phi, \forall \phi' \in \{\Phi \setminus \phi\} \quad (3.99)$$

$$|q_{i,\phi,t} - q_{i,\phi',t}| = \Delta\phi_q \quad \forall \phi \in \Phi, \forall \phi' \in \{\Phi \setminus \phi\} \quad (3.100)$$

3.4.2 Three-Phase Case Study

A case study was performed to confirm and test the constraints proposed in Section 3.4 and evaluate their impact on the system. These results are published in [51]. In this three-phase unbalanced model, $\mathcal{O}(p_{i,\phi,t})$ and $\mathcal{O}(q_{i,\phi,t})$ are defined as in (3.101) and (3.102). This objective function finds the least cost sum of generation for the unbalanced three-phase system.

$$\begin{aligned} \mathcal{O}(p_{i,\phi,t}) = & \sum_{\phi,t} \lambda_t^{p_0} \cdot p_{0,\phi,t} + \sum_{i,w,\phi,t} c_{i,w,\phi,t}^{G,P} \cdot p_{i,w,\phi,t}^G + \sum_{i,\phi,t} \hat{c}_{i,\phi,t}^{B,P} \cdot \hat{p}_{i,\phi,t}^B \\ & - \sum_{i,\phi,t} \tilde{c}_{i,\phi,t}^{B,P} \cdot \tilde{p}_{i,\phi,t}^B + \sum_{i,\phi,t} \xi^D \cdot s_{i,\phi,t}^{D,P} \end{aligned} \quad (3.101)$$

$$\mathcal{O}(q_{i,\phi,t}) = \sum_{\phi,t} \lambda_t^{q_0} \cdot q_{0,\phi,t} + \sum_{i,w,\phi,t} c_{i,w,\phi,t}^{G,Q} \cdot q_{i,w,\phi,t}^G \quad (3.102)$$

Here, $\lambda_t^{p_0}$ and $\lambda_t^{q_0}$ are the real and reactive LMP prices at the substation node, and $p_{0,\phi,t}$ and $q_{0,\phi,t}$ are the real and reactive net power injections at the substation node. DGs bid at

a cost of $c_{i,w,\phi,t}^{G,P}$ for real power and $c_{i,w,\phi,t}^{G,Q}$ for reactive power, where subscript w indicates the segment energy and bid block using a piecewise bidding method to approximate the supply cost of DGs. Variables $p_{i,w,\phi,t}^G$ and $q_{i,w,\phi,t}^G$ indicate the real and reactive segment power the generators supply. These values must lie within their respective segment constraints and sum to their total output $p_{i,\phi,t}^G$ and $q_{i,\phi,t}^G$. The reactive power output of the DG must lie within a fraction, $+\kappa^G$, of the real power output. The BESS units bid at a cost of $\hat{c}_{i,\phi,t}^{B,P}$ for extraction of power from the battery and $\check{c}_{i,\phi,t}^{B,P}$ for injection of power into the battery. Variables $\hat{p}_{i,\phi,t}^B$ and $\check{p}_{i,\phi,t}^B$ indicate the power the BESS unit consumes or supplies, respectively. Reactive power from the BESS is held to $+\kappa^B$ of the real power. Although not present in the objective function, the reactive power of the renewable energy sources ($q_{i,\phi,t}^R$) is held to $+\kappa^R$ of the real power ($p_{i,\phi,t}^R$). The final term in (3.101) indicates the value of lost load, ξ^D , times the sum of the real power demand curtailment, $s_{i,\phi,t}^{D,P}$, to penalize any load not served.

Further, in this model, Dem and Gen in (3.4) and (3.5) include real and reactive power demands and power supplied from DGs, BESSs, and VREs.

Finally, the three-phase unbalanced power flow problem with losses is considered as $\mathbf{P}_3$ and is defined as:

$\mathbf{P}_3$: min(3.1)

subject to: (3.4)-(3.5), (3.9)-(3.14), (3.18)-(3.42), (3.65)-(3.71), and (3.99)-(3.100)

A modified 69-node PG&E system was used to investigate three-phase real and reactive DLMP and its components. A one-line diagram of the system is shown in Figure 3.9. Unbalanced loads are indicated using arrows at bus locations. The GAMS platform with a CPLEX MILP solver was used to conduct simulations [130]. The following two cases are created:

Case 1: Typical radial distribution with a low-cost 1.5 MW DG at Node 62 and no VRE or BESS units.

Case 2: Heavily unbalanced amount of DERs. DG at Node 62 for all phases. VRE units at Nodes 10, 15, 16, 17, 21, 22, 35, 38, 39, 41, 44, 45, 49, 54, 60,

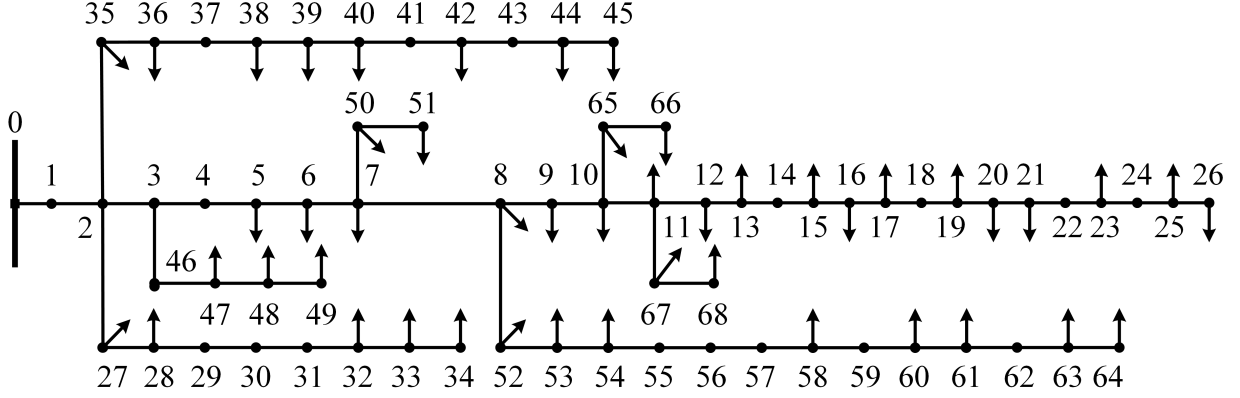


Figure 3.9: Modified three-phase PG&E 69-node system. Published in [51].

and 64 for Phase A, Nodes 22 and 49 for Phase B, and Node 49 for Phase C. Finally, there is a 0.5 MWh BESS with a minimum charging rate of 0.02 MW and a maximum charging rate of 0.05 MW at Node 2 for each phase, of which, the DSO has full operational control. This gives a 28.5%, 2.6%, and 2.2% VRE portfolio for Phases A, B, and C, respectively.

Impact of Low-Cost DG

Due to the DG selling at costs much lower than the substation LMP, the DG is producing power until the upper voltage constraint is met. Figure 3.10 shows the component-wise three-phase real and reactive DLMP values at Node 8, in which the black line with asterisks shows the total DLMP, i.e., a sum of the component-wise DLMP. Negative voltage components occur on Phases A and B across multiple timeslots. (Most Phase B voltage components are minimal and therefore not visible in the illustration.) Negative voltage components indicate the voltage profile of the distribution system would be improved if more energy were to be consumed at Node 8 in these timeslots. However, the total real power DLMP values are still positive due to the large positive value of the energy component. Congestion occurs in each phase near the peak load hours. The positive congestion component discourages consumption at this node by setting a high price signal. The unavoidable DLMP loss components occur at every node, but in this case, the values are very small compared to the other components. Therefore, these values are scaled to appear in the visualization.

These results also stress the importance of reactive power pricing. As seen in Figure 3.10, real power pricing does not become highly negative in any phase. Reactive power pricing, on the other hand, encounters negative DLMP values. For example, at Timeslots 1 and 3-8, Phase A charges customers a visibly high price to discourage reactive power demand, while Phase C pays customers to consume reactive power. This is an attempt to meet in the middle, to match the reactive load on Phase B, and balance the reactive power load across all three phases as imposed by 3.100. Here, $\Delta\phi_p = \Delta\phi_q = 0.2$. A similar balancing result occurs for real power at various timeslots, but the prices do not become highly negative as they do for the reactive power case. The value of reactive power pricing is emphasized here because real power constraints may be acceptable while reactive power limits are binding.

There are many timeslots on Phases B and C that appear to be zero in Figure 3.10. Some of these timeslots have small DLMP values because the generator supplying the next marginal unit is the low-cost DG. Therefore, the cost to consume the next unit of power is low. In other cases, the DG is at maximum capacity, so the substation is the marginal node serving the next unit of power, thus higher energy component prices.

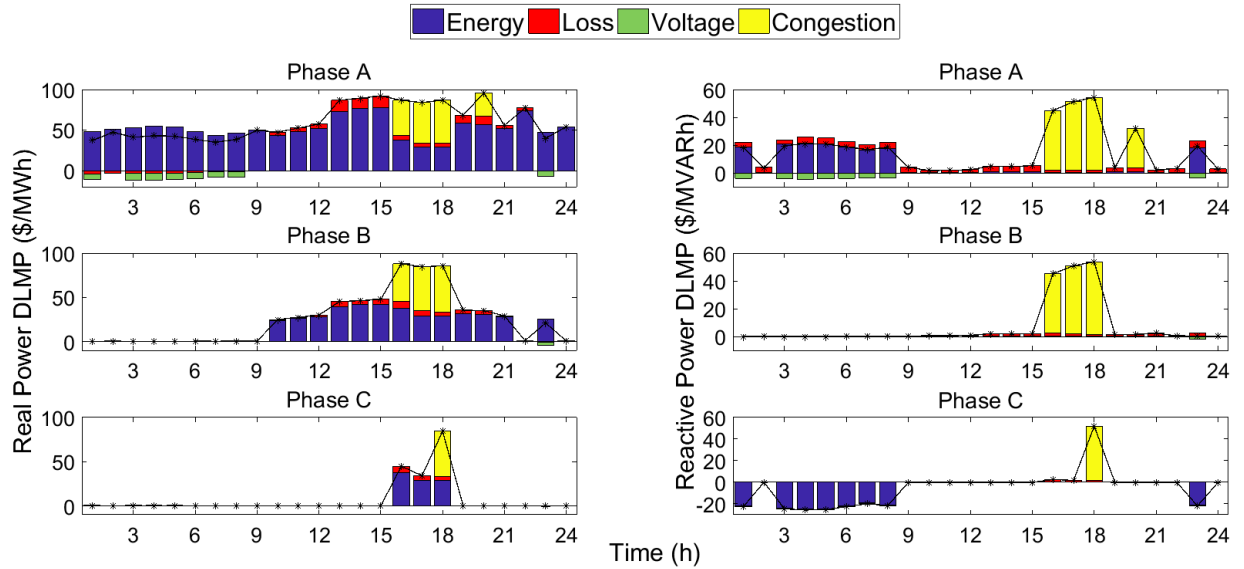


Figure 3.10: Three-phase real and reactive component-wise DLMP values for Case 1 at Node 8. Published in [51].

Impact of Heavily Unbalanced DERs

As certain phases can have highly contrasting load and local generation profiles (Case 2), the importance of three-phase DLMP modeling is emphasized in Figure 3.11. This is a potential future case where one phase of a feeder serves single-family homes capable of widespread rooftop PV, while another serves commercial or apartment complex customers, where rooftop PV is uncommon. With high VRE penetration, Phase A encounters zero value real DLMPs when the sun is shining, while Phases B and C, with low VRE penetration, do not see zero DLMP values. Here, the zero-variable-cost VRE units are the marginal units supplying the next unit of power on Phase A. Similar results occur for reactive power pricing. The added local generation in Case 2 helps meet more demand than in Case 1, but VRE units are still curtailed. In this case, 23% of the VRE units are curtailed on Phase A. This result shows the importance of smart DER planning across phases and locations.

The BESS charges on Phase A at Hours 9-17 when the VRE penetration is high during

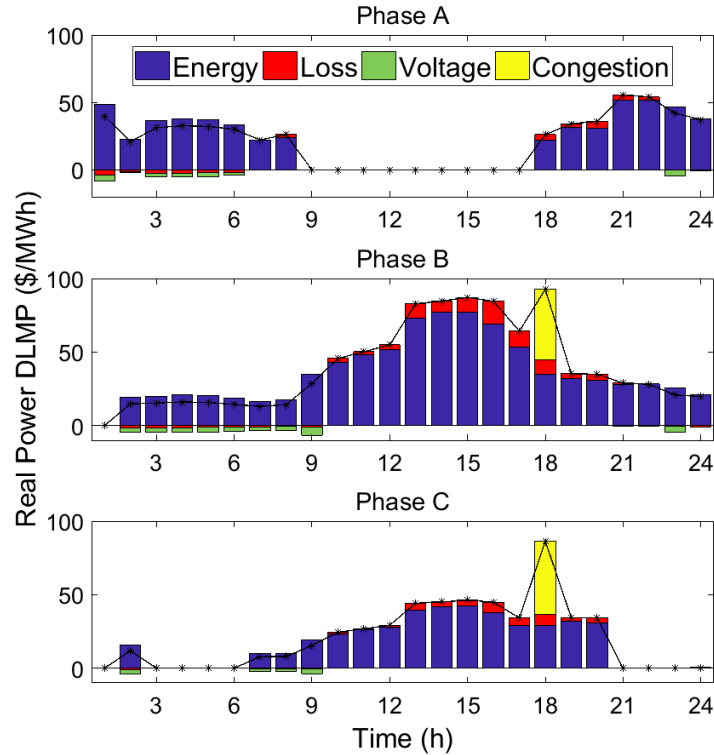


Figure 3.11: Three-phase real component-wise DLMP values for Case 2 at Node 8 with balance constraints (3.99)-(3.100). Published in [51].

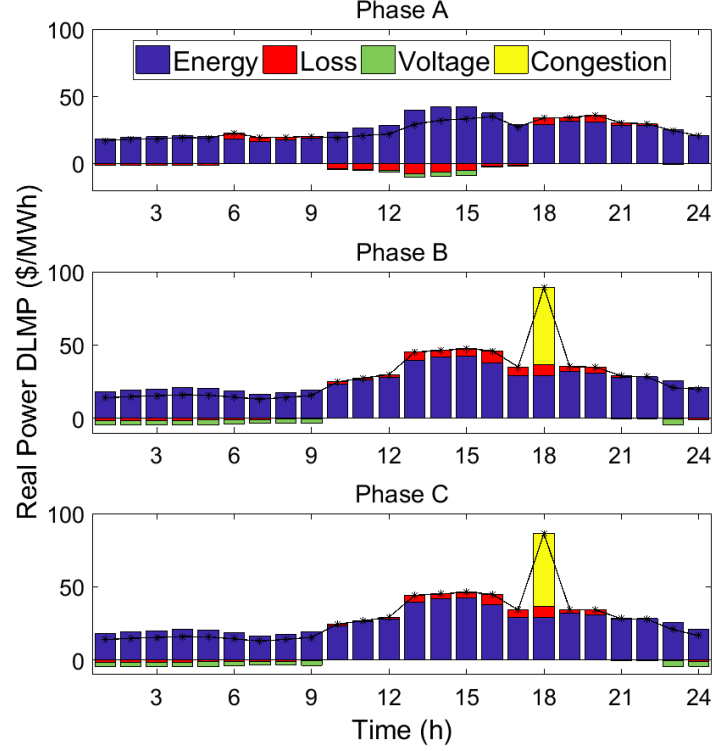


Figure 3.12: Three-phase real component-wise DLMP values for Case 2 at Node 8 without balance constraints (3.99)-(3.100). Published in [51].

this case. The BESSs on Phases B and C discharge during these hours to ease the burden of the unbalanced generation profile on Phase A. DLMP values reflect nodal prices in the distribution system, at which the BESS would pay or get paid. If the DLMP is high, the BESS would be paid at that high rate for injecting power and is thus better incentivized for providing phase balancing services.

Impact of Imbalance Constraint

To ensure the economic price signal is managing imbalance across phases, constraints (3.99)-(3.100) are removed to see the resulting DLMP. The DER parameters are the same as those in Case 2. The proposed model now minimizes the cost of operating each phase individually, with no coupling between the phases. The results for three-phase real DLMP at Node 8 can be observed in Figure 3.12. Here, the energy component across each phase is equal at each timeslot and follows the real power LMP at the substation node. The substation is the

marginal node serving the next MW as VRE units are dispatched at full capacity. When comparing Figures 3.11 and 3.12, there is no longer an attempt at balancing the phases using the DLMP mechanism. The energy component is the portion of the DLMP impacted by the imbalance constraint being met. In this case, reactive power energy components are also equal across phases. The results suggest the necessity to consider the three-phase balancing constraints in the DLMP model since it provides an inherent mechanism to balance the phases.

3.5 DLMP Application in HEMS

This section of research aims to provide a framework for applying blockchain technology to home energy management systems (HEMSs) for secure data transfer of DLMPs and forecasted loads with the DSO. Through the use of smart contracts, the intention is to ensure privacy for homeowners when participating in demand response (DR) activities and therefore encourage user participation. In the first stage, a smart contract keeps the homeowner's identity private when sending future demand forecasts to the DSO. The DSO only needs to know the aggregated load in a single bus and not individual homeowner information for power balancing purposes. Therefore, the proposed smart contract aggregates the total load in a bus and sends this information to the DSO through the blockchain, maintaining user privacy. After the DSO solves the power balancing problem and determines the energy allocated to each homeowner, the second stage of the smart contract sends this information to each homeowner's HEMS device. The HEMS device will then use this information to enable and disable the correct home appliances to stay below the allowed energy for the next timeslot. This process is repeated every timeslot. The length of each timeslot is determined beforehand and typically ranges from 15 minutes to an hour. This work combines blockchain technology and smart contracts with HEMS devices to ensure user privacy and secure data transfers with the DSO.

Our proposed framework and smart contract should be implemented in a private blockchain, as this blockchain is not intended to be open to the public. Only a certain

number of people will need access to this blockchain, and their addresses will be whitelisted beforehand. The DSO’s address will also be defined in a trusted manner. Upon user verification, HEMS users have permission to call user-related functions in the smart contract. It is assumed it is in all players’ best interest to behave in an honest manner.

3.5.1 DLMP Application in HEMS Case Study

A project framework was developed to test the objectives presented in Section 3.5. These results are published in [18]. An unbalanced distribution system is considered, shown in Figure 3.13, which serves a different number of homes in each phase of its three-phase nodes [134]. Residential homes on every phase are of either regular or smart (HEMS-equipped) type. Here, along with the home’s non-controllable load, a smart home has been considered to own photovoltaic panels coupled with energy storage, a water heater, and a heating, ventilation, and air conditioning system, which are entirely controlled by its HEMS. Other appliances can be similarly included. To determine if there will be any congestion or voltage violation in the distribution network, the DSO initially implements a reliability assessment by solving a first-stage optimization problem based on future nodal demand bids from loads as well as supply bids from distributed generation, if any, at the three-phase feeder level, e.g., each of the 68 nodes in Figure 3.13. However, the DSO can solve its first stage optimization problem without any need for demand or supply bids, and can maximize social welfare by dispatching as much power as required and allowed by the grid constraints. Distribution locational marginal price values that are composed of energy, loss, congestion, and voltage violation components of each node at each timeslot, are computed using the first-stage optimization solution and sensitivity analysis [50, 51, 75, 134]. When congestion or voltage violation prices are shown, signaling an operational issue, the DSO immediately seeks flexibility service from HEMSs to alleviate the issue(s) while maintaining three-phase power balance at the substation node. Using DLMP components, the DSO can send two price signals (a lower and an upper) to each HEMS and request a flexible demand range.

In the next step, each HEMS can compute and send back to the DSO their re-

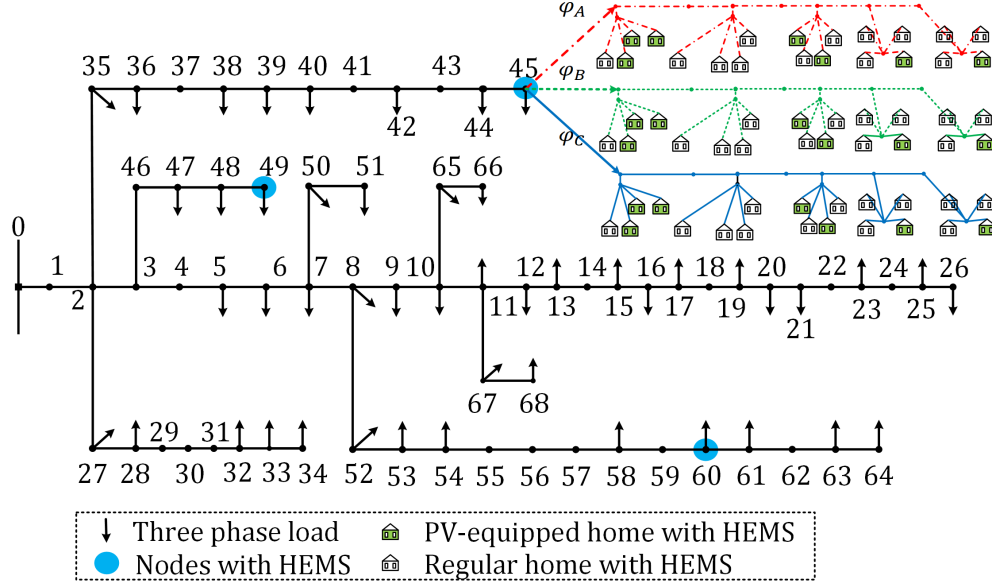


Figure 3.13: An example of distributed networks with HEMSs. Published in [18].

requested demand range by incorporating the DSO's DLMP prices into its approximate dynamic programming-based stochastic optimization problem and finding optimal consumption amounts (demand) of its controllable appliances. In the second stage, by aggregating the flexibility ranges of all the participating HEMS, the DSO can determine an optimal dispatch point without distribution system congestion or voltage violations and send it back to each HEMS. Each HEMS sets the dispatch point as the maximum consumption for its controllable appliances in its second stage.

The communication process between the HEMS users and DSO begins with the DSO submitting an upper and lower DLMP range for the next timeslot to the blockchain. The users can trust these price signals as the blockchain is immutable and tamper-evident. Therefore, users know an attacker did not modify the value sent. For each timeslot, HEMS devices will calculate the lower and upper bound of predicted load based on the published DLMP from the DSO. Each user will securely submit this load prediction to a user-defined call in the smart contract. Users are encouraged to use a virtual private network or Tor, enabling users to communicate anonymously and protect their IP addresses and, thus, locations.

After all HEMS users have submitted their predicted load ranges, or after a specific timeframe has passed, the lower and upper demand range limits will be aggregated. The DSO

can trust these values as the blockchain and smart contract functions are tamper-evident. In this case, the DSO can only read the summed value of predicted power consumption in a single node rather than the prediction values of each home. In the context of privacy, the personnel in the DSO and other HEMS users have no access to the encrypted predicted load of a given house without a password, and unauthorized users have no access to the private blockchain, so protection of HEMS users' information is verified.

After the utility gets the aggregated load forecast signal from the smart contract, the operator will solve the convex optimization power-balancing problem based on the lower and upper bound of the load range. The objective function minimizes the cost to the user by using the DLMP at each node. The global optimal solution indicator for allowable load for each HEMS user is captured in λ and is sent to each HEMS device through the blockchain. From Equation (3.103), λ is a decimal number between zero and one, which is useless to the attacker unless they have knowledge of the lower (L_{min}^i) and upper bounds (L_{max}^i) of the forecast signal that each customer submitted to the smart contract in the first stage, which is not possible without a private password as the data is encrypted. Here, $P_{dispatch}^i$ is the allowed power to each HEMS, where i is each HEMS in the system. The DSO will submit λ to the smart contract, and an event invocation will save the value in a block. Finally, the smart contract gives the dispatch information, λ , to each HEMS when requested by a user-defined function. The DSO shares one single λ that applies to all HEMS users; therefore, the run time for this stage is extremely short.

$$P_{dispatch}^i = \lambda \cdot L_{max}^i + (1 - \lambda) \cdot L_{min}^i \quad (3.103)$$

The proposed smart contract was implemented in Ethereum for testing. Figure 3.14 presents a graphical representation of the procedure for this simulation. Ideally, this concept will be implemented in a private blockchain, but for the purpose of rapid testing, Ethereum is used through the Ropsten test network, where user access is controlled. This test network allows functions to be called from several different addresses. Therefore, to test the proposed concept, one address acts as the DSO, and a minimum of two addresses act as homeowners

with HEMS devices. Note, that the DSO and users' addresses will be known and permissioned accordingly in the proposed private blockchain framework. As testing was carried out in a public network, addresses are assigned to each user and DSO through a claiming framework. To begin testing, addresses associated with the DSO the users are defined. This procedure is implemented in Ethereum using function calls 'claimDSO()' and 'claimUser()', with each input being a unique address in the blockchain. Each type is allowed specific permissions within the smart contract.

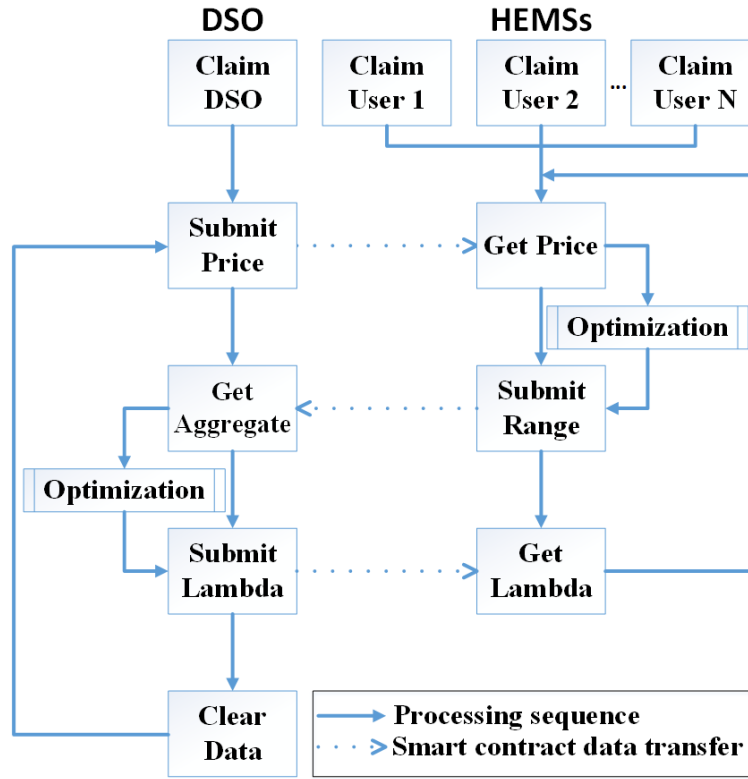


Figure 3.14: Processing sequence for the implemented smart contract framework in Ethereum. Published in [18].

Next, the DSO shares an upper and lower DLMP value to the blockchain by function call 'submitPrice()'. Each HEMS uses these values to optimize its load forecast schedule for the next timeslot based on this electricity price range. These values are obtainable by function call 'getPrice()'. Once this is completed, each homeowner submits a range of forecasted demand data for the next timeslot. Forecasts are formatted as a lower and upper bound of the forecasted demand and sent to the smart contract through function call 'submitRange()'.

HEMS users must encrypt this data as it is publicly published on the blockchain. Prior to encryption, it would be published in the block in hexadecimal format, as depicted in Table 3.1. The first eight hexadecimal characters in the “Input Data” section is the call to the ‘submitRange()’ function. The remaining data is the string parameter, the non-encrypted load forecast submission (‘9, 10’ in this case), in hexadecimal. Here, the ellipsis in the input data are zeros and are removed to save space.

Table 3.1: Transaction details summary.

Range Submission Transaction Details Summary	
Hash	0x3e7602fb4f587296ac786fe5a18e12fceb76670dccd452b13ec1c109c6bf8d2d
Status	Success
Timestamp	<i>Block publishing time and date</i>
From	<i>User address</i>
To	<i>Contract address</i>
Value	0 Ether
Input Data	0x102c2751...09...0a

After all HEMSs in a bus have submitted their load ranges, the DSO calls function ‘getAgg()’ in the smart contract to aggregate the decrypted total load range in a single bus.

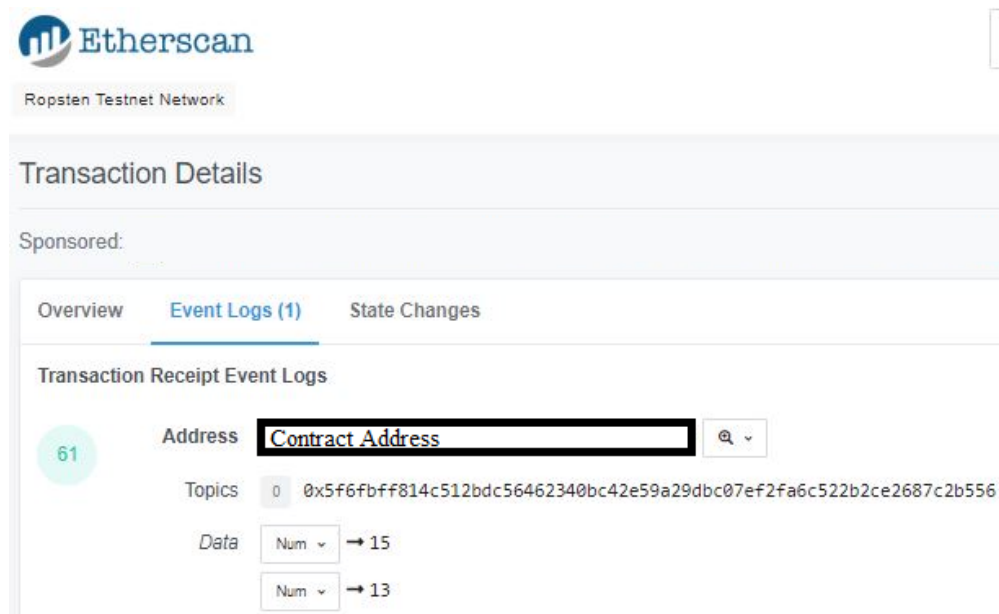


Figure 3.15: Transaction details of calling ‘getAgg()’ function. Displays only the sum of forecasted load data (13,15) in the event log. Published in [18].

Figure 3.15 provides the transaction event details of calling this function. The data displays only the sum of the users' forecasts and not individual load forecast values. Note the time delay for load aggregation in testing was not included. Ideally, the smart contract would operate after a certain time, even if all users had not submitted their forecasts. Offline, the DSO calculates the optimized allowed demand for each home using the aggregated demand range. The DSO then submits the optimal allowed power signal (λ) to the blockchain, using 'submitLambda()'. At each new timeslot, each homeowner requests this value through another function in the contract, called 'getLambda()'. The lambda value allows each HEMS owner to know their maximum allowable demand for the next timeslot. The DSO then clears all submitted values from the contract using 'clearPrice()', 'clearRange()', and 'clearLambda()' to prepare for the new submissions in the next timeslot. This process is repeated every timeslot. The pseudocode used for this simulation is provided in Algorithm 1.

Algorithm 1 Smart Contract-Enabled Communication Framework

```

initialization:
    claimDSO(address)
    claimUser(address)
for every timeslot  $t \in T$  do
    DSO calls submitPrice(upperPrice, lowerPrice)
    Users call getPrice(upperPrice, lowerPrice)
    Users call submitRange(upperRange, lowerRange)
    Once all users have submitted range, DSO calls getAgg() to get upperAgg, lowerAgg
    DSO calls submitLambda( $\lambda$ )
    Users call getLambda( $\lambda$ )
    DSO calls clearPrice(), clearRange(), clearLambda()
end for

```

Results show that the homeowner's privacy is maintained as their load forecasts are encrypted, and the total forecasted load in a node is aggregated and sent to the DSO through the blockchain. The DSO can also communicate the allowable load to each homeowner for the next timeslot in a secure manner.

3.6 Conclusion

To address challenges brought about by the increased penetration level of DERs, a three-phase, component-wise, and real and reactive DLMP mechanism was formulated and tested. Components for energy, loss, voltage violation, and congestion were derived through comprehensive sensitivity analyses and leveraged in this work. Further, the data-driven PEP method enables the uncertainty of the VRE units to be efficiently addressed. Numerical results show that the DLMP mechanism can serve as a tool to balance real and reactive power across phases to encourage or discourage real and reactive power consumption using an economic price signal. It was also demonstrated that three-phase pricing allows for better control of diverse DERs in active distribution systems, which have been extensively modeled in this chapter. The distribution system model was tested against the open-source MATPOWER software and proved to provide acceptable results.

In addition, the proposal and testing of a potential future application of the DLMP was undergone, where the DLMP was used as a price signal sent to HEMS-equipped homes through the blockchain. The proposed smart contract concept was verified through simulation and testing. All vulnerable information was securely transferred through the smart contract. A property of the blockchain itself protects the data, i.e., blockchains are immutable. The privacy-preserving aggregation is therefore achieved using the smart contract. Compared to the commonly proposed aggregator method, where the individual user's forecasted electricity usage is exposed to the DSO, the self-running smart contract provides an isolated data transfer network. The DSO will only obtain the aggregated forecast data and have no clear information on individual homeowner activity.

Chapter 4

Water Model and WEN Coupling¹

This chapter investigates the coupling between an electricity distribution network and a drinking water network within the water-energy nexus (WEN). A linear water network model is proposed and tested to examine the impact of this coupling on the electricity distribution network with uncertain variable renewable energy (VRE) sources and on the distribution locational marginal price (DLMP).

4.1 Background

A mixed-integer linear programming (MILP) model of merged power and water networks is proposed to optimally schedule pumping, tank storage, and distributed energy resources (DERs), considering both electricity and water network constraints. The pumping schedules are coupled with electricity utility demands and therefore serve as a flexible load. The water pumps respond to the price of electricity and available VRE generation and can run at higher capacities than what is necessary for the current water demand. The additional pumped water is stored in tanks for later use and, in turn, reduces electricity costs and VRE curtailment. In general, VRE generation curtailment occurs when there is insufficient ramping down capability in thermal units or when there is congestion on power lines, inhibiting the use of available wind and solar energy [135]. Since the proposed electricity distribution

¹This chapter is a slightly modified version of our published article [52].

model does not incorporate thermal units with ramping limits, VRE units are curtailed to avoid congested lines. This model is optimized from the perspective of the electricity distribution system operator (DSO) while considering the physical constraints of both networks. A significant operational cost to the water utility is the cost of supplying power to pumps. If the cost of supplying electricity is minimized, electricity costs to the water utility can also be reduced.

Case studies are performed on a modified Institute of Electrical and Electronics Engineers (IEEE) 13-node electricity distribution network coupled with a 10-node water distribution network, and on a larger coupled IEEE 37-node electricity and 30-node water distribution network. An investigation into the capability of water tanks to serve as storage devices of excess renewable energy under the future case of a distribution market, as summarized in Reference [4], is undergone. A key focus of future distribution markets is centered around supplying energy using marginal operating or social welfare costs. Therefore, the impact of the water network on the DLMP is investigated. Simulation results test the theory presented in this chapter.

4.2 Electricity Distribution Model

In this coupled model, $\mathcal{O}(p_{i,\phi,t})$ and $\mathcal{O}(q_{i,\phi,t})$ in (3.1) are defined as in (4.1) and (4.2). Subscript ϕ is omitted as this model is assumed to be balanced three-phase. The objective function is the least cost sum of operating the electrical distribution system.

$$\mathcal{O}(p_{i,\phi,t}) = \sum_t \lambda_t^{p0} \cdot p_{0,t} + \sum_{i,w,t} c_{i,w,t}^{G,P} \cdot p_{i,w,t}^G + \sum_{i,t} \hat{c}_{i,t}^{B,P} \cdot \hat{p}_{i,t}^B - \sum_{i,t} \check{c}_{i,t}^{B,P} \cdot \check{p}_{i,t}^B + \sum_{i,t} \xi^D \cdot s_{i,t}^D \quad (4.1)$$

$$\mathcal{O}(q_{i,\phi,t}) = \sum_t \lambda_t^{q0} \cdot q_{0,t} + \sum_{i,w,t} c_{i,w,t}^{G,Q} \cdot q_{i,w,t}^G \quad (4.2)$$

Here, λ_t^{p0} , λ_t^{q0} are the real and reactive locational marginal prices (LMPs) at the substation node connected to the transmission system, and $p_{0,t}$, $q_{0,t}$ are the real and reactive net power injections at the substation node, which is assumed to be an infinite source. If these

net power injections are negative, the DSO buys real or reactive power from the distribution system at the respective LMP of the substation node. Distributed generators (DGs) bid at a cost of $c_{i,w,t}^{G,P}$ for real power and $c_{i,w,t}^{G,Q}$ for reactive power, where subscript w indicates the segment energy and bid block using a piecewise bidding method to approximate the fuel cost of the DGs. Variables $p_{i,w,t}^G$ and $q_{i,w,t}^G$ indicate the real and reactive segment power the generators supply. These values must lie within their respective segment constraints and sum to their total output $p_{i,t}^G$ and $q_{i,t}^G$. The reactive power output of the DG must lie within a fraction, $+\kappa^G$, of the real power output. The battery energy storage system (BESS) units bid at a cost of $\hat{c}_{i,t}^{B,P}$ for extraction of power from the battery and $\check{c}_{i,t}^{B,P}$ for injection of power into the battery, where $\hat{c}_{i,t}^{B,P} \geq \check{c}_{i,t}^{B,P}$ to create a positive revenue. Variables $\hat{p}_{i,t}^B$ and $\check{p}_{i,t}^B$ indicate the power the BESS unit consumes or supplies, respectively. Not considered in the objective function, the reactive power outputs of the BESS and VRE units must lie within $+\kappa^B$ and $\pm\kappa^R$ of their respective real power counterparts. The final term in (4.1) indicates the value of lost load, ξ^D , and the sum of the real power demand curtailment, $s_{i,t}^D$, to penalize any load not served.

Further, in this coupled water-energy model, Dem in (3.4) and (3.5) include real and reactive traditional power demands as well as the pump power demands. Meanwhile, Gen in (3.4) and (3.5) includes and real and reactive power supplied from distributed generators, BESSs, and variable renewable outputs ($\bar{p}_{i,t}^R$) determined by the PEP method in Section 3.3.2.

4.3 Water Distribution Model

This section defines the water distribution model used in this work. The water supply network is modeled as a directed graph $\mathcal{G} = (\mathcal{J}, \mathcal{P})$ with junctions, $\mathcal{J}$, and pipes, $\mathcal{P}$, as nodes and lines of the system. Pipes with pumps ($\mathcal{U}$) and valves ($\mathcal{V}$) are (disjoint, mutually exclusive, independent) subsets of all pipes ($\mathcal{U}, \mathcal{V} \in \mathcal{P}$), and reservoirs ($\mathcal{R}$) and tanks ($\mathcal{K}$) are disjoint subsets of junctions ($\mathcal{R}, \mathcal{K} \in \mathcal{J}$). Similar to the electricity distribution system model defined in Chapter 3, time $t \in \mathcal{T}$ is considered. Also, indices i and j' denote the junctions

and pipes for the water network. Note, index j , without the prime notation, is used when describing the pipes in the water network in the mathematical model for simplicity, even though the electricity lines and water pipes are independently notated (see Figure 4.4.).

Additionally, due to multiple nonconvex constraints, the water model, as is, is NP-hard [86, 87]. Therefore, exact solutions for the optimal water flow problem are hard to compute without using solution techniques, even when the network is small. Here, equations are linearized to reduce the computational burden. Convex relaxation and piecewise linear methods are used. Similar water models can be found in References [86] and [87].

4.3.1 Junctions

Water demand, $d_{i,t}$, is considered constant (m^3/h) over the one hour duration of each time slot. The volumetric flow rate through pipe j is denoted as $f_{j,t}$. Conservation of mass must be followed between two connecting junctions described by their node-line incidence matrix, B , as in (4.3). Here, $B \in \mathbb{R}^{(\mathcal{J} \times \mathcal{P})}$ is one if pipe j leaves junction i , negative one if pipe j enters junction i , and zero otherwise. This constraint is considered $\forall i \in \mathcal{J}, \forall t \in \mathcal{T}$. Each junction i is assigned a minimum and maximum pressure head, $\underline{h}_i, \bar{h}_i$, by system operators. For $\forall i \in \mathcal{J}, \forall t \in \mathcal{T}$, the head at each junction ($h_{i,t}$) must lie within these two values, as in (4.4).

$$B \cdot f_{j,t} = d_{i,t} \tag{4.3}$$

$$\underline{h}_i \leq h_{i,t} \leq \bar{h}_i \tag{4.4}$$

4.3.2 Reservoirs

Reservoirs serve as infinite sources of water to the network, i.e., Equation (4.3) does not hold, where the junction pressure head (in meters) is zero $\forall i \in \mathcal{R}, \forall t \in \mathcal{T}$ as described in (4.5).

$$h_{i,t} = 0 \tag{4.5}$$

4.3.3 Tanks

Tanks are modeled such that the water balance constraint (4.6) must hold $\forall i \in \mathcal{K}, \forall t \in \mathcal{T}$. Here, the volume (m^3) in the tank is denoted as $u_{i,t}$, and Δt is the time interval between time slots in hours. Note, $u_{i,t-1} = u_{i,0}$ for $t = 1$, where $u_{i,0}$ is the initial volume in the tank. Equation (4.7) restricts the volume of water in the tank to reside between the maximum volume of the tank, $\bar{u}_i$, and the minimum reserve volume, $\underline{u}_i$. The pressure head at the tank, $h_{i,t}$, is defined in (4.8), and must be greater than zero, as in (4.9). The bounds for the volumetric flow rate entering (f_{in}) and leaving (f_{out}) the tank are modeled in (4.10), where in this instance j is the upstream and downstream pipes of tank i . Note, $h_{i,t-1} = \frac{u_{i,0}}{A_i}$ for $t = 1$, where A_i is the area of the tank.

$$u_{i,t} = u_{i,t-1} + \Delta t[B \cdot f_{j,t}] \quad (4.6)$$

$$\underline{u}_i \leq u_{i,t} \leq \bar{u}_i \quad (4.7)$$

$$h_{i,t} = h_{i,t-1} + \frac{\Delta t}{A_i}[B \cdot f_{j,t}] \quad (4.8)$$

$$h_{i,t} \geq 0 \quad (4.9)$$

$$f_{j,t} \leq f_{in}, f_{out} \quad (4.10)$$

4.3.4 Pipes without Pumps or Valves

Head loss across a pipe without a pump or valve ($\check{h}_{j,t}$) can be modeled using the nonlinear Darcy-Weisbach equation, as in (4.11), $\forall j \in \mathcal{P}/\mathcal{U} \cup \mathcal{V}, \forall t \in \mathcal{T}$. For simplicity, all water pipes are assumed to be smooth and are modeled using a constant friction factor. Here, $\mathcal{F}_j = \frac{\mu_j l_j}{2m_j W_j^2 g}$ is a constant related to pipe characteristics such as length (l_j), diameter (m_j), cross-sectional wetted area (W_j), Darcy friction factor (μ_j), and local gravity (g). For volumetric flows in m^3/h , a conversion factor must be included in $\mathcal{F}_j$. Head loss is also calculated as the difference between two junctions surrounding a pipe, as in (4.12). The flow across a pipe must be positive (4.13) as bidirectional flow in the water model is not considered.

$$\check{h}_{j,t} = \mathcal{F}_j(f_{j,t})^2 \quad (4.11)$$

$$\check{h}_{j,t} = B^T \cdot h_{i,t} \quad (4.12)$$

$$f_{j,t} \geq 0 \quad (4.13)$$

A piecewise linear function further approximates the head loss in (4.11). Figure 4.1 depicts an example of this linearization with four splits. A binary variable is used to indicate the section the approximation lies within.

4.3.5 Variable-Speed Pumps

A variable speed pump (VSP) moves water through a network [136], by increasing the pressure head across a pipe, $\forall j \in \mathcal{U}, \forall t \in \mathcal{T}$. This increase (in meters) is captured in the head gain variable, $\hat{h}_{j,t}$, which is modeled by the nonlinear equation (4.14), where $\omega_{j,t}$ is the actual over nominal pump rotational speed (in rad/s). This value must remain between the

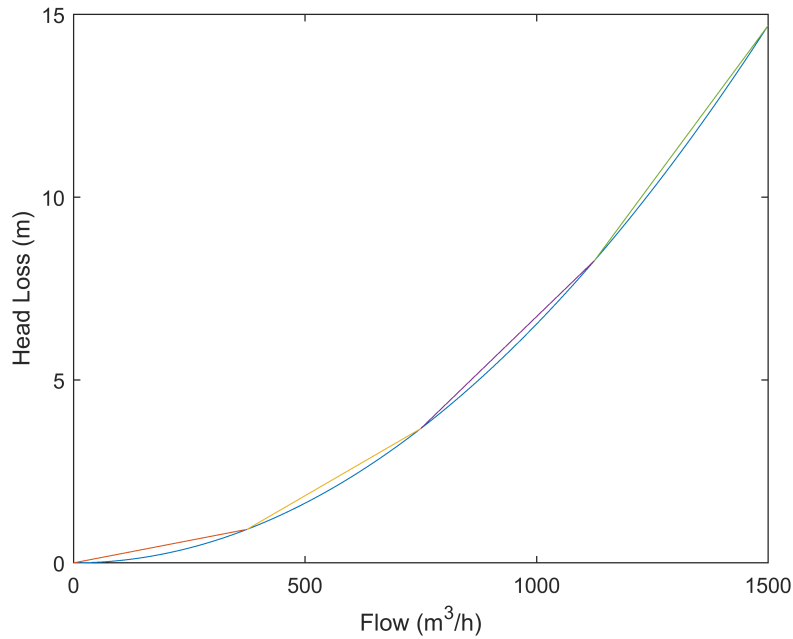


Figure 4.1: Head loss piecewise linear approximation.

minimum and maximum allowable ratios $\underline{\omega}_j, \bar{\omega}_j$, if the pump is ON, as indicated by binary variable $\mathbb{x}_{j,t}$, as in (4.15). Also, note that a_j, b_j , and c_j are the coefficients of the hydraulic characteristics of the pump, where $a_j < 0$; $b_j, c_j > 0$. For simplicity, the efficiency of the pump is assumed a constant.

$$\hat{h}_{j,t} = a_j(f_{j,t})^2 + b_j f_{j,t} \omega_{j,t} + c_j (\omega_{j,t})^2 \quad (4.14)$$

$$\underline{\omega}_j \cdot \mathbb{x}_{j,t} \leq \omega_{j,t} \leq \bar{\omega}_j \cdot \mathbb{x}_{j,t} \quad (4.15)$$

Similar to head loss, the head gain between nodes is approximated using a piecewise linear approximation. First, nonlinear equation (4.14) is modified to eliminate $\omega_{j,t}$, as in (4.16), where $b_j^{max} = b_j \cdot \bar{\omega}_j$ and $c_j^{max} = c_j \cdot \bar{\omega}_j^2$. This convex relaxation technique is adopted from Reference [86] to define an upper bound for the pump head gain. The technique is extended here to enforce a lower bound for the head gain. The right-hand side ($RHS_{j,t}$) of (4.16) is linearized using a piecewise linear approximation. Similarly, to set a lower bound for the head gain, (4.17) is used, where $b_j^{min} = b_j \cdot \underline{\omega}_j$ and $c_j^{min} = c_j \cdot \underline{\omega}_j^2$. The approximated head gain must be zero or greater than the $LHS_{j,t}$. Piecewise linear functions are used to approximate the upper and lower bounds of the head gain, defined in (4.16) and (4.17), respectively. Figure 4.2 shows an example of this technique with four, piecewise splits. The pump rotational speed ratio, $\omega_{j,t}$, can be obtained post-solve.

$$\hat{h}_{j,t} \leq a_j(f_{j,t})^2 + b_j^{max} f_{j,t} + c_j^{max} = RHS_{j,t} \quad (4.16)$$

$$\hat{h}_{j,t} \geq a_j(f_{j,t})^2 + b_j^{min} f_{j,t} + c_j^{min} = LHS_{j,t} \cdot \mathbb{x}_{j,t} \quad (4.17)$$

If the pump is ON, the head gain is also captured in the pressure head difference between the two junctions on either side of the pump, as in (4.18). By use of a binary variable and a large positive constant, M , the pressure head values on either end of the pump are uncoupled if the pump is OFF. The head gain must be a positive value (4.19), and the water flowing

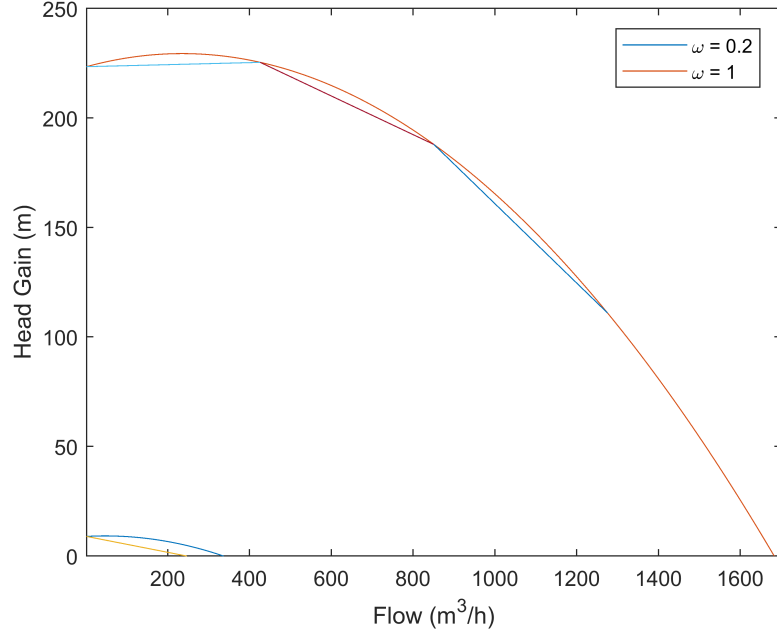


Figure 4.2: Head gain piecewise linear approximation.

through the pump must be between m and M if the pump is ON (4.20).

$$-M(1 - \mathbb{x}_{j,t}) \leq [B^T \cdot h_{i,t}] - \hat{\hat{h}}_{j,t} \leq M(1 - \mathbb{x}_{j,t}) \quad (4.18)$$

$$\hat{\hat{h}}_{j,t} \geq 0 \quad (4.19)$$

$$m \cdot \mathbb{x}_{j,t} \leq f_{j,t} \leq M \cdot \mathbb{x}_{j,t} \quad (4.20)$$

4.3.6 Pressure Reducing Valves

Similar to (4.18) for pumps, but $\forall j \in \mathcal{V}$, $\forall t \in \mathcal{T}$ and where binary variable $\mathbb{y}_{j,t}$ indicates valve ON or OFF state, the head loss, $\check{\check{h}}_{j,t}$, is modeled as the difference between the junctions on either end of the valve if the valve is ON (physically meaning open) (4.21). If the valve is OFF (physically meaning closed), the pressure heads at either end are uncoupled. If the valve is ON, the head loss must be greater than zero (4.22), and the flow through the valve must be positive (4.23).

$$-M(1 - \mathbb{Y}_{j,t}) \leq [B^T \cdot h_{i,t}] - \check{h}_{j,t} \leq M(1 - \mathbb{Y}_{j,t}) \quad (4.21)$$

$$\check{h}_{j,t} \geq 0 \quad (4.22)$$

$$m \cdot \mathbb{Y}_{j,t} \leq f_{j,t} \leq M \cdot \mathbb{Y}_{j,t} \quad (4.23)$$

When the valve is ON, i.e., open, the valve acts like a pipe. Therefore, pressure head loss across the pipe is also modeled using the approximation in (4.11), $\forall j \in \mathcal{V}, \forall t \in \mathcal{T}$.

4.3.7 Power Consumption of Pumps

The real power consumed by the pump, denoted by variable $p_{j,t}^{D,U}$, $\forall j \in \mathcal{U}, \forall t \in \mathcal{T}$ is modeled in nonlinear equation (4.24), where ρ_w , g , and η_j denote the water density, acceleration due to gravity, and the efficiency of the pump, respectively. The reactive power of the pump, $q_{j,t}^{D,U}$, is assumed as κ^W of the real power.

$$p_{j,t}^{D,U} = \frac{\rho_w g \hat{h}_{j,t}}{\eta_j} f_{j,t} \quad (4.24)$$

The power consumed by the pump is approximated using a 2D piecewise linear method, namely convex combination triangulation, $\forall j \in \mathcal{U}, \forall t \in \mathcal{T}$, as in (4.25). Variables $\mathcal{A}_{tri}$, $\mathcal{B}_{tri}$, and $\mathcal{C}_{tri}$ are determined by using the results of Equation (4.24) evaluated at the boundaries, $f_{tri,j,t}$ and $\hat{h}_{tri,j,t}$, of each nonoverlapping triangle. A binary indicator, $\mathbb{T}_{tri,j,t}$, is used to determine which triangle approximates the pump power. Convex combination theory is used to locate the flow and head gain values into a single triangle. This technique is believed to be sufficient as the resulting graph of the pump power has no drastic curves and allows for a straightforward mapping of the linear convex polytopes, as shown in the linear approximation mapping in Figure 4.3. The red dashed lines indicate the 2D triangular approximation bounds that intercept the actual, nonlinear pump power graph within a specific segment of

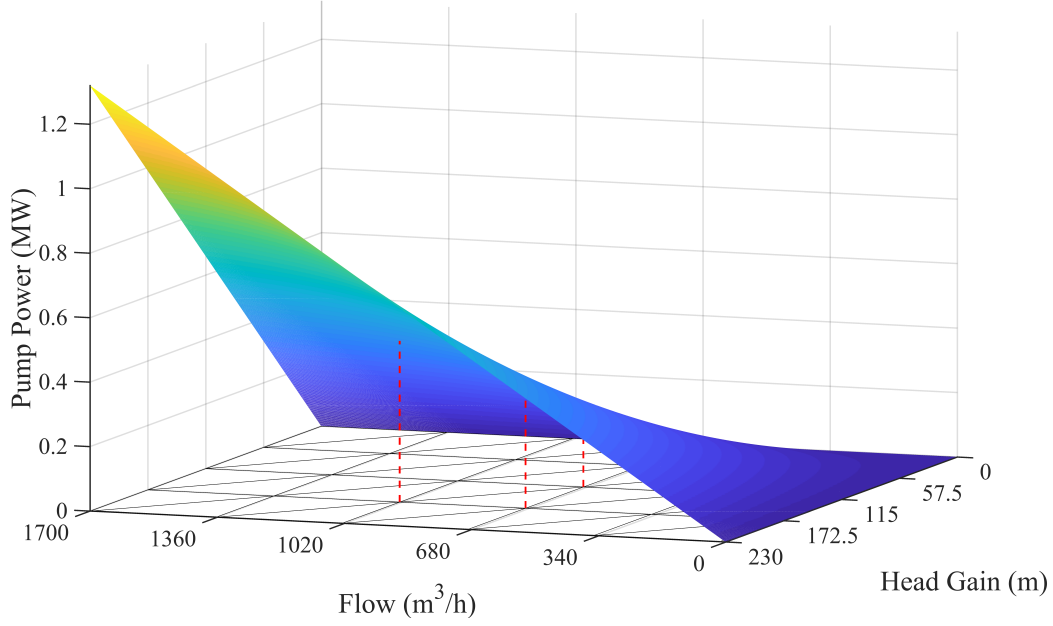


Figure 4.3: Pump power linear approximation using the 2D piecewise linearization method. Published in [52].

head gain and volumetric flow rate values.

$$p_{j,t}^{D,U} = \sum_{tri} \mathcal{A}_{tri} \cdot f_{tri,j,t} + \mathcal{B}_{tri} \cdot \hat{h}_{tri,j,t} + \mathcal{C}_{tri} \cdot \mathbb{T}_{tri,j,t} \quad (4.25)$$

The linear water flow problem now consists of constraints (4.11)-(4.10), (4.12)-(4.13), (4.16)-(4.23), (4.25), and the additional constraints associated with the linear approximation of head gain, head loss, and pump power. Note, the accuracy of the water model will improve with more piecewise linearization segments or triangles at the cost of lower computational efficiency. The longer solving times that arise from more segments or triangles should be managed in the day-ahead scheduling timeframe.

4.3.8 Pump Cost Calculation

The pump electricity cost calculation, as in (4.26), is captured by C_w and is found by multiplying the real and reactive power consumed by the pumps ($p_{i,t}^{D,U}$, $q_{i,t}^{D,U}$) applied to connected node i , and the total real and reactive DLMP ($\Omega_{i,t}^P$, $\Omega_{i,t}^Q$) at the node the pump's

load is applied.

$$C_w = \sum_{i,t} p_{i,t}^{D,U} \cdot \Omega_{i,t}^P + \sum_{i,t} q_{i,t}^{D,U} \cdot \Omega_{i,t}^Q \quad (4.26)$$

4.3.9 Merged Water and Power Flow Problem

Finally, the merged optimal water and power flow problem is considered as $\mathbf{P}_4$. In this model, the water network as a demand-responsive system is considered. The water network is not optimized for the least cost of pumping, but all water constraints must be met. Here, $p_{i,t}^{Dem}$ in Equation (3.4) is a summation of the non-pump electrical demand, $p_{i,t}^{D,N}$, and the calculated pump demand associated with its respective node i , $p_{i,t}^{D,U}$. A similar coupling can be made for reactive power demand. The coupled optimal water and power flow problem, $\mathbf{P}_4$, is defined as:

$\mathbf{P}_4$: min(3.1)

subject to: (3.4)-(3.5), (3.9)-(3.14), (3.18)-(3.42), (3.65)-(3.71), (4.3)-(4.10), (4.12)-(4.13), (4.16)-(4.23), (4.25), and linear approximation constraints.

It is acknowledged that an MILP model with piecewise linear approximations requires more time to solve than other methods, such as a second-order cone model, as verified in Reference [92]. That said, the MILP model has an advantage over the second-order cone model presented in Reference [86] when used with nodal DLMPs. The objective function of the second-order cone model in Reference [86] must minimize energy losses in the water network. Therefore, the energy consumed by the pumps is not minimized using dynamic electricity prices, such as DLMPs, but is calculated post-solve. Also, the pump power consumption is only modeled post-solve and, thus, is not suitable for the proposed merged model without modification. Therefore, the MILP model is used in this work. Furthermore, the DSO is assumed to be equipped with the computational capability to handle computationally intensive problems within a reasonable timeframe. This assumption holds even if a large number of historical VRE samples are employed by the PEP method. This is believed to be a valid

assumption based on the quality and number of commercially available MILP solvers today. However, if issues arise from computational complexities, sample reduction, bundling, or other state-of-the-art techniques can ease the solver’s burden.

4.4 Impact of WEN Coupling on DLMP

This section investigates the impact of a coupled water-energy network in various aspects. First determined is the VRE output based on the PEP probability level, β . Scenarios with and without an elevated water tank network are compared to investigate the significance of storage capabilities within the merged water-energy network. The influence of the PEP probability level on the coupled network is investigated. The impact of merged networks with and without a water tank on the DLMP are compared. Also, the consequence of failure in one network on another is investigated. Finally, to see how the results of a larger water-energy network would compare to a relatively smaller network, a larger system is designed and tested in a similar manner.

4.4.1 Small Water-Energy Network

To validate the proposed model, a modified IEEE 13-bus distribution system connected to a 10-bus water distribution network is considered, as Figure 4.4 displays. These results are published in [52]. This network mimics a realistic small-town or urban electrical distribution network, serving a peak power demand of approximately 1.3 MW with a feeder length of 1.65 miles. VRE generation units are at Nodes 3, 4, 8, and 12, and BESS units are at Nodes 2 and 6. The energy demands for the pumps in the water network are included in the electrical demand for Nodes 1 and 2. A yearlong sample of hourly wind and PV generation at two sites was obtained from the Western Wind and Solar Integration Study (WWSIS) historical data sets [133]. These data were used to obtain the daily VRE generation time series using the PEP method and then scaled to match the system. Identical sets of data were used for VRE units located close to one another.

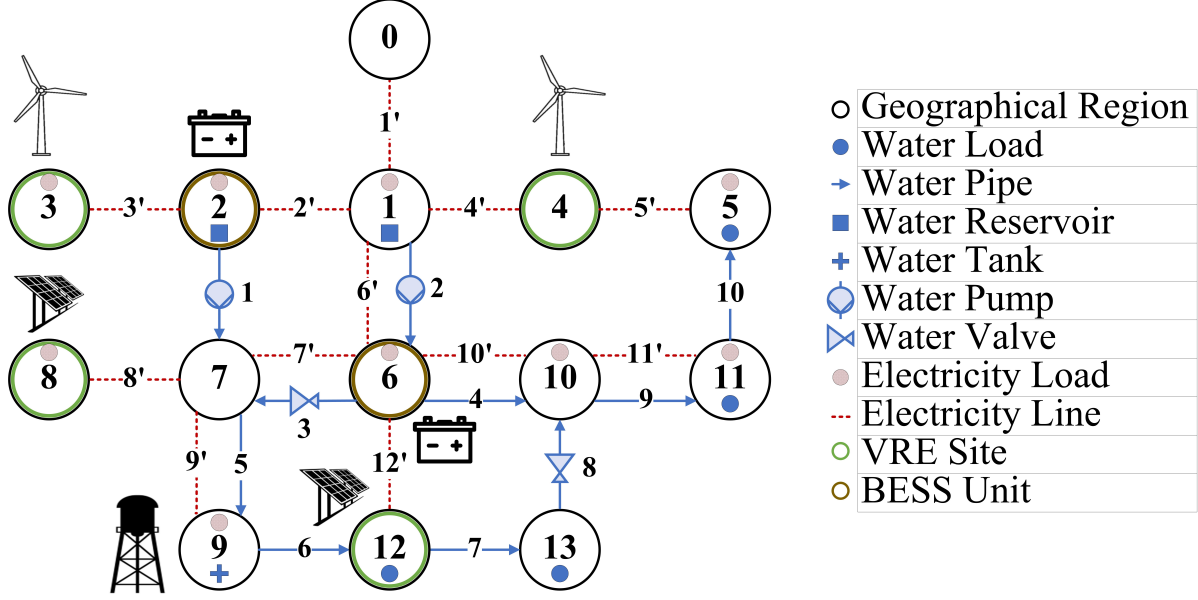


Figure 4.4: Integrated IEEE 13-node electricity and 10-node water distribution networks. Published in [52].

Of similar topology to References [87] and [137], the water supply network consists of two reservoirs, two VSPs, one tank, and two valves. The elevation of all junctions in the water network are assumed to be zero (m). The minimum head at demand nodes is $\underline{h}_i = 5$ (m). The tank area is $A_9 = 490.87$ (m²), and the maximum volume of the tank is $\bar{u}_9 = 14,726.1$ (m³), i.e., the tank is 30 meters tall. The minimum allowable volume, $\underline{u}_9$, is 10% of the maximum volume, and the initial volume in the tank is $u_{9,0} = 9,100$ (m³), which is approximately 18.5 (m) of water. The maximum allowable flow in and out of the tank is 1,100 (m³/h). The pipe and activated valve parameters are modified versions of the network in Reference [137], and the Darcy friction factor of each pipe used in Equation (4.11) is considered to be $\mu_j = 0.014$. From Reference [136], the parameters of the VSPs are $a_j = -1.0941 \times 10^{-4}$, $b_j = 5.1516 \times 10^{-2}$, $c_j = 223.32$, $\bar{\omega} = 1$, and $\underline{\omega} = 0.2$. The pump efficiency is assumed to be constant at all speeds, $\eta_j = 80.75\%$. The total water demand is depicted in Figure 4.6. The power and water flows are considered to be in steady-state within the one hour timeslots. This time resolution is sufficient for the day-ahead energy trading market. Further, the model could equivalently serve in the real time market with 5- to 15-minute time intervals. GAMS/CPLEX 28.1.0 [130] is used to solve the proposed MILP, $\mathbf{P}_4$. The

following scenarios are created:

Scenario 1: PEP Probability Level–Comparison of VRE outputs at $\beta = 25\%$, $\beta = 50\%$, and $\beta = 75\%$. Note, probabilities and probability levels are assumed to be known to the DSO a priori.

Scenario 2: High VRE–Coupled water and electricity networks ($\mathbf{P}_4$) with high VRE penetration are compared with and without a water tank.

Impact of PEP Probability Level on VRE Output

Changing the PEP probability level, as in Scenario 1, has a considerable impact on the expected VRE generation, as shown in Figure 4.5. Hourly wind and solar generation data are obtained from WWSIS and used to find the probability efficient point at different probability levels using the PEP method. The higher the probability level (β), the higher the expected wind and solar generation. Wind generation outputs face more substantial differences between probability levels because the data has a broader range of historical samples than the relatively narrow band of PV data. The output at a given PEP is applied to each VRE site, respective of the generation type. The same result for different sites of the same technology is assumed as the generation units are considered near each other and therefore see the same resource.

Impact of Tank as Storage Device

Considering the parameters of Scenario 2, an investigation into the impact of the tank as an energy storage device is conducted. Instead of curtailing wind and solar energy, the water network utilizes pumps to store water in tanks for later use when non-pump electricity demands are higher. Table 4.1 outlines the cost and demand comparison of a system with and without a tank at probability level $\beta = 75\%$. The costs for each network are very similar in each case, yet the pump demand is increased for the case with a tank. The negative electricity cost is due to the selling of excess VRE to the grid in all timeslots. Though the difference in the VRE utilization factors (the amount of dispatched VRE over the total

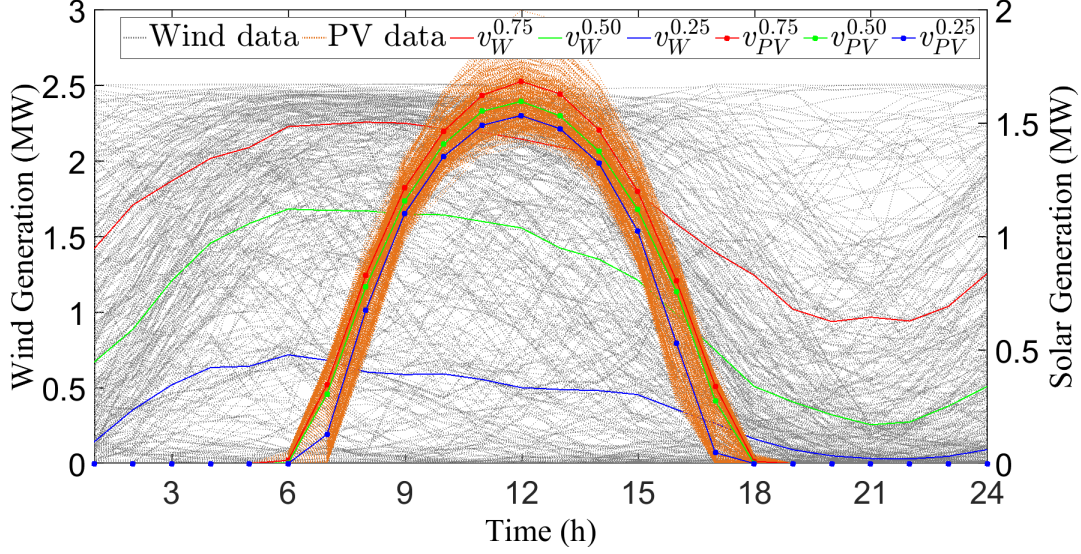


Figure 4.5: Historical wind (W) and PV data and the PEP result at 25%, 50%, and 75% probability levels. Published in [52].

generated) is small, the case with the tank recovers 124.3 kWh of VRE that is otherwise curtailed in the case without a tank.

Table 4.1: Scenario 2 daily results at $\beta=75\%$ (*Calculated post-solve using (4.26).)

	Tank	No Tank
C_e	-\$1,954.59	-\$1,953.15
C_w	\$5.18*	\$5.85*
Pump Energy	442.7 kWh	337.3 kWh
Energy Consumed	23.19 MWh	23.08 MWh
VRE Recovery	124.3 kWh	—
VRE Utilization	93.4%	93.2%

The differences in pump schedules for cases with and without a tank in the water network at different PEP probability levels are depicted in Figure 4.6. For the case with a tank, the pump schedule shifts the peak power consumption to no longer align with the peaks and valleys of the water demand, as it must for the case without a tank. In the cases with probability level $\beta = 25\%$, the available VRE is lower, and therefore, the difference in the pump schedule with and without a tank is minimal compared to $\beta = 75\%$. The case with a tank and $\beta = 75\%$, in general, sees more substantial pump power demands in the first half of the day. The additional power supplied to the pumps is an attempt to better utilize the

high VRE generation by storing water in the tank during the daytime and enables the water network to serve as a demand response mechanism. Note, in a stand-alone water network without considering VREs, one can expect the pump power demand to decrease with the addition of a water tank in the network. However, this is not the case for this work as the water tank acts as an electricity storage device and consumes excess VRE power; thus, pump power demand increases with the addition of a water tank in the proposed merged water and energy problem. These results demonstrate the necessity of a coordinated operation of water and electricity distribution networks when VRE generation is in place.

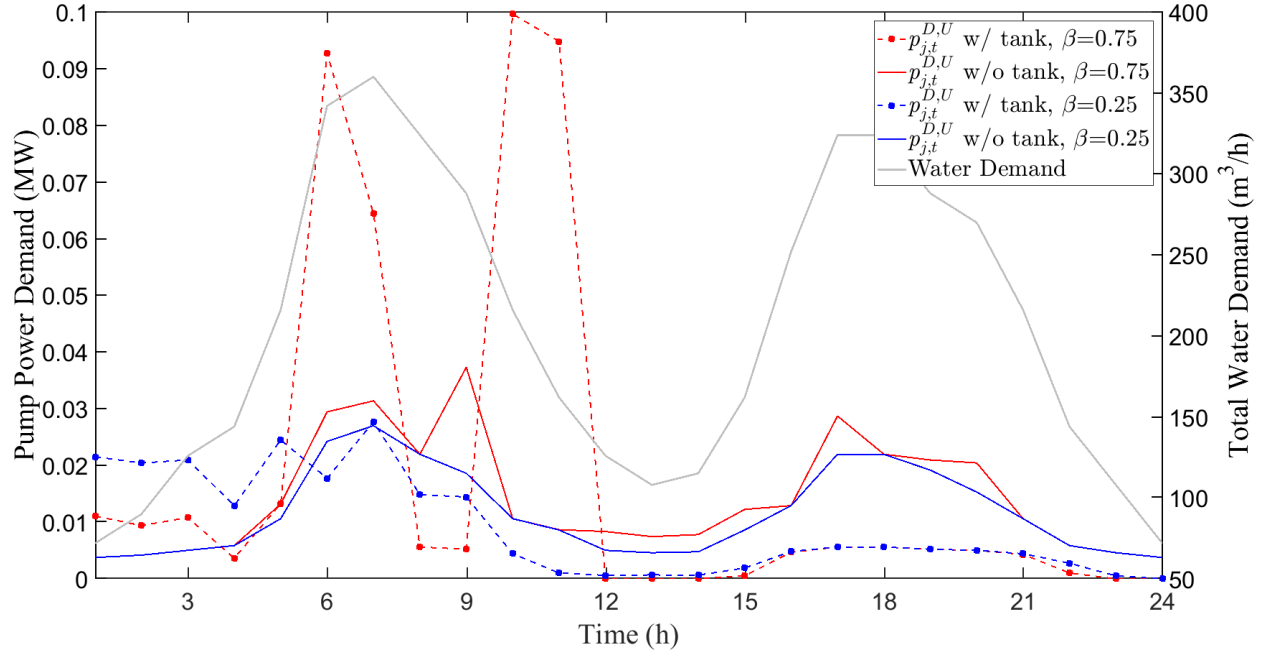


Figure 4.6: Summed pump power ($\sum_j p_{j,t}^{D,U}$, where $j \in \mathcal{U}$) schedule versus water demand at probability levels 25% and 75%. Published in [52].

Impact of PEP Probability Level

The water storage in the tank at different probability levels is graphically represented in Figure 4.7. As expected, the VRE curtailment is higher in the cases without a tank. Note, the cases with a tank at probability levels $\beta = 75\%$ and $\beta = 50\%$ slightly reduce the VRE curtailment by storing water in the tank. The case with probability level $\beta = 25\%$ does not curtail VRE generation as the system entirely uses the VRE output both with and without

a tank. The reduction in VRE curtailment is limited by the maximum inflow constraint into the tank and potential voltage violations and line congestion in the electricity network from moving large amounts of power to the nodes with flexible water pumps. Also, the comparatively smaller power demands of the pumps limit the impact of reducing VRE curtailment. The tank fills to aid in the electricity network's health by reducing line congestion and voltage violations. The final tank volume for $\beta = 75\%$ is greater than the other two probability levels because the tank acts as a battery and stores a greater amount of excess VRE in this case.

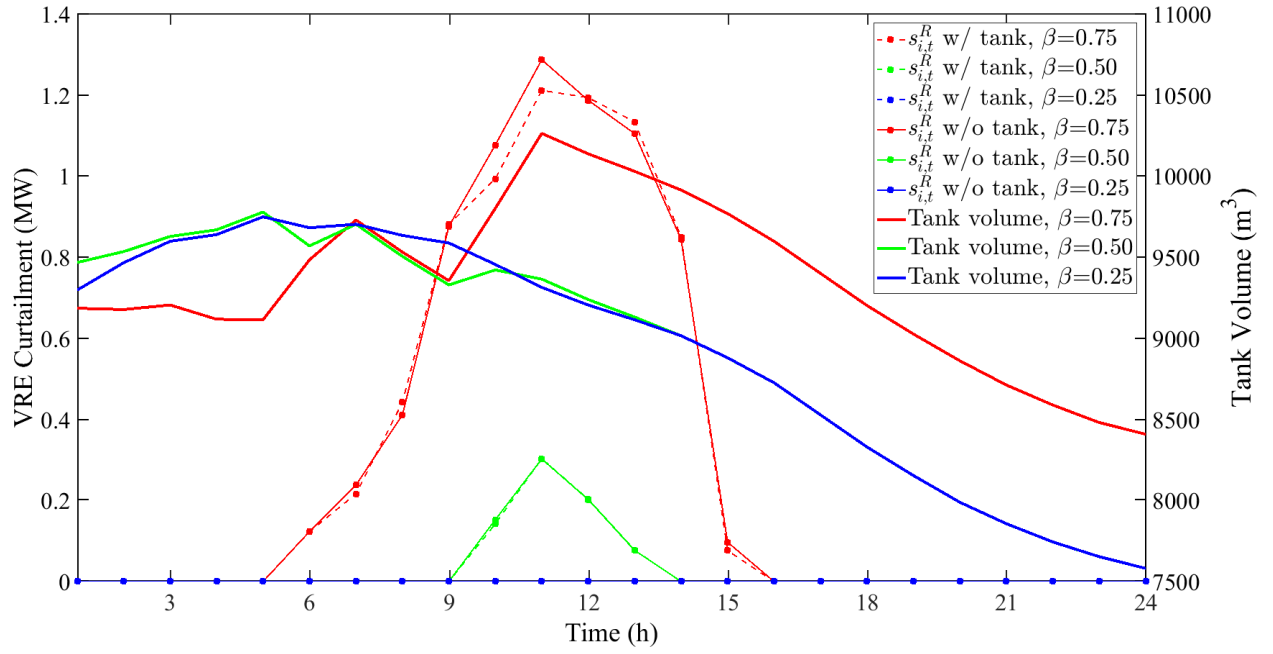


Figure 4.7: VRE curtailment summed over the generation locations ($\sum_i s_{i,t}^R$, where $i \in G$) and tank volume at 25%, 50%, and 75% probability levels for cases with and without a tank. Published in [52].

Table 4.2 outlines the amount of VRE generation recovered in the case with a tank versus the case without a tank at different probability levels. The water tank allows less VRE generation to be curtailed in a case of excess VRE generation. As the probability level decreases, and subsequently, the VRE generation, the VRE recovery decreases because the system is able to use more of the VRE generation. Again, the system completely uses all VRE generation at probability level $\beta = 25\%$, so there is no excess VRE generation to store as potential energy in the water tank in this case.

Table 4.2: Scenario 2 results with changing β .

Probability Level	VRE Recovery
$\beta=0.75$	124.3 kWh
$\beta=0.50$	7.9 kWh
$\beta=0.25$	0 kWh

Impact of Tank on DLMP

Considering the constraints of Scenario 2 and the PEP probability level at $\beta = 75\%$ again, the impact of the tank on the real power DLMP is observed, as shown in Figure 4.8. Negative real power components indicate some part of the system, respective of each component, would benefit from more real power consumption at that node. However, the total nodal DLMP (red line with asterisks) may still be positive overall. Also, losses are unavoidable and, therefore, loss DLMP components occur in every timeslot.

Figure 4.8 graphically depicts the differences in the component-wise DLMP for the case with and without a tank on Node 1. Due to the selling of excess VRE generation to the grid, congestion occurs on Lines 1' and 3' in many timeslots. In the case with the tank, the congestion is completely removed from Line 1' in Timeslots 10 and 11. With the freed line capacity in the case with a tank, the VRE units sell power until the maximum voltage constraint is met on Nodes 3, 8, and 12, and larger voltage DLMP components replace the congestion DLMP components in Timeslots 10 and 11. Note, the voltage DLMP components in Timeslots 10 and 11 in the case without a tank are relatively small and are not visible in the figure. The allowance of curtailing VRE generation is to avoid voltage violations and congestion and achieve system feasibility.

Adding the tank produces small changes in the VRE curtailment reduction and DLMPs. This impact could be amplified with additional or larger tanks in the water network and longer simulated timeframes. Storage devices will be necessary to reduce VRE generation curtailments in a future case with large amounts of VRE penetration in the distribution network. Storing water in existing water tanks may be a low-cost option that can positively impact the electricity network, even if in a small way by reducing voltage violations and line

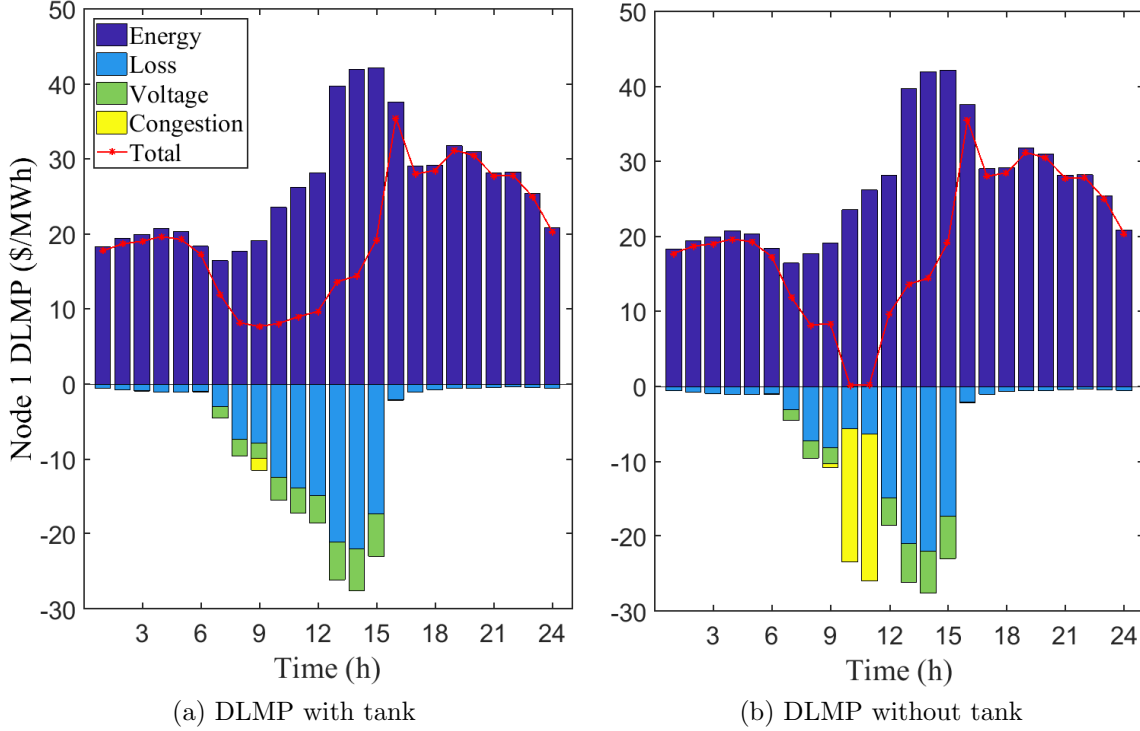


Figure 4.8: Node 1 component-wise DLMP at a 75% probability level for cases with and without a tank. Published in [52].

congestion. Utilizing water tanks as storage devices may not altogether remove the VRE overgeneration, and the system may see more benefits from a diverse storage profile. That said, the cooperation of the water and electricity networks can adequately serve as demand response and storage technologies and improve the health of the electric distribution network while still meeting water demands.

Impact of Failures

To investigate the impact of failures in the proposed model, the system behavior when a component in the coupled model fails is tested. A failed component could be caused by damage in an extreme event, such as a weather-related occurrence or even a malicious, targeted attack on the system. A case where the valve on Pipe 8 (see Figure 4.4) faces a failure is considered, i.e., Valve 8 is forced closed and does not allow water flow over the pipe. Figure 4.9 shows the result of this study. Figure 4.9a compares the VRE curtailment and

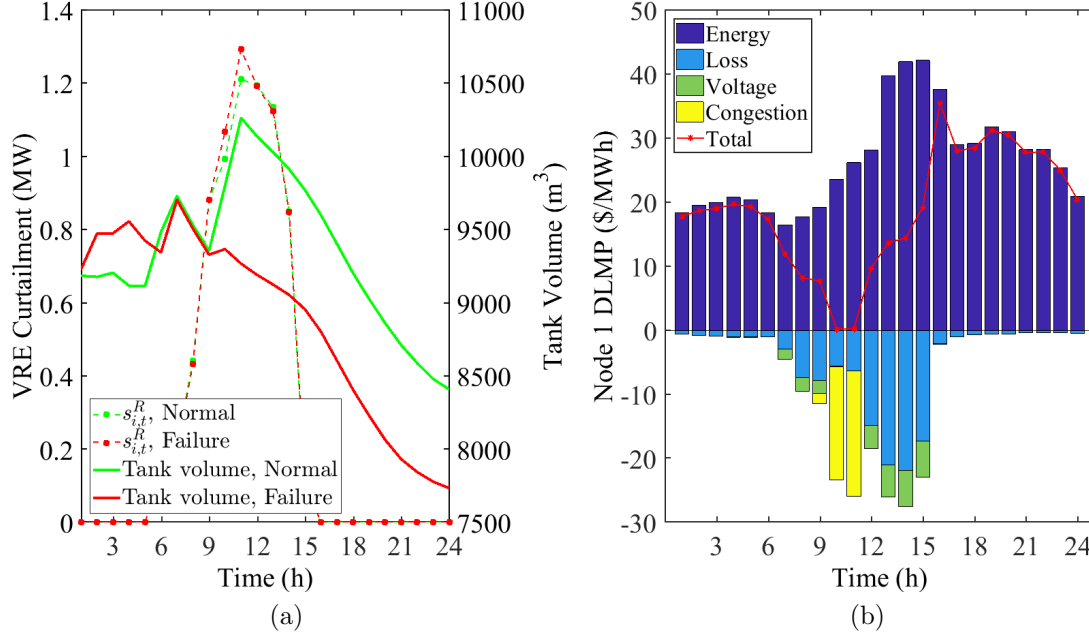


Figure 4.9: VRE curtailment and tank volume for normal operating conditions versus system behavior with Valve 8 failure (a); resulting DLMP of Node 1 with Valve 8 failure (b). Both subplots consider $\beta=75\%$ and tank inclusion in the model. Published in [52].

tank volume over the scheduling period for normal and failed operating conditions. Figure 4.9b depicts the resulting DLMP of Node 1 after the failure of Valve 8. Congestion occurs on Line 1' in Timeslots 9, 10, and 11.

Interestingly, the DLMP looks very similar to the DLMP in Figure 4.8b. There is a larger congestion DLMP component in Timeslot 9 in the system with Valve 8 failure than in the case without a tank. This congestion is caused by the desire to sell excess VRE generation to the grid at LMP (to the substation node) rather than fill the tank to satisfy water demands later. In the system with a failed Valve 8, the tank can only serve the water demands at Junctions 12 and 13. Note, in Timeslots 11-24, the water tank completely fulfills the water demands at Junctions 12 and 13, i.e., Pump 1 is not operating and Valve 3 is open.

Furthermore, the tank can no longer reach the water demands at Junctions 5, 10, and 11, whose additional water demands were a great motivator in filling the tank in a case with excess VRE. This observation is further illustrated in Figure 4.9a as the tank does not store as much water as it would under normal operating conditions. With a failure at Valve 8,

Pump 2 runs in every timeslot to meet the water demands of Junctions 10, 11, and 5. Even though Pump 2 is on in all timeslots, both pumps' total daily energy consumed is still less than the fully operational case with a tank. Therefore, the system with Valve 8 failure also sees slightly more VRE curtailment than its fully functional counterpart. This study shows failures in the water network can impact the DLMP and overall health of the electricity distribution network.

4.4.2 Large Water-Energy Network

To investigate the coupling impact of water-energy coordination in a larger network, a coordinated 30-node water network and modified IEEE 37-node electricity distribution network is considered, as shown in Figure 4.10. The larger water network considers three reservoirs, three pumps, three tanks, two valves, and sixteen junctions with water demands. All parameters not related to network topology or power and water demands remain the same as the smaller coupled network, except the initial volume in the tanks, where $u_{3,0} = u_{12,0} = u_{31,0} = 8000 \text{ m}^3$. Further, VRE stochasticity is not considered, and ϵ in Equation (3.9) is 6% for the larger electricity network. The IEEE 37-bus model defined in [138] is modified to limit apparent power flow to 80% of the line's capacity, and the extremely small resistance and reactance values are increased fivefold.

In addition, for improved accuracy of the water model, the consideration of minor losses is included. This addition does not increase the number of variables to solve. It does, however, improve the accuracy of the water model by accounting for physical pipe configuration at junctions. The minor losses, modeled as in (4.27), are added to the linearization of Equation (4.11) for pipes and valves that are ON. Here, e_{v_j} is the minor loss coefficient that depends on junction topology [139]. Recall, $\check{h}_{j,t}$ is head loss, $f_{j,t}$ is the volumetric flow rate, and g is gravity.

$$\check{h}_{j,t} = \frac{f_{j,t}^2}{2g} \cdot \sum_j e_{v_j} \quad (4.27)$$

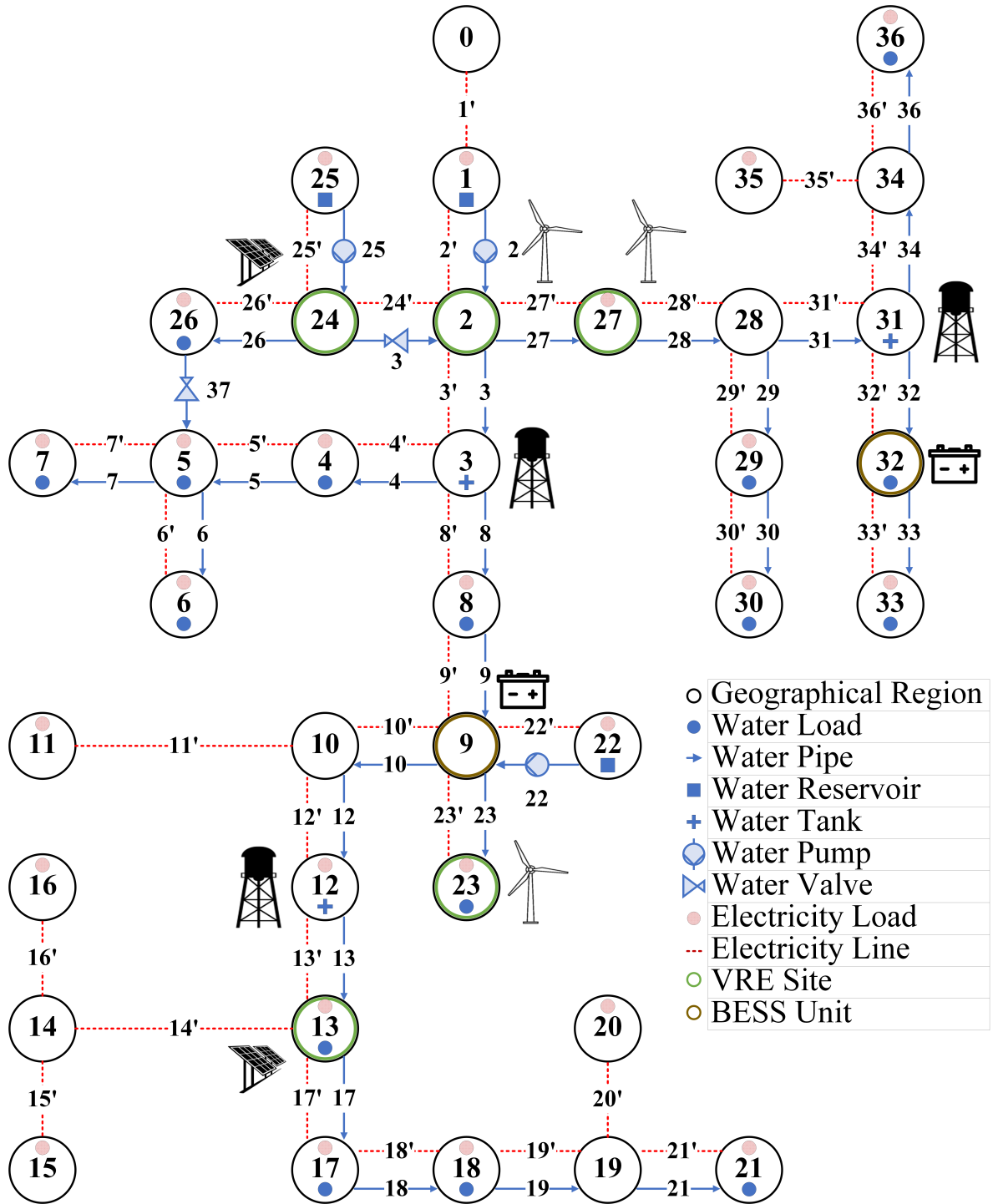


Figure 4.10: Integrated IEEE 37-node electricity and 30-node water distribution networks.

As indicated in Table 4.3, the number of variables is almost doubled in the larger water-energy network while the solution time tripled for this case. Other solves of this model with different parameters required even longer solving times, which may be unacceptable

for certain applications. Authors in [140] state existing techniques that provide satisfactory solutions for optimizing water operations are limited to small water networks. The authors further state optimal planning of water distribution operations is one of the most challenging problems to solve in water systems planning. Therefore, authors in [141] recommend techniques such as decomposition, coordination, and aggregation to solve large water network optimization and control problems. These solutions may be required as the water network increases further in size.

Table 4.3: Computational comparison of small and large water-energy networks.

Case	No. of Variables	No. of Discrete Variables	Solving Time (s)
Coupled 10/13 Node Network	66,521	13,980	85.38
Coupled 30/37 Node Network	131,617	28,584	256.31

Due to the increase in the number of pumps and tanks, the outcome of this coupling was expected to be greater than the results obtained from the smaller coupled network. Similar to the smaller network, the tanks in the larger water network achieve shifting the pump demands so that they no longer align with the peaks of the water demand, as illustrated in Figure 4.11. As there is an additional pump in the system compared to the smaller case, the power consumed by the pumps is greater. Further, the pumps require more power to meet water demands and minimum pressure heads in this physically larger network. This provides a greater platform for demand response techniques.

Additionally, as indicated in Figure 4.12, the utilization of the VRE in the case with the tank improved compared to the case without a tank. The curtailment in the case with the tank is decreased in Timeslot 3. This aligns with a greater pump demand in the same timeslot. Therefore, the pumps can operate to consume excess VRE to fill the water tanks, which also show a peak in tank volume at this time in Figure 4.12. In both cases, the rest of the timeslots see full utilization of the VRE generation. The combined volume of water in the tanks increases again around Timeslot 7 when there is a spike in pump demand. The tanks generally discharge in the last half of the day to meet water demands without requiring significant pump operation.

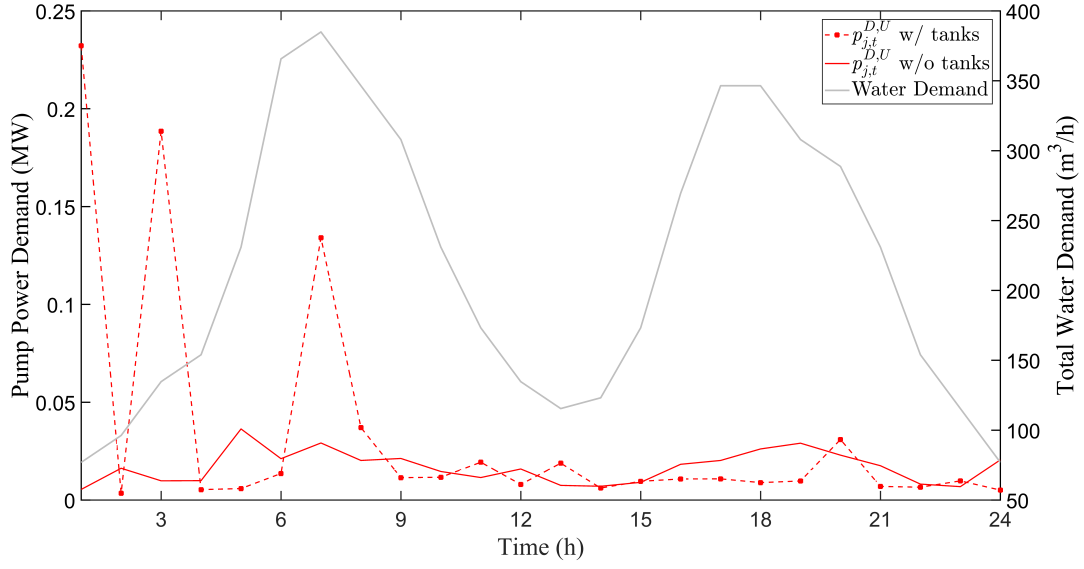


Figure 4.11: Summed pump power ($\sum_j p_{j,t}^{D,U}$, where $j \in \mathcal{U}$) schedule versus water demand in the large water-energy network.

Although the coupling of the water network with elevated water tanks to the electricity network can improve the VRE utilization and optimally shift pump demands to best serve the electricity network, it is not guaranteed that this coupling will improve or drastically change

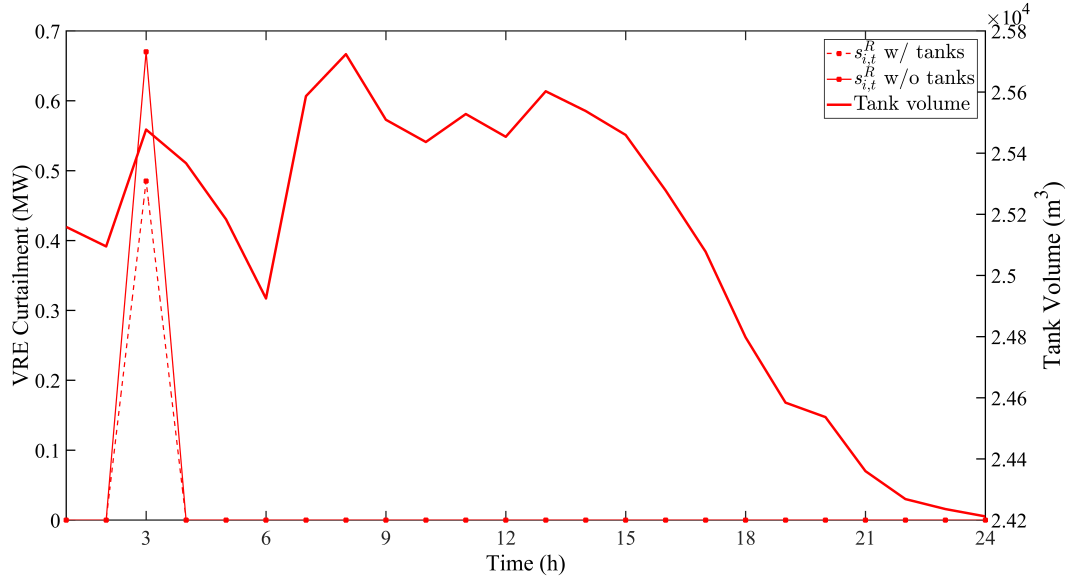


Figure 4.12: VRE curtailment summed over the generation locations ($\sum_i s_{i,t}^R$, where $i \in G$) and tank volume for cases with and without a tank in the large water-energy network.

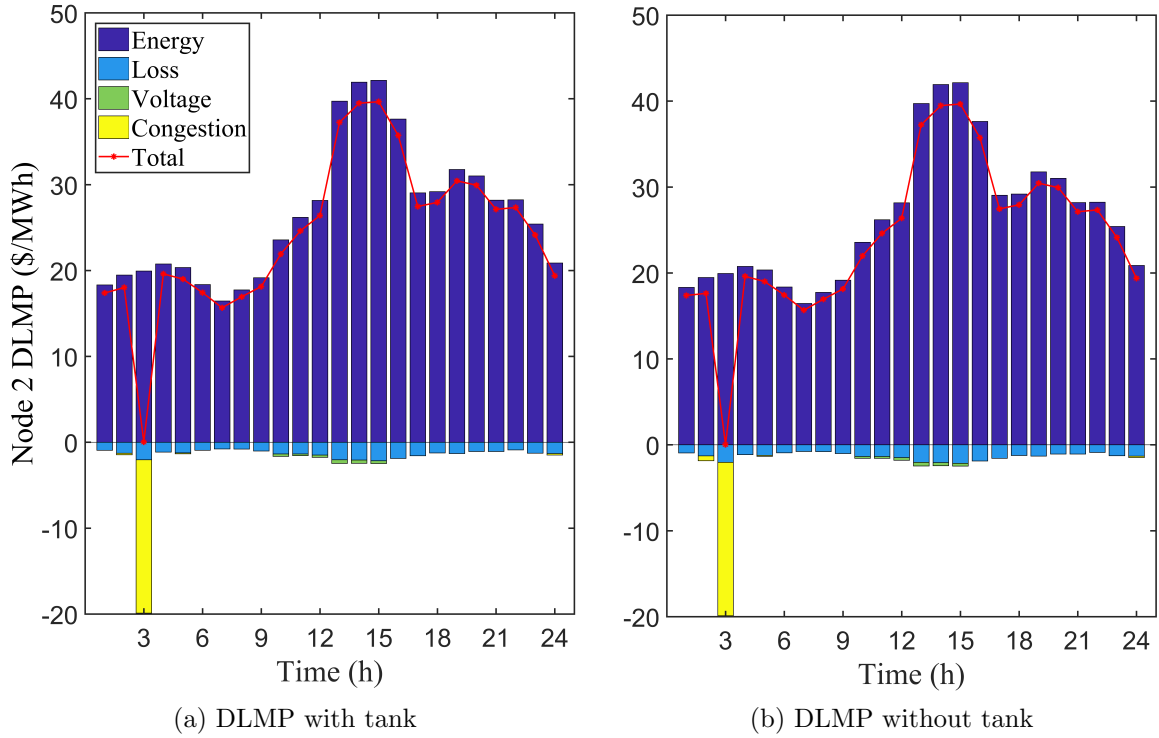


Figure 4.13: Node 2 component-wise DLMP for cases with and without a tank in the large water-energy network.

the DLMP. This claim is supported by the observation of Node 2's DLMP in each case in Figure 4.13. In Timeslot 2, the congestion component for the case with a tank (Figure 4.13a) is slightly reduced compared to the case without a tank (Figure 4.13b). However, the case with the tank does not reduce or remove the congestion in Timeslot 3 in this scenario. Line 2 incurs congestion in this timeslot because the apparent power flow limit is met when selling excess VRE to the substation node at LMP. Congestion in Timeslot 3 causes curtailment of the VRE at Node 23.

Additionally, small voltage components in Timeslots 10-15 are present in both cases. Node 13's upper voltage constraint is met in these timeslots. Therefore, Node 2 sees activated voltage components for its part in causing such problems in Node 13. Further, the case with the tank can potentially worsen the DLMP profile compared to the case without the tank, as the tank allows for smaller pump demands in some cases, which can lead to congestion of lines, voltage violations, and more VRE curtailment. However, the pumps draw more energy

(+0.4 MWh) in the case with the tank, indicating they are acting to provide services to the grid.

The grid-serving shortcomings in the larger model could be due to a number of reasons. For example, a sensitivity analysis on the number of tanks in a stand-alone water distribution network is carried out in [88]. It was found that after a certain point, adding tanks to the water network only provides marginal profit increases, indicating the addition of tanks may follow the law of diminishing returns. This may be related to why the larger water-energy network in this work did not provide significantly greater results than the smaller model. Also, a greater number of tanks in the network can better serve the water demands, allowing for less power demand from the pumps. Further, the water network used may be ill-conditioned as a database of realistic water networks, like the IEEE test feeder set for electricity networks, does not exist to my knowledge. Such models would ensure proper typologies and parameters are applied to specific water networks.

Additional limitations in the larger coupled network could have to do with the electrical distance between nodes. In the smaller network, nodes with pump demands and VRE sites were electrically closer to one another than in the larger network, where they are more spread out. Note, a node's voltage depends on the surrounding (upstream and downstream) nodes and their power injections and losses, as in Equation (3.71). As an example, it was assumed that Pump 22 could operate to reduce the voltage violation at Node 23 in Timeslots 10-15. Yet, Pump 22 does not opt to consume power in these timeslots. Perhaps this is because the impact is too small because Nodes 22 and 23 are more distant from one another, as they are separated by Node 9. However, the BESS at Node 9 consumes at its maximum rate in this timeslot. Note, Pumps 2 and 25 have VRE sites located at their nearest neighbor, Nodes 2 and 24, respectively. This was also the case in the smaller water-energy network, where pumps are one node away from VRE sites. Closer evaluation is needed to understand the impact of power injection and losses at a node further away than closer nodes. Additionally, results may be improved with the consideration of a VRE curtailment penalty in the objective function, which would discourage waste of available VRE generation.

4.5 Conclusion

Numerical results show the advantages of combining these two networks and utilizing water pumps and tanks as jointly flexible loads. For the first time, the following observations can be made.

- The water network can positively impact the DLMP by minimally reducing voltage violation and congestion penalties when VRE penetration is high. By optimally scheduling the water tank, the congestion on certain electricity distribution lines can be eliminated. The water tank storage can prevent line congestion and binding nodal voltage constraints. As a result, it can ease the operational challenges in the electricity distribution network.
- In a high VRE scenario, the tank aids in lowering the curtailment of VREs by filling over time to absorb excess VRE generation in the system, though typically by a small amount due to relatively small pump demands and limited tank capacity.
- The use of the water tank allows the peak pump demand to shift away from the non-pump peak electricity demand, reducing the total peak electricity demand. From the perspective of the electricity DSO, an advantage of combining the two networks comes in the form of congestion relief in the electricity distribution network.
- When combined with VRE generation, the coordinated water and electricity network offers a unique storage solution of excess VRE generation through the use of the water tank. Similar to a battery, the tank can store water to use later when there is more VRE generation in the system than there is demand.
- The data-driven PEP method with different probability levels can impact the coordinated operation of the water and electricity networks and the VRE curtailment, which provides a means to manage the VRE uncertainty.
- Failed components in one network are capable of changing system behavior in the other network.

- Larger coupled water-energy networks have the potential to impact VRE utilization, grid conditions, and the DLMP in different ways. However, more studies are needed to investigate the extent of the impact.

In this chapter, a novel coordinated water and energy model was formulated and validated on a coupled IEEE 13-node electrical distribution network and 10-node water network, and extended to a coupled IEEE 37-node electricity network and 30-node water network. The proposed method can impact interdependent water and energy network policies, especially those seeing significant increases in VRE generation. Under the consideration of VRE uncertainty, the impact of coupling of the water and electricity networks on the DLMP was shown for the first time. Further, it was shown how the coupling of the water and electricity distribution networks could supplement future distribution markets that consider DLMP. Note that this work does not consider the cost of storing energy in water tanks. Interesting further work includes quantifying a financial incentive beyond the benefits from DLMP that can be allocated to water utilities for providing demand response services to the electricity DSO. The financial incentive should include compensation for accelerated aging of the pumps, increased energy prices, etc. This financial incentive can be easily added to the proposed model. This cooperation could help water utilities reduce operational costs.

The proposed model and method can offer utilities a new tool in managing the coordinated operation of water and electricity distribution networks under uncertain VRE generation. With the recent call for more energy-efficient systems, the approach provided in this work can serve as an energy-saving solution to water and electric utility operators. As longer solving times in day-ahead optimization problems are not a pressing issue, this model should scale to a certain point with ease, as discussed in the larger water-energy case study. If the larger system is unable to solve in a reasonable time, authors in Reference [142] have proposed a clustering technique to combat this issue. While energy storage and demand response through drinking water storage tanks are considered here, this study can be extended to various types of flexible loads that can act as an energy storage medium, each with its own benefits, challenges, and limitations.

Chapter 5

Ammonia Plant and Fuel Cell Model and FEW Coupling¹

In this chapter, an investigation into the coupling of a the electricity distribution system and a demand-responsive green ammonia synthesis plant within the food-energy-water (FEW) nexus is conducted. The capability of chemical energy storage in ammonia and the impact on the distribution locational marginal price (DLMP) is examined in a case study with high renewable energy (RE) resources.

5.1 Background

The novelty of the work presented here resides in the quantitative consideration of a combined electricity distribution system and ammonia production plant with constraints in a day-ahead or real-time scheduling problem. The impact of the coordination of the ammonia plant on the DLMP will be explored to discover the optimal operation of an electricity distribution system and an ammonia plant.

For the first time, an investigation into the viability of a green ammonia production plant to serve as a demand-responsive load to the electric power system is proposed and

¹This chapter is a slightly modified version of our articles [48] and [53].

tested on a realistic electricity distribution system. To achieve this, a mixed-integer linear programming (MILP) model of a merged power system and ammonia plant is proposed to optimally schedule distributed energy resources (DERs), electricity loads, and ammonia production, which is the first model of this kind. Here, the flexible electricity demand from the ammonia production is coupled with the total electricity demand. Power-to-ammonia-to-power (P2A2P) applications are also considered using a direct ammonia fuel cell to provide power to the electricity grid. When the demand is greater than the generation in the power system or when the price of producing electricity is high, the ammonia plant responds to this price by reducing its electricity load to aid in the power balancing of the electric grid. When there is excess RE generation in the local system, the plant produces and stores more ammonia. The excess ammonia is stored in tanks and sold into the ammonia market or even fed back into the power system through direct ammonia fuel cells. This P2A2P process using a fuel cell has a round-trip efficiency of around 30% [143]. This procedure is only favorable in islanded or emergency situations due to the costliness of consuming ammonia which could otherwise sell for higher profits in the bulk ammonia market. Further, the present-day power output of commercial fuel cells is still relatively small, typically in kilowatts.

The coupling proposed in this chapter can reduce electricity costs and renewable energy curtailment. When there is insufficient ramping down capability in thermal units or power line congestion, RE curtailment typically occurs, reducing the utilization of available wind and photovoltaic (PV) energy [135]. The proposed electricity model does not consist of thermal units with ramping constraints; therefore, RE curtailment is caused by congested lines and voltage violations. This model is optimized from the perspective of the distribution system operator (DSO) and considers physical constraints of both the ammonia plant and the electricity distribution system. The electricity costs of powering the green ammonia plant determine a significant portion of the operational costs and control the economics to make this process competitive with brown ammonia plants. Therefore, ammonia plant operational costs are reduced when the cost of supplying electricity is minimized.

A community microgrid based on a modified Pacific Gas & Electric (PG&E) 69-node electricity distribution system is coupled with a demand-responsive ammonia plant is used

to perform case studies. Under the future case of a distribution market (as described in [4]), the capability of anhydrous ammonia to serve as a storage medium of excess renewable energy is examined. Supplying energy using marginal operating costs is a central focus of future distribution markets. Thus, the impact on the DLMP from the cooperation of the green ammonia plant is studied. Simulation results verify the theory presented in this chapter.

5.2 Electricity Distribution Model

In this agricultural microgrid coupled model, $\mathcal{O}(p_{i,\phi,t})$ and $\mathcal{O}(q_{i,\phi,t})$ in (3.1) are defined as in (5.1) and (5.2). This objective function minimizes the least-cost operation of the electricity distribution system.

$$\mathcal{O}(p_{i,\phi,t}) = \sum_{\phi,t} \lambda_t^{p_0} \cdot p_{0,\phi,t} + \sum_{i,\phi,t} c_{i,\phi,t}^{G,P} \cdot p_{i,\phi,t}^G + \sum_{i,\phi,t} \xi^R \cdot s_{i,\phi,t}^R \quad (5.1)$$

$$\mathcal{O}(q_{i,\phi,t}) = \sum_{\phi,t} \lambda_t^{q_0} \cdot q_{0,\phi,t} + \sum_{i,\phi,t} c_{i,\phi,t}^{G,Q} \cdot q_{i,\phi,t}^G \quad (5.2)$$

The real and reactive locational marginal prices (LMPs) at the substation node connected to the transmission system are represented by $\lambda_t^{p_0}$ and $\lambda_t^{q_0}$, and the real and reactive net power injections at the substation node are $p_{0,\phi,t}$ and $q_{0,\phi,t}$, which is assumed to be an infinite source. Negative net power injections indicate the DSO is buying real or reactive power from the distribution system at the LMP of the substation node. Distributed generators (DGs) bid at $c_{i,\phi,t}^{G,P}$ for real power and $c_{i,\phi,t}^{G,Q}$ for reactive power. Here, the marginal cost of the generator is used as the bid of the DG. The real and reactive power supplied by the generators are indicated by $p_{i,\phi,t}^G$ and $q_{i,\phi,t}^G$. The reactive power output of the DG must lie within a fraction, $+\kappa^G$, of the real power output. The RE resources bid at \$0/MWh and are therefore not present in the objective function. Similarly, under the assumption these assets are owned by the DSO, the battery energy storage system (BESS) units and the direct ammonia fuel cell do not bid into the market. Instead, these resources operate to best serve the needs of the system. Not considered in the objective function, the reactive power outputs of the BESS

and RE units must lie within $+\kappa^B$ and $+\kappa^R$ of their respective real power counterparts. The final term in (5.1) penalizes renewable energy curtailment ($s_{i,\phi,t}^R$) at a value of ξ^R . This is to discourage inefficient utilization of the RE resources in the system. Note the RE generation is curtailed equally across all phases.

Further, in this coupled ammonia microgrid model, Dem in (3.4) include real and reactive traditional power demands and ammonia plant demands. Meanwhile, Gen in (3.5) includes real and reactive power supplied from DGs, BESSs, RE sources, and direct ammonia fuel cells ($p_{i,\phi,t}^{FC}$, $q_{i,\phi,t}^{FC}$).

5.3 Ammonia Plant and Fuel Cell Models

Similar to the electricity distribution system defined in Chapter 3, indices $i \in N$, $\phi \in \Phi$, $t \in \mathcal{T}$ are used. Here, i is the node where the ammonia plant and fuel cell connect to the electricity distribution system. A balanced, three-phase, real and reactive load for the green ammonia plant is considered. Through the use of advanced power electronics, the direct ammonia fuel cell is capable of providing real and reactive power to the system [144, 145].

5.3.1 Ammonia Plant Model

The electricity demand and production tracking of an ammonia plant are modeled by constraints (5.3)–(5.18). The electrical load for ammonia ($p_{i,\phi,t}^{D,A}$) is comprised of hydrogen production from water electrolysis, nitrogen production from air separation, and ammonia condensation through the Haber-Bosch process. The chemical formula for ammonia production using this procedure is $6\text{H}_2\text{O} + 2\text{N}_2 \rightarrow 4\text{NH}_3 + 3\text{O}_2$. Hydrogen production requires, by far, the largest amount of energy to run. Assumed at a consumption of 41.79 MWh/ton_{NH₃} of H₂, this process requires 17.6% of the tons of ammonia produced in H₂ [47]. The nitrogen production assumes a rate of 0.243 MWh/ton_{NH₃} of N₂ while requiring 82.4% of the tons of ammonia produced in N₂ [47]. The Haber-Bosch process requires 0.144 MWh/ton_{NH₃} of energy to operate. In total, and as defined in (5.3), the energy demand per metric ton

(MWh/ton_{NH₃}) rate ($p^{D,AR}$) for this process is 7.7 MWh/ton_{NH₃} [96].

The power demand of the ammonia plant depends on the operational mode of the plant and is captured in (5.3). The load is considered equivalent across all three phases of the distribution feeder; therefore, the total power demand is divided by three and equally assigned to each phase. To ensure the ammonia produced is categorized as “green” ammonia, the total demand must be less than the total renewable power in the system at a given time, $\sum_{i,\phi} p_{i,\phi,t}^R$, as in (5.4). Binary indicators $\mathbb{I}_{i,\phi,t}^A$ and $\mathbb{I}_{i,\phi,t}^P$ allow for ‘on’, ‘off’, and ‘warming’ modes. If the plant is ‘on’ ($\mathbb{I}_{i,\phi,t}^A = 1$) and producing ammonia ($\mathbb{I}_{i,\phi,t}^P = 1$), the power demand is a linear relationship between the production rate and the amount of ammonia produced in metric tons in that timeslot, $A_{i,t}^P$. To reduce the energy consumption when the price of electricity is high, a ‘warming’ mode is considered. The Haber-Bosch reactor can be warmed at a significantly lower power demand than when producing ammonia due to the high energy demand of water electrolysis. Considering maintaining British thermal units, a warming model allows for the minimization of shut-down and start-up operations. If the plant is ‘on’ ($\mathbb{I}_{i,\phi,t}^A = 1$), but not producing ammonia ($\mathbb{I}_{i,\phi,t}^P = 0$), it is in the ‘warming’ mode and the power demand is a constant based on the energy necessary for warming the reactor, $p^{D,W}$. Finally, if the plant is ‘off’ ($\mathbb{I}_{i,\phi,t}^A = 0$), which is a rare case but is included in this model for completeness, there is no power demand. Note, the plant is not allowed to be ‘off’ ($\mathbb{I}_{i,\phi,t}^A = 0$) and producing ammonia ($\mathbb{I}_{i,\phi,t}^P = 1$) at the same time, as enforced in (5.5). Note, the power demand for the ‘off’ mode is also reflected in (5.3) when $\mathbb{I}_{i,\phi,t}^A$ and $\mathbb{I}_{i,\phi,t}^P$ both equal ‘0’ and there is no ammonia produced when $\mathbb{I}_{i,\phi,t}^A$ is ‘0’, as enforced in (5.6).

The ammonia plant is considered to be a demand response system that produces $A_{i,t}^P$ tons of ammonia in an hour. The amount of ammonia produced in a timeslot must fall between the minimum ($\underline{A}^P$) and maximum ($\overline{A}^P$) amount of ammonia capable of being produced in that time frame, as in (5.6). Note, if the plant is not producing ammonia, the amount produced in that timeslot is zero. At the end of the time frame ($\mathcal{T}$), the summed amount of ammonia produced in a timeslot ($A_{i,t}^P$) and the ammonia consumed by the fuel cell ($A_{i,\phi,t}^{FC}$), must total to at least $\underline{A}_i^S$ metric tons per day (TPD), as determined by the ammonia plant owner, as in (5.7). In the case of excess renewables and thus low-cost electricity, the ammonia

plant can produce more ammonia to best benefit the utility in reducing voltage violations and line congestion. The excess renewable energy is stored as ammonia. It can then be used as fertilizer on-site, sold into the ammonia market, or consumed to produce electricity using a fuel cell.

The feedstock of ammonia ($A_{i,t}^S$), and the reduction due to its use by the fuel cell, is tracked as in (5.8), and must not exceed the maximum amount of ammonia capable of being stored on-site, $\overline{A}_i^S$. In the first timeslot, $A_{i,t-1}^S$ is the initial value of the feedstock of ammonia and is available for fuel cell use at the beginning of the day.

$$p_{i,\phi,t}^{D,A} = \frac{p^{D,W}}{3} \cdot (\mathbb{I}_{i,\phi,t}^A - \mathbb{I}_{i,\phi,t}^P) + \frac{p^{D,AR}}{3} \cdot A_{i,t}^P \quad (5.3)$$

$$\sum_{i,\phi} p_{i,\phi,t}^{D,A} \leq \sum_{i,\phi} p_{i,\phi,t}^R \quad (5.4)$$

$$\mathbb{I}_{i,\phi,t}^P \leq \mathbb{I}_{i,\phi,t}^A \quad (5.5)$$

$$\underline{A}^P \cdot \mathbb{I}_{i,\phi,t}^P \leq A_{i,t}^P \leq \overline{A}^P \cdot \mathbb{I}_{i,\phi,t}^P \quad (5.6)$$

$$A_{i,\mathcal{T}}^S \geq A_{i,0}^S + \underline{A}_i^S \quad (5.7)$$

$$A_{i,t}^S = A_{i,t-1}^S + A_{i,t}^P - \sum_{\phi} A_{i,\phi,t}^{FC} \leq \overline{A}_i^S \quad (5.8)$$

For best performance, the ammonia plant is forced to remain ‘on’ for a minimum of UT_i number of hours and ‘off’ for a maximum of DT_i hours. Equations (5.9) and (5.12) ensure the ‘on’ ($T_{i,\phi,t}^{on}$) and ‘off’ ($T_{i,\phi,t}^{off}$) time counters are positive and do not exceed the scheduling horizon limit ($\mathcal{T}$). Equations (5.10) and (5.13) increase the respective counter by one if the unit remains ‘on’ or ‘off’. The minimum number of consecutive hours ‘on’ and the maximum number of consecutive hours ‘off’ are constrained by (5.11) and (5.14) with the use of binary ‘on’ and ‘off’ indicators, $\mathbb{I}_{i,\phi,t}^{on}$ and $\mathbb{I}_{i,\phi,t}^{off}$, which are ‘1’ in the timeslot the plant turns ‘on’ or ‘off’, and ‘0’ otherwise. These indicators must not both be activated in the same timeslot, as enforced in (5.15). If there is a change in the plant’s ‘on’/‘off’ status within two timeslots the respective indicator will capture this change (5.16).

$$0 \leq T_{i,\phi,t}^{on} \leq \mathcal{T} \cdot \mathbb{I}_{i,\phi,t}^A \quad (5.9)$$

$$(\mathcal{T} + 1) \cdot \mathbb{I}_{i,\phi,t}^A - \mathcal{T} \leq T_{i,\phi,t}^{on} - T_{i,\phi,t-1}^{on} \leq 1 \quad (5.10)$$

$$T_{i,\phi,t}^{on} \geq UT_i \cdot \mathbb{I}_{i,\phi,t+1}^{off} \quad (5.11)$$

$$0 \leq T_{i,\phi,t}^{off} \leq \mathcal{T} \cdot (1 - \mathbb{I}_{i,\phi,t}^A) \quad (5.12)$$

$$1 - (\mathcal{T} + 1) \cdot \mathbb{I}_{i,\phi,t}^A \leq T_{i,\phi,t}^{off} - T_{i,\phi,t-1}^{off} \leq 1 \quad (5.13)$$

$$T_{i,\phi,t}^{off} \geq DT_i \cdot (1 - \mathbb{I}_{i,\phi,t+1}^{on}) \quad (5.14)$$

$$\mathbb{I}_{i,\phi,t}^{on} + \mathbb{I}_{i,\phi,t}^{off} \leq 1 \quad (5.15)$$

$$\mathbb{I}_{i,\phi,t}^{on} - \mathbb{I}_{i,\phi,t}^{off} = \mathbb{I}_{i,\phi,t}^A - \mathbb{I}_{i,\phi,t-1}^A \quad (5.16)$$

The ammonia plant can be turned ‘on’ and ‘off’ at a rapid rate, on the order of minutes. Therefore, within an hour timeslot, the on and off time lags can be ignored in the model. Further, the ammonia plant is not able to instantaneously change its power consumption, but rather ramps up at RU_i MW/h (5.17) and ramps down at RD_i MW/h (5.18).

$$p_{i,\phi,t}^{D,A} - p_{i,\phi,t-1}^{D,A} \leq RU_i \quad (5.17)$$

$$p_{i,\phi,t-1}^{D,A} - p_{i,\phi,t}^{D,A} \leq RD_i \quad (5.18)$$

5.3.2 Fuel Cell Model

The power produced by the fuel cell ($p_{i,\phi,t}^{FC}$) is determined by the linear relationship between the amount of ammonia consumed by the fuel cell and the conversion rate, $p^{FC,R}$, as modeled in (5.19). The fuel cell is ‘on’ when the ammonia consumed by the fuel cell ($A_{i,\phi,t}^{FC}$) is between the minimum ($\underline{A_{i,\phi,t}^{FC}}$) and maximum ($\overline{A_{i,\phi,t}^{FC}}$) consumption rate of the fuel cell in tons, and is indicated by binary variable $\mathbb{I}_{i,\phi,t}^{FC}$, mathematically modeled in (5.20). The ammonia used by the fuel cell must be less than the amount of the on-site ammonia feedstock in the previous timeslot and the ammonia produced in that timeslot, as in (5.21).

$$p_{i,\phi,t}^{FC} = p^{FC,R} \cdot A_{i,\phi,t}^{FC} \quad (5.19)$$

$$\underline{A_{i,\phi,t}^{FC}} \cdot \mathbb{I}_{i,\phi,t}^{FC} \leq A_{i,\phi,t}^{FC} \leq \overline{A_{i,\phi,t}^{FC}} \cdot \mathbb{I}_{i,\phi,t}^{FC} \quad (5.20)$$

$$\sum_{\phi} A_{i,\phi,t}^{FC} \leq A_{i,t-1}^S + A_{i,t}^P \quad (5.21)$$

5.3.3 Merged Ammonia Plant and Power Flow Problem

The coupled electricity and ammonia plant model is captured in the optimization problem **P₅**. In this model, the ammonia plant is considered to be a demand-responsive system. The ammonia production is not optimized for the the most profit, but all constraints, including the minimum required metric tons of ammonia per day, must be met. Here, $p_{i,\phi,t}^{Dem}$ in (3.4) is a summation of the non-ammonia electrical demand and the optimized ammonia demand, $p_{i,\phi,t}^{D,A}$, associated with its respective node i . A similar coupling can be made for reactive power demand. The fuel cell real and reactive generation is included in Gen in the nodal power balance constraints (3.4) and (3.5). The coupled optimal power flow and ammonia production problem, **P₅**, is defined as:

P₅: min(3.1)

subject to: (3.4)-(3.5), (3.9)-(3.10), (3.13)-(3.14), (3.18)-(3.42), (3.65)-(3.71),
(3.99)-(3.100), and (5.3)-(5.21)

5.4 Case Study

A modified, unbalanced three-phase agricultural community microgrid based on the PG&E 69-node distribution system connected to a small-scale, electricity-run ammonia plant is considered to validate the proposed model and investigate its impact on the DLMP. These results are to be published in [48, 53]. Figure 5.1 shows a oneline diagram of the system. A high renewable case is considered with renewable generation units at Nodes 21, 22, 42, 44, 48, 49, and 61, with a maximum availability of 12.72 MW per phase. Three single-phase 0.5

Table 5.1: Green ammonia plant parameters used in case study.

UT_i	2 h	DT_i	6 h
RU_i	1 MW	RD_i	2 MW
$\overline{A_i^S}$	5 tons	$\overline{A_i^S}$	200 tons
$\overline{A^P}$	0.05 tons	$\overline{A^P}$	5 tons
$p^{D,AR}$	7.7 MWh/ton	$p^{D,W}$	0.002 MW
$\overline{A_{i,\phi,t}^{FC}}$	0.0025 ton/h	$\overline{A_{i,\phi,t}^{FC}}$	0.1 ton/h
$p^{FC,R}$		1.6 MWh/ton	

MWh BESS units are on each phase at Node 2. The BESS was sized to aid in balancing the system. The unbalanced system, which follows a typical summer day load curve, sees a (non-ammonia) three-phase peak load of 14.55 MW. This is representative of a distribution feeder, which typically range from 0.6 to 28.5 MW per phase [93]. Further, a typical summer day is used, which exhibits the peak electrical load.

The balanced, three-phase energy demands of the green ammonia plant are included in the electrical demand for Node 7, and the fuel cell can independently provide power to each phase at Node 7. The substation LMP ranges from \$16.56/MWh to \$42.14/MWh, modeled after a typical summer day. A balanced, three-phase, 4.5 MW distributed generator is located at Node 62. This DG bids into the market at a cost higher than the LMP, \$61.69/MWh per phase, under the assumption that the marginal cost of a DG is more expensive than buying power from the grid. The historical data of Western Wind and Solar Integration Study [133] is modified and used for hourly samples of wind and PV generation.

The green ammonia plant, at minimum, must produce a desired 5 TPD of ammonia. Table 5.1 shows the green ammonia plant parameters considered in this study. The fuel cell is modeled after a futuristic, scaled-up direct ammonia fuel cell currently in the commercial market, the Gencell A5 fuel cell [146]. GAMS/CPLEX 28.1.0 [130] was used to solve the proposed MILP, $\mathbf{P}_5$. The following cases are defined:

Case 1–Decoupled Electricity and Ammonia Models: The ammonia plant operates without consideration of the grid conditions. The ammonia demand is fixed and must be met in the electricity model. The output of ammonia is exactly

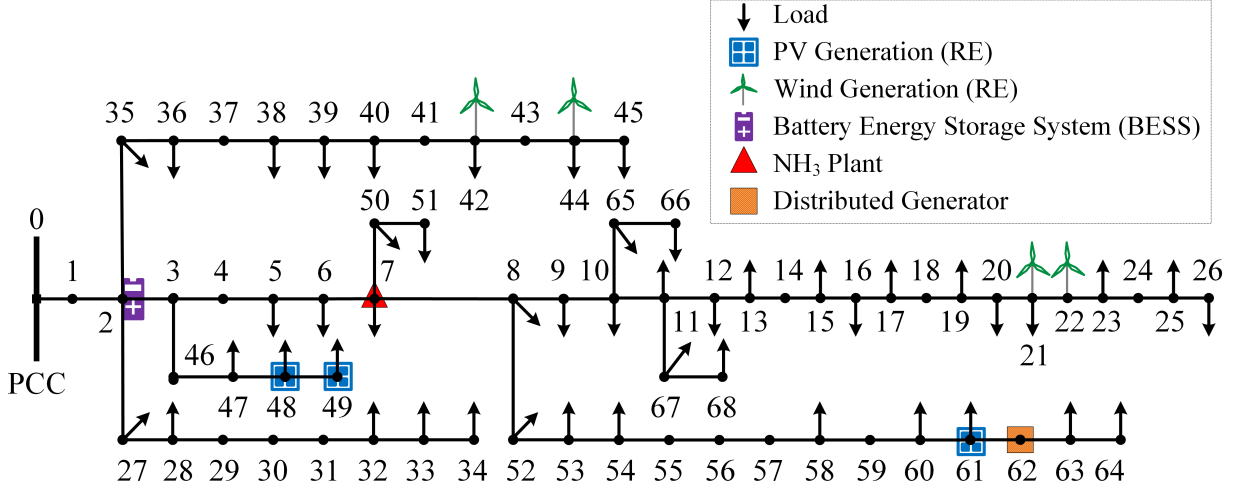


Figure 5.1: An agricultural community microgrid based on a modified three-phase PG&E 69-node distribution system with diverse distributed energy resources coupled with an electricity-run ammonia production plant and a direct ammonia fuel cell. To be published in [48].

$\underline{A}_i^S$ tons. The electrical system is grid-connected and can buy and sell energy at the LMP of the substation node.

Case 2–Coupled Electricity and Ammonia Model: The electric utility operates the ammonia plant, which acts as a demand-responsive system to best serve the electricity grid. The output of ammonia must be at least $\underline{A}_i^S$ tons but may exceed this value. The electrical system is grid-connected.

Case 3–Coupled Islanded Mode: The agricultural microgrid is islanded. Buying and selling energy from the grid at the substation node is not allowed. The system must meet all demands with the available DERs. The output of ammonia must be at least $\underline{A}_i^S$ tons but may exceed this value.

Case 4–Coupled Islanded Mode with Fuel Cell: In this islanded agricultural microgrid, buying and selling energy from the substation node is not allowed. This case is an emergency situation where, perhaps, a natural disaster (e.g., hurricane) destroyed essential transmission lines that fed power to this system. Some of the distributed wind turbines must be shut down due to high wind speeds. The need for power outweighs the high cost of electricity. Therefore, the

electric utility operates the typically high-cost fuel cell to best serve the islanded agricultural microgrid. The fuel cell operation has a cost associated with it, but at a relatively lower rate than the DG to discourage overuse of the fuel cell but allowing for liberal operation. The fuel used by the DG may have other uses during an emergency, so the cost associated with DG operation is higher than the fuel cell. In contrast, ammonia does not have other uses in a crisis.

The power demand is 30% of the normal demand. Wind speeds in the area are considered too high, and the wind turbines at buses 21, 22, 42, and 44 are shut down for safety purposes. Furthermore, a cloudy day is considered; therefore, the PV output is reduced and does not follow the typical sunny day curve. The desired TPD limit and ‘on’/‘off’ constraints of the ammonia plant are relaxed in this emergency case. The initial stock of on-site ammonia for use by the fuel cell is 40 tons.

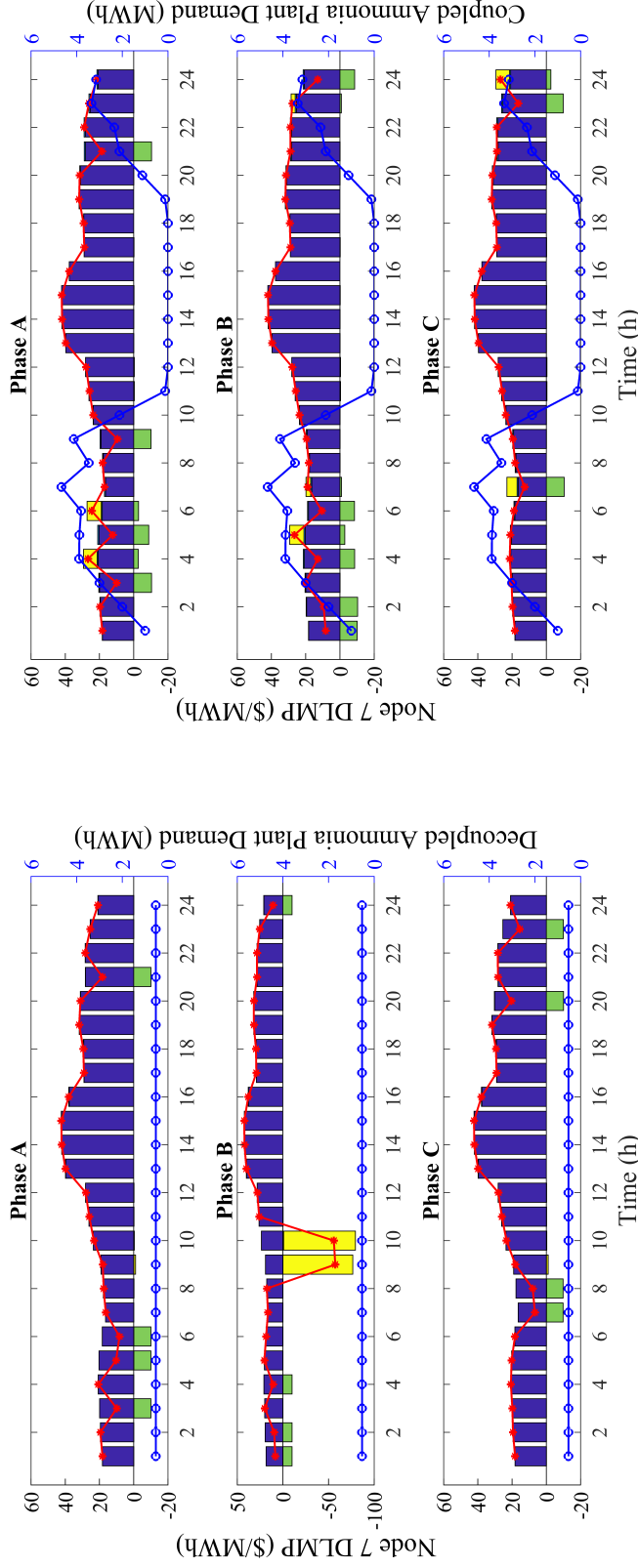
5.4.1 Impact of FEW Coupling on DLMP

The coupling of the green ammonia plant and the electricity distribution system has a distinct impact on the three-phase DLMP, as shown in Figure 5.2. Decoupled Case 1 considers the ammonia plant running at a constant load to produce the desired 5 tons by the end of the day. Case 1 sees many voltage violations and line congestion occurrences throughout the day, as shown with voltage and congestion DLMP components in Figure 5.2a, which are scaled-down to better understand the visualization. Further, power loss is unavoidable. Therefore, the system has loss DLMP components at every timeslot, though not all are visible due to their small size. Negative DLMP components indicate that the system would pay for extra load consumption to relieve operational issues. For example, many timeslots see negative voltage DLMP components due to the maximum voltage limit being met. The system would therefore benefit from more energy demand at that node to reduce the nodal voltage.

The decoupled green ammonia plant is unable to respond to the needs of the electrical system that are reflected in the DLMPs. Therefore, a coupled green ammonia plant and

electrical system is considered in Case 2. The ammonia plant can serve as a demand-responsive load to the electricity distribution system and therefore improve the DLMP of the system by reducing voltage violations, line congestion, and RE curtailment to the best of the plant's ability. As shown in Figure 5.2b, the ammonia plant demand is higher when the DLMP is lower (indicating fewer issues in the electrical system) and lower when the DLMP is high. For example, the ammonia plant is in the 'warming' or 'off' state for Timeslots 12-18 in Case 2 due to the high DLMPs at this time.

Further, the coupled system completely removed the large, negative congestion DLMP components on Phase B in Timeslots 9 and 10 in the decoupled case. The ammonia plant consumes a balanced three-phase power, which must be considered when serving the electrical system. For example, Timeslot 4 sees congestion in the system on Phase A but a negative voltage component on Phase B. Considering the overall DLMP and all other constraints, the ammonia plant best serves the system by operating during this timeslot.



(a) Case 1 DLMP-Decoupled

(b) Case 2 DLMP-Coupled

Figure 5.2: Node 7 three-phase, component-wise DLMP comparison of decoupled and coupled models for the electricity distribution system and green ammonia plant (Cases 1 and 2). The flexible, green ammonia plant operates to ease operational burdens (voltage violation, line congestion) in the electric grid in the coupled case, improving the DLMP. To be published in [48].

5.4.2 Impact of Demand-Responsive Green Ammonia Plant

In addition to the improvements on the DLMP mentioned previously, the coupled green ammonia plant also reduced the amount of RE curtailed in the system, as shown in Figure 5.3. In all timeslots, the RE curtailment is lower in the coupled case. In Timeslots 8 and 20, the coupled system is able to completely remove the RE curtailment in the system by allowing the green ammonia plant to consume excess RE generation. The decoupled case requires a constant demand and increases the base, non-ammonia plant demand equally throughout the day. The coupled system increases the total demand in the system by storing excess RE in ammonia. In some timeslots, the renewable energy is completely utilized by the base demand. For example, the ammonia plant is ‘warming’ in Timeslots 12-16 and ‘off’ in Timeslots 17-18 to not increase the load further and require more expensive energy from the substation node or the distributed generator as the total energy cost is minimized in the objective function. The green ammonia plant operates in a manner that attempts to level out the demand throughout the day.

Notice in most timeslots, the RE is still curtailed even in the coupled case. Nodal voltage limits being met and or congested lines in the system cause the RE curtailment, which is graphically depicted in Figure 5.2b. This curtailment indicates the importance of smart DER planning and grid upgrades to handle large amounts of distributed renewable energy resources expected in future distribution systems. Further, in both cases, the renewable energy is sold to the substation node at LMP until a constraint is met and it can no longer sell the excess energy. The flexible demand from the ammonia plant allows some of the curtailed RE in the previous case to be consumed by the ammonia plant. Due to the incentive in the objective function for selling excess energy, the system will attempt this option first and then store excess RE as ammonia. Therefore, next considered is an islanded system to compare the impact of the green ammonia plant on the system when there is no option to sell excess renewable energy to the larger grid.

The comparison between coupled grid-connected and islanded models is depicted in Figure 5.4. As expected, the renewable energy curtailment is greater in the case of the islanded

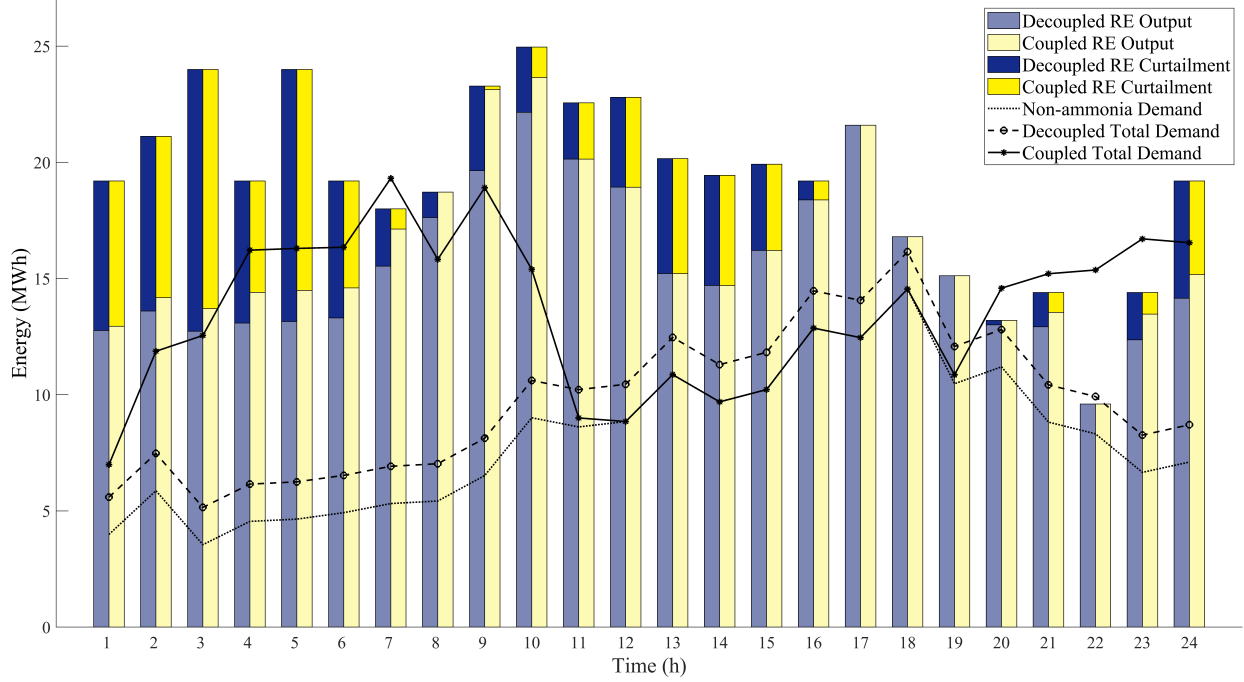


Figure 5.3: Comparison of decoupled and coupled electrical system and green ammonia plant (Cases 1 and 2). Renewable energy curtailment reduces in the coupled case as the flexible demand from the green ammonia plant increases. To be published in [48].

model (shown in red) in all timeslots except 9, as the excess RE can not be exported to the grid. A voltage limit is met in Timeslot 9 on Node 22 that forces the curtailment in Case 2. The green ammonia plant consumes as much of the excess RE in the islanded case that the constraints for both the ammonia plant and the agricultural microgrid allow, and the rest is curtailed at a penalty. Therefore, a larger stock of ammonia is observed at the end of the day in the islanded case, Case 3. In Case 2 (shown in blue), the hourly ammonia production is zero for Timeslots 12-18. The system would rather sell as much excess RE as the system allows than produce excess green ammonia. The ammonia produced and the utilization of the renewable energy in the system for each case are outlined in Table 5.2. Case 2 shows an improvement in renewable energy utilization over Case 1 while producing over three times the amount of ammonia by the end of the day. The RE utilization decreases in Case 3 as the system is islanded, and excess RE can no longer be sold back to the grid. However, more ammonia is produced by the end of the day to maximize the amount of RE used in the system. Under the emergency scenario in Case 4, the total available renewable energy was

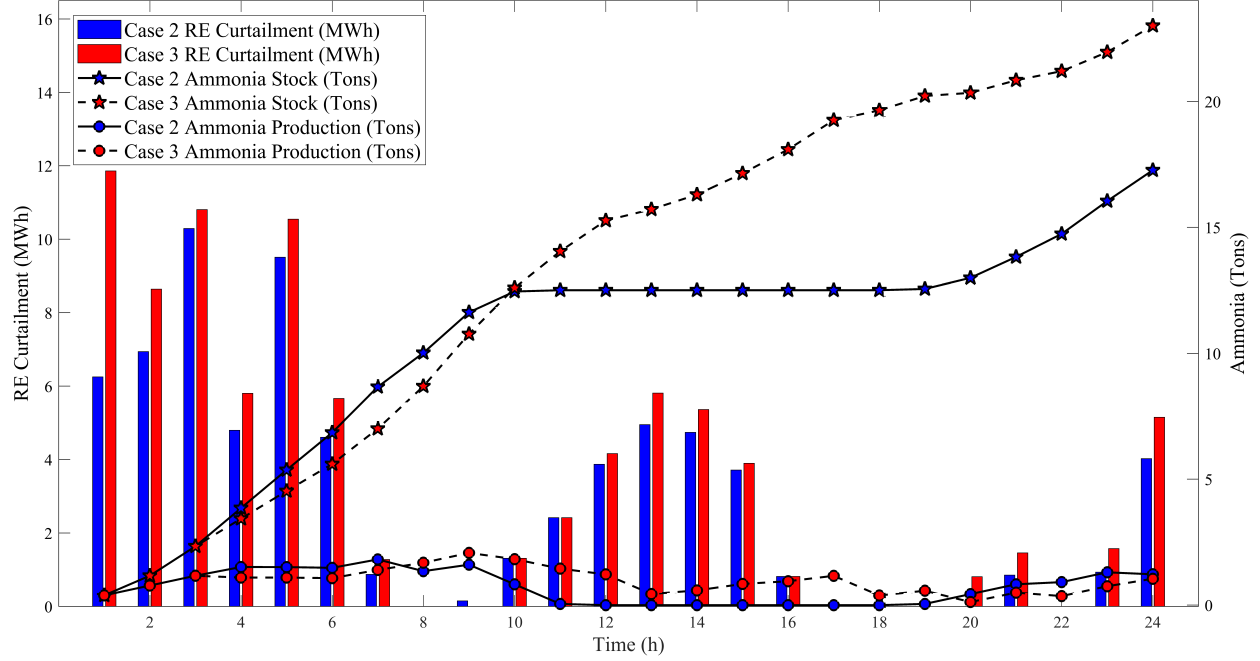


Figure 5.4: Comparison of coupled grid-connected and islanded models (Cases 2 and 3). The curtailment increases in the islanded agricultural microgrid case as excess renewable energy can not be sold to the grid. However, more ammonia is produced in Case 3 in attempt to reduce this curtailment. To be published in [48].

utilized while producing ammonia only in timeslots with excess RE. Case 4 will be further discussed in the following section.

Table 5.2: Comparison of green ammonia plant case study results.

	Case 1	Case 2	Case 3	Case 4
Tons of Ammonia	5	17.27	23.00	0.72
RE Utilization	81.02%	84.56%	81.01%	100%

To investigate the financial impact of this coupling, simplified ammonia plant electricity costs and profits are calculated post-solve. The real and reactive DLMPs at Node 7 are multiplied to the ammonia plant electricity demand in Cases 1 and 2 to calculate the true electricity costs of the ammonia plant. Electricity costs of \$869.36 and \$2,665.66 were computed for Cases 1 and 2, respectively. Recall the ammonia produced in Case 1 is 5.00 tons, and the amount produced in Case 2 is 17.27 tons. Ammonia prices are historically quite variable, with prices soaring over \$1,000 per ton in 2021 [147]. However, the minimum

average selling price of ammonia in years 2008-2014 was \$499 per ton of ammonia [148]. Therefore, this conservative market value is used to find the simplified profit (only considering electricity costs) from selling ammonia. The daily profits calculated for Case 1 and Case 2 are, respectively, \$1,625.64 and \$5,952.71.

A decoupled case producing 17.27 tons of ammonia per day and a coupled case producing 5.00 TPD are studied for a better comparison. However, the decoupled case is designed to use a constant power consumption across all timeslots by the ammonia plant. The total electricity cost of this case is \$3,512.13, nearly a 32% increase in the coupled case's (Case 2) electricity cost. This higher cost results in the coupled case's daily profit exceeding that of the decoupled case by more than 16%. Next, a coupled case held to 5.00 TPD is compared to Case 1. The flexible plant produced ammonia when DLMPs were low. Electricity costs drop by nearly a third, with the electricity cost of the ammonia plant being \$590.64. Ammonia plant daily profits increase 17% in this case. The ammonia plant financially benefits from the flexible coordination with the electricity DSO. Table 5.3 summarizes the results of this analysis.

Table 5.3: Daily economic performance for alternative configurations of ammonia production.

Configuration	Tons NH ₃	Ammonia Revenue	Electricity Cost	Ammonia Profit
Coupled	5.00	\$2,495.00	\$590.64	\$1,904.36
Decoupled (Case 1)	5.00	\$2,495.00	\$869.36	\$1,625.64
Coupled (Case 2)	17.27	\$8,618.38	\$2,665.66	\$5,952.71
Decoupled	17.27	\$8,618.38	\$3,512.13	\$5,106.24

5.4.3 Impact of Ammonia Fuel Cell in Emergency State

The total system energy in Case 4 for each timeslot is depicted in Figure 5.5. The renewable energy exceeds the base, non-ammonia plant demand in Timeslots 8 and 11-16. Under the assumption that all critical loads are met, excess RE can be consumed by the ammonia plant and made available for future energy use through the fuel cell. Due to the duration of the outage being unknown, energy storage is recommended during this time so valuable energy is not wasted. In all other timeslots, the renewable energy in the system is not enough to

meet the base demand. Therefore, the system relies on the BESS, direct ammonia fuel cell, and the distributed generator. The battery does not bid into the system and is used freely to best serve the system. Thus, the BESS charges during times of high RE and discharges at timeslots later in the day that do not have RE available. The fuel cell bids at a lower cost than the DG, and the system utilizes this resource in many timeslots. The fuel cell alone is not enough in most cases, as it has a relatively small power output. Therefore, the high-cost DG operates to make up for the necessary generation.

Note, in most cases, the green ammonia itself is the value-added commodity. In the case of an emergency, when the price of electricity is extremely high, converting the green ammonia back to electrons may be more cost-effective than selling to the bulk ammonia market. In an emergency, supplying power to the most critical loads (e.g., life-supporting loads) is more important than the cost of electricity.

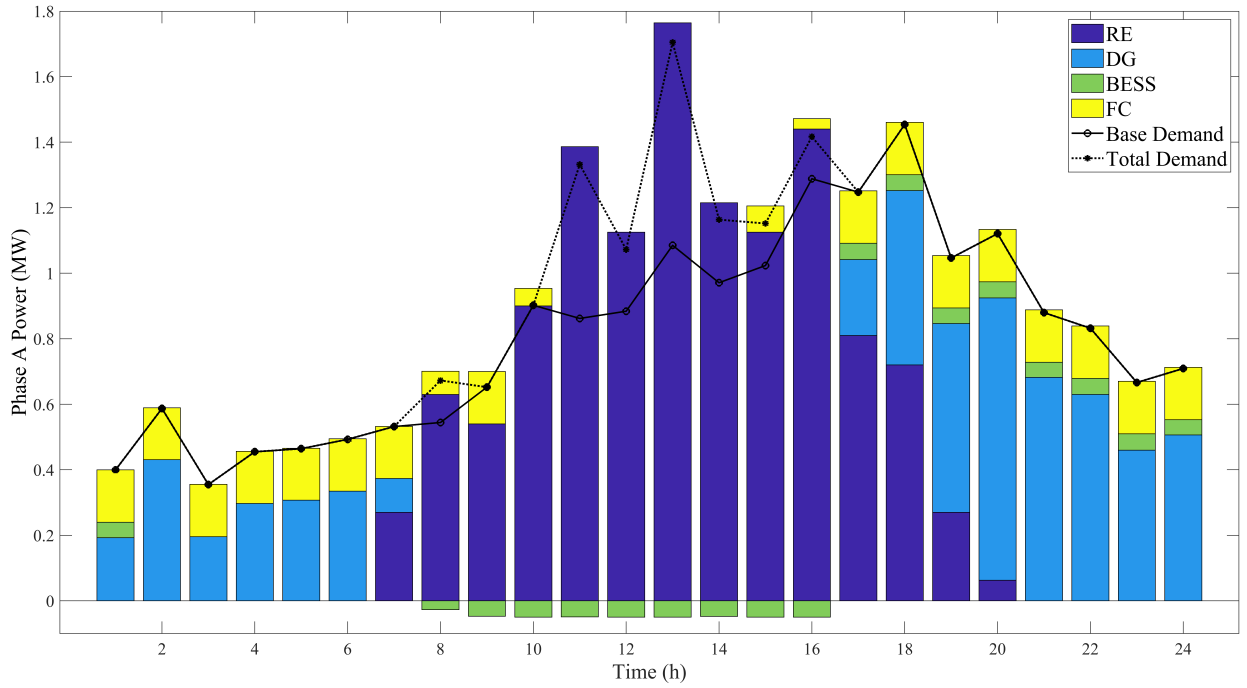


Figure 5.5: Phase A total power generation and demand in an emergency state (Case 4). The flexible green ammonia plant operates when the RE generation goes beyond the critical demand. The fuel cell operates to provide essential power to the weakened agricultural microgrid. To be published in [48].

5.5 Conclusion

The case studies provide numerical evidence that indicate the advantages of using a green ammonia plant as a flexible load and storage solution for agricultural community microgrids. The following observations are made for the first time.

- The DLMP can be favorably impacted by coupling the flexible green ammonia plant to the agricultural microgrid. Congestion and or voltage violations can be reduced or removed by optimally scheduling the ammonia plant with respect to grid conditions. Operational challenges in the microgrid with high levels of RE can be mitigated as a result of this coordination.
- The flexible operation of the green ammonia plant reduces the curtailment of renewable energy sources in a high penetration scenario. This is achieved by creating additional ammonia to consume excess renewable generation.
- By optimally controlling the green ammonia plant, the electricity demand shifts away from the peak electricity time to times with greater available renewable energy. A benefit of the coordination between the microgrid and the ammonia plant is the ability to shift demands to times where renewable energy would have otherwise been curtailed in a high renewable energy scenario. Also, reducing peak demands by allowing the ammonia plant to consume minimal energy in the ‘warming’ mode provides additional relief to the microgrid.
- As a result of this coupling, ammonia plant economics can be improved. Case studies showed electricity costs of the coupled ammonia plant could be reduced due to the plant operating in timeslots with lower DLMPs. Therefore, ammonia plants can gain higher profits when coupled with the optimal operation of the electricity grid.
- Through the chemical energy storage capabilities of ammonia, the coordinated agricultural microgrid and green ammonia plant offer a unique solution for storing excess renewable energy. The excess renewable energy will be stored in ammonia and sold to

the bulk ammonia or hydrogen market or used as electricity through the direct ammonia fuel cell. An advantage of chemical energy storage in ammonia over traditional batteries is long-term storage capability.

- The fuel cell offers additional power generation to the agricultural microgrid in emergencies or when the price of electricity is very high. Otherwise, green ammonia is more profitable when sold to the bulk ammonia or hydrogen market. The fuel cell allows this form of energy storage to be sold back to the grid, similar to a traditional battery but at a lower round-trip efficiency. The ability to sell ammonia directly differentiates this storage solution from a traditional battery.

A novel coordinated electricity and green ammonia plant model was formulated and validated on an agricultural community microgrid based on the PG&E 69-node distribution system. The impact of coupling the electrical system and the green ammonia plant on the DLMP was shown for the first time. This cooperation could strengthen future electricity distribution markets that consider DLMP. Further, the proposed model and method can offer utilities a unique tool in managing high renewable energy scenarios by coupling electricity distribution systems and green ammonia plants for storage and demand response solutions.

Not studied in this work is the cost of electricity incurred to the ammonia plant by storing excess renewable energy in ammonia. Quantifying a financial incentive for demand response services beyond the benefits of DLMP is interesting future work and can be easily added to the proposed model. Further, this work may impact policies regarding agricultural community microgrids with significant amounts of renewable energy resources.

To enhance the impact of the demand-responsive green ammonia plant, the anhydrous ammonia and direct ammonia fuel cell can be moved to other locations (nodes) in the system in the case of voltage instability, thermal line limits being met, or an emergency. Therefore, mobile fuel cells allow not only the temporal storage of electricity but also locational storage. The power generated by the fuel cell could serve any node in need and is not limited to a single node as most stationary power generators are. The total cost of this, including fuel and fuel cell transport, would have to be less than the elevated DLMP at this location.

Chapter 6

Conclusion and Future Work

This chapter concludes the dissertation with the main research results and outlines areas for future work. Chapter-specific conclusions are included in their respective chapters.

6.1 Conclusion

In this dissertation, interdependencies within the food-energy-water (FEW) nexus that provide unique demand response and storage platforms have been investigated to facilitate the efficient integration of distributed renewable energy generation with the distribution locational marginal pricing (DLMP) mechanism as the basis of this work. With the provided background, this dissertation addresses three major research questions that aim to address solutions to challenges when integrating variable renewable energy (VRE) resources into the distribution grid, such as balancing generation and load. Therefore, novel coupling opportunities within the FEW nexus are investigated for their demand response and energy storage capabilities. Further, methods to accurately reward such balancing actions through the DLMP are explored. The answers to these research questions can help forward-looking utilities and agriculture communities in efficient power management of their respective systems and reducing electricity costs. The accomplishments of this dissertation are summarized as follows.

Chapter 3 defines a three-phase, real and reactive, component-wise DLMP mechanism. Distributed energy resource (DER) physical constraints, grid constraints, power flows, and power losses were meticulously modeled using a mixed-integer linear programming (MILP) model to represent future distribution systems. Further, the data-driven probability efficient point (PEP) method was adopted to address VRE uncertainty. The proposed model was implemented and tested in several case studies. Simulation results demonstrate the significance of real and reactive, component-wise, and three-phase pricing. Finally, the DLMP price signal was tested in a home energy management system (HEMS) application, utilizing a private blockchain for HEMS users to communicate with the distribution system operator.

In Chapter 4, a novel coordinated water-energy model was formulated. Along with the electricity distribution model from Chapter 3, an MILP water network model was defined. The model was simulated in both a small and large coupled system. Results indicate that demand response services from the water network through elevated water tanks can support electricity distribution networks that consider DLMP and face high levels of VRE. The impact of this coupling on the DLMP was shown for the first time.

Finally, Chapter 5 investigates the coupling of a demand-responsive green ammonia plant to an electricity distribution system or community microgrid. The physical constraints of a small-scale green ammonia plant and direct ammonia fuel cell are modeled using an MILP model and were combined with the electricity distribution system defined in Chapter 3. Simulations show the impact of flexible plant demand and chemical energy storage through anhydrous ammonia on the electrical system and the DLMP. In an emergency, the fuel cell can provide power back to the grid to further help with balancing actions and provide essential power.

6.2 Future Work

This section summarizes potential research directions as follows. Chapter 3 analyzes the use of a DLMP market mechanism for future distribution markets. Interesting future work includes studying the effect of the balancing restriction on the DLMP and decomposing an

unbalance component. Optimal placement of DERs with respect to the benefits indicated by the component-wise DLMP could be an intriguing topic to investigate. A comparison of existing practices (time-of-use, net metering, etc.) and the DLMP mechanism, along with their impact on grid operations, would be an interesting area of research. Comparing the PEP method to other existing techniques that handle uncertainty is another compelling research direction. Extending the DLMP model to include fairness, based on work in [149], could be another area of further inquiry.

Chapter 4 considers a linear, coupled electricity model. This work can be extended to a bi-level operational model to maintain privacy in the networks. A stochastic programming model to address uncertainty could be another extension of this work. Cyber-attacks and their impact on interdependent networks can also be considered. Further, work can be done to improve the accuracy in the nonlinear water model. Similar to other works, the consideration of energy demands for water purification could be added to this model to provide further load flexibility to the electricity distribution system.

Chapter 5 investigates the viability of an agricultural community microgrid that flexibly operates an ammonia synthesis plant and fuel cell based on electricity grid conditions. This work can be improved in the future by updating the ammonia plant model to be more realistic using small-scale ammonia plant historical data, which is largely unavailable today. Further, this model can also be extended to a bi-level model, which considers uncertainty of variable renewable resources and demands. When run under various conditions, this operational model can be used for scenario generation for a long-term planning model for an agricultural microgrid.

The DLMP market mechanism is used as the foundation for the research in this dissertation. It is necessary to investigate the applicability of DLMP in future distribution markets and outline the pathway, including the advantages, drawbacks, and challenges, to move from the current operation to a future system that allows for more efficient integration of distributed renewable generation. Further, an investigation into the cooperation of many interdependent sectors could be vital in improving energy efficiencies and decreasing the world's dependence on non-renewable resources.

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Appendix A

Acronyms

ACOPF	alternating current optimal power flow
ADMM	alternating direction method of multipliers
BESS	battery energy storage system
CAISO	California Independent System Operator
CCO	chance-constrained optimization
DAFC	direct ammonia fuel cell
DAM	day-ahead model
DCOPF	direct current optimal power flow
DR	demand response
DC	direct current
DER	distributed energy resource
DG	distributed generator
DLMP	distribution locational marginal price
DSO	distribution system operator
HEMS	home energy management system
FEW	food-energy-water
GAMS	General Algebraic Model System
IEEE	Institute of Electrical and Electronics Engineers

IoT Internet of Things
 IO interval optimization
 LMP locational marginal price
 MILP mixed-integer linear programming
 MVA megavolt-ampere
 MVAR megavolt-ampere reactive
 P2A power-to-ammonia
 P2A2P power-to-ammonia-to-power
 P2G power-to-gas
 PG&E Pacific Gas & Electric
 pu per unit
 PV photovoltaic
 PCC point of common coupling
 PDF probability distribution function
 PEP probability efficient point
 RE renewable energy
 RES renewable energy sources
 RL responsive load
 RO robust optimization
 SOC state of charge
 SO stochastic optimization
 TPD tons per day
 VRE variable renewable energy
 VSP variable speed pump
 WEN water-energy nexus
 WWSIS Western Wind and Solar Integration Study

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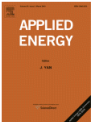
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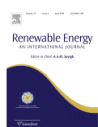
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Coordinated operation of water and electricity distribution networks with variable renewable energy and distribution locational marginal pricing

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