ANKARA YILDIRIM BEYAZIT UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES



OPTIMAL MANAGEMENT OF A VIRTUAL POWER PLANT CONSIDERING RENEWABLE ENERGY RESOURCE PLUS ENERGY STORAGE UNIT

PhD Thesis by

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Department of Energy Systems Engineering

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OPTIMAL MANAGEMENT OF A VIRTUAL POWER PLANT CONSIDERING RENEWABLE ENERGY RESOURCE PLUS ENERGY STORAGE UNIT

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PhD. THESIS EXAMINATION RESULT FORM

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OPTIMAL MANAGEMENT OF A VIRTUAL POWER PLANT CONSIDERING RENEWABLE ENERGY RESOURCE PLUS ENERGY STORAGE UNIT

ABSTRACT

The global effort to address extreme carbon emissions has garnered significant attention from both public and private sectors, notably through initiatives spearheaded by the United Nations, such as the Sustainable Development Goal 7 (SDG7).Within this context, renewables are crucial for achieving the SDG7; however, the inherent intermittency and unpredictability of RES outputs impose serious reliability challenges on power systems, often resulting in unforeseen power imbalances, outages, and abrupt shutdowns. To manage these technical challenges, this study proposes a data-driven modeling approach utilizing Battery Energy Storage Systems (BESS) and Diesel Generators (DGs) in a Distributionally Robust Joint Chance-Constrained Optimization (DR-JCCO) framework, formulated through Mixed-Integer Linear Programming (MILP) to maintain convexity. This study integrates tractable algorithms, specifically the Conditional Value-at-Risk (CVaR) and H-X algorithms, to improve system performance within Integrated Energy Modeling Systems (IEMs). The findings indicate that CVaR provides efficient BESS operation and operational cost minimization without necessitating wind power curtailment, though it is associated with higher computational burden. In contrast, the H-X algorithm demonstrates superiority in terms of tractability, achieves faster BESS cycling, and results in reasonable profit output margins. Furthermore, the H-X algorithm establishes a new benchmark for enhancing existing optimization models such as REopt applied in IEM applications. Finally, Binomial Expansion (BE) has been applied to selectively reformulate a non-linear upper-level objective function, to demonstrate the robustness and efficiency of linear models solved by the off-the-shelf solvers such as Gurobi.

Keywords: virtual power plant, conditional value at risk, diesel generator, battery energy storage system, renewable energy resource, integrated energy systems

YENİLENEBİLİR ENERJİ KAYNAĞI VE ENERJİ DEPOLAMA ÜNİTESİ DİKKATE ALINARAK SANAL ENERJİ SANTRALİNİN OPTİMAL YÖNETİMİ

ÖZ

Aşırı karbon emisyonlarının azaltılmasına yönelik küresel çabalar, özellikle Birleşmiş Milletler tarafından yürütülen Sürdürülebilir Kalkınma Amaçları (SKA'lar) kapsamında, kamu ve özel sektörün dikkatini çekmektedir. Bu bağlamda, yenilenebilir enerji kaynakları (YEK'ler), sürdürülebilir kalkınma hedeflerine ulaşmada kilit bir rol üstlenmektedir. Ancak, YEK üretiminin süreksizliği ve öngörülemezliği, güç sistemlerinin güvenilirliğini tehdit etmekte; bu da ani dengesizliklere, kesintilere ve sistem arızalarına neden olabilmektedir. Bu teknik sorunlara çözüm sunmak amacıyla, bu çalışma, Batarya Enerji Depolama Sistemleri (BEDS) ve Dizel Jeneratörler (DG) içeren veriye dayalı bir modelleme yaklaşımı önermektedir. Önerilen model, dışbükeyliği koruyan Karışık Tamsayılı Doğrusal Programlama (KTDP) yöntemiyle formüle edilmiş Dağıtımsal Olarak Sağlam Ortak Şans Kısıtlı Optimizasyon (DOSOŞKO) çerçevesine dayanmaktadır. Çalışmada, Entegre Enerji Modellemesi Sistemleri (EEMs) bağlamında sistem performansını artırmak için Koşullu Riske Maruz Değer (KRMD) ve H-X algoritmaları entegre edilmiştir. KRMD, BEDS işletimini optimize ederek maliyetleri düşürmekte ancak yüksek hesaplama yükü yaratmaktadır. Buna karşın, H-X algoritması hesaplanabilirlik açısından üstünlük göstermekte, daha hızlı işlem süresi ve yeterli kârlılık sağlayarak hesaplama verimliliği sunmaktadır. Ayrıca H-X, ReOpt gibi mevcut optimizasyon modellerinin geliştirilmesine katkı sağlamaktadır. Son olarak, Binom Açılımı (BE) doğrusal olmayan üst seviye amaç fonksiyonunun doğrusal hale getirilmesinde kullanılarak, Gurobi gibi çözücülerle çözüm etkinliği ortaya konmuştur.

Anahtar Kelimeler: sanal enerji santrali, koşullu riske maruz değer, dizel jeneratör, batarya enerji depolama sistemi, yenilenebilir enerji kaynağı, entegre enerji sistemleri

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NOMENCLATURE

Greek Letter Symbols

Subscripts

ξ	K-dimensional vector
χ	Convex set in compact form

Acronyms

ALO	Ant Lion Optimization
C&CGA	Column and Constraint Generation Algorithm
CAISO	Carlifornia Independent System Operator
CPDF	Conditional Probability Density Function
DER	Distributed Energy Resource
DG	Diesel Generator
DisCOM	Distribution Company
ENS	Energy Not Supplied
GEN	Generator
GenCO	Generation company
JCCP	Joint Chance-Constraints Problem
MCP	Market Clearing Price
NSGA	Non-dominated Sorting Genetic Algorithm II
OPF	Optimal Power FLow
PNLFF	Probabilistic net load forecasting framework
PPE	Percentile Pair Estimation
PSO-GSA	Particle Swarm Optimization and Gravitational Search Algorithm
ROP	Robust Optimization Problem

SMPC	Stochastic Model Predictive Control
STNN	Spatial -Temporal Neural Network
STNN-VB	Spatial-temporal Neural Network Variational Bayesian
TLBO	Teaching-Learning-Based Optimization
USP	Upper Slave Problem

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CHAPTER 1

INTRODUCTION

This PhD work represents a multidiscipinary approach of three sectors−power network systems, operational research especially in the application of chance-constrained programming and the key concepts in economics, which are investigated through review of existing market systems that strategically provide avenues for power producers, consumers and other key stakeholders to interact in an efficient and more economical way. The producers in this regard encompass independent power producers (IPPs) who can be categorized depending on the type of energy source they posses, they can be owners of large-scale BESS or renewable power plants such as wind and solar , they can also own hydro power plants etc. Also, without forgetting producers who can choose to integrate their supply in a VPP network and then trade as a block, this in essence is a big factor when it comes to curtailment plans of renewables, the duck curve concept is one that example [1] which has tremendously played a unique role in decision-making of supply and demand in South Australia and has had an impact on how to develop flexible demand response tools, Figure 1.1.

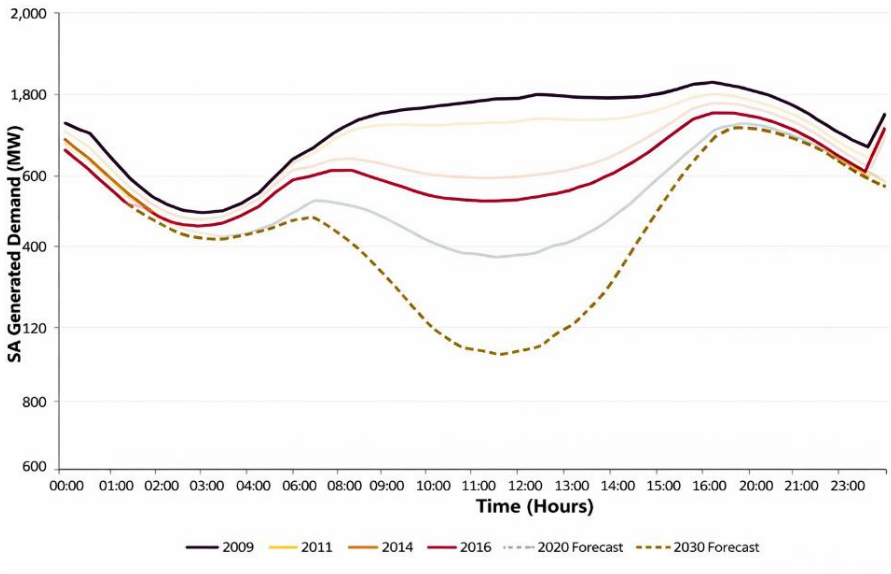

Figure 1. 1 South Australian (SA) Duck Curve Net Electricity Demand, Source: AEMO (2018a).

The duck-curve concept in SA shows the nature of demand variation with respect to the rooftop solar generation, which then has negative consequences when supply and demand are not balanced in real -time, the difference can be seen between hour 4 and 6 with an emergent of a steep ramp which ideally means quick-dispatch of non-renewable sources,i.e., coal and natural gas-fired power plants to meet the increasing demand. This has potentially gained a lot of research as the world forges towards digitilization of power grid networks.

Likewise consumers can be categorized as residential or industrial they can also strategize their demand profile to incur low operational costs. All in all, the grid transformation agenda has been received considerably well as the three sectors have been seamlessly integrated to achieve system reliability and participation of generation units in electricity markets. In regard to power networks, the issue to be investigated is reliability of these systems that are usually susceptible to external perturbations. These disturbances culminate into techno-economical losses and due to the complexity of the transmission and the distribution systems , replacing damaged equipment usually takes time in procurement and commissioning processes. In provision, is the concept of strategic bidding [2] which involve tactics that can benefit the asset owners to maximize profits while incurring minimal risk during trading. The three disciplines reveal relevant studies and explicit interdependencies which form the basis on which a research methodology based on a bi-level modeling framework that incorporate a joint-chance constrained problem is formulated.

In this introductory chapter the problem and motivation behind this work and other integral parts that support this research are outlined.

1.1 Problem Definition

Distribution networks face a myriad of challenges that potentially hinder energy delivery to the consumers, failure to act or respond in time, techno-economical straining can be felt by power stakeholders. And often, blackouts of certain regions within the distribution network are a common occurrence, and even worse loss of life is imminent when certain nodes are still energized without the knowledge of the

maintenance crew. In most parts of the world, where the grid networks are advanced in the sense of distribution management systems such issues are low-level risk compared to some parts of the world, i.e., south Asia and in most African nations.

The United Nations' Sustainable Development Goal 7 (SDG7) emphasizes the need for affordable and clean energy. This goal compels countries to reduce emissions and adopt renewable energy sources. Therefore, ensuring a sustainable, reliable energy system with integrated Virtual Power Plants (VPPs) in power markets is crucial for achieving Nationally Determined Contributions (NDCs) [3]. VPPs and other strategies can help increase renewable energy production and manage the inherent uncertainties associated with these sources

1.2 Motivation for Thesis Research

Motivation behind this research can be categorized into three parts:

The first part is to harmonize the reliability of power systems with the view of conforming to the climate change agenda. The second part offers state-of-the-art distribution systems for the future; lastly, the third part is being able to manage uncertainties at an operational confidence interval.

1.2.1 Power System Reliability

The first part, is very critical as science has through time argued on the danger of having global temperatures rising above 1.5 degrees Celsius, this has necessitated industrial participation in keeping carbon emissions within a pre-defined level to achieve net zero by the year 2050 [4]. This, in effect, demands more penetration of renewables into the grid network such as wind and solar PV, and minimal consumption of fossil fuels for power generation, i.e., coal and gas which are mainly used for thermal heat and power, and have a direct impact on the current energy global affairs. Renewable sources are stochastic in nature and largely depend on the weather conditions of the day and have proven overtime to be key players in facilitating low carbon emissions in the atmosphere, in order to achieve a balanced grid system,

renewables have to be at the center of the energy transition programs with improved or better integration strategies.

1.2.2 Future Distribution Networks

The second part entails distribution level networks of the future which will likely undergo tranformation in terms of distribution of power and participation in power markets, creating a pathway for decentralization of network resources and integration of more renewables into the grid. It is well known frequent reliability issues are unavoidable given the complexity of the distribution network. Largely, attributed by failure of electrical components or substation equipments due to external causes, i.e., natural disasters and human causes such as tampering of transformers and vandalisation of overhead cables. As a result, DISCOMs and GENCOs experience extreme techno-economic losses in terms of acquisition and replacement in part or whole network infrastructure.

In most cases, outages originate from voltage imbalances or when generation units shutdown completely and unexpectedly, the supposed future distribution network is projected to align with climate change mitigation agendas and renewables have gained great attention in research and government support, as much as they are the best alternative for fossil fuel, they cannot be predicted with absolute certainty, a setback that hinders smooth integration into the grid. They can result in serious power quality issues which can lead to power mismatches and faults. If proper correction measures are not taken, damage of electrical components will be unavoidable and can lead to negative impacts to complex industrial zones.

In addition, failure of one or two generation units can numerically be quantified as n-1 and n-2, respectively. Literature sources, study the impact created by loss of 1 or two electrical units or equipment and formulate the problem as contigency constrained. There are instances when large-scale n-k contigency constrained problem need to be solved, this problem is associated with multiple malfunctioning of electrical equipment or generation units over a wide geographical location , and solutions that have been investigated so far include having robust solutions, and quick intervention strategies

to counter electrical hitches from being propagated elsewhere, otherwise late intervention usually leads to the shutdown of the whole system and the initiation of the black start process, which is a time consuming and a delicate phase in power systems,[5] study n-k contingency constrained unit commitment problem, which they solve using ancillary service demand response (ASDR) programs recommended by the federal energy regulatory commission (FERC), the authors propose a mixed integer programming problem (MIPP) solved using primal-dual optimization, the latest formulation in literature. Additionally, monitoring of distributed generation systems (DGs) for any faults before the grid network is restored is suggested, a process to be done using EMS control strategies [6], the research is on ways of maximumly extracting power from photovoltaic and wind sources or hybrid power plants. Note, there has not been enough research on n-k contingency issues. As complexity level increases, so as the solution to n-k contingency problems, which call for research on more agile and dynamic solutions to prevent and correct immediate fault occurrences.

Another aspect of distribution level networks of the future is application of VPP as a solution for integration of DERs. A VPP will be aware of the whole system network, DGs units performance in regard to ramp rates, provision of ancillary services or reserves that ensure smooth operation of an entire power network, [7] presents hierarchical control methods for VPPs , the control methods enable VPP to provide ancillary services as a dispatcher of network resources and avenues involving primary and secondary control strategies that are critical in operation of power systems, the mentioned services as per the authors are meant to ensure supply and demand are in equilibrium. Furthermore, it is established that VPP through the hierarchical control methods, can perform voltage and frequency regulation, grid restoration process, export and import of power at the point of common coupling, scheduling of network resources to maintain stability and resiliency of the power distribution network to accommodate diverse energy generation sources especially inverter-based and decentralized power supply systems, which have varying supply and demand [8].

Arguably, world population is projected to increase and so is the increase in power demand, which to some extent complicates generation, transmission, and distribution

of electrical power. A situation likely to pose grid network congestion and uncertainty management issues. In addition, a separate category of consumers will arise, who will be able to produce and consume power, they are termed as prosumers, they will be able to buy energy at lower prices and sell at higher prices to maximize profits [9], all these developments will not be an easy feat, implying distribution network operators have to be ready to scale their systems and proactively manage any impeding challenges as a result of more renewables.

1.2.3 Renewables Integration

In this third part, uncertainties that originate from renewables have to be managed close to a specified confidence interval, solar PV and Wind in most cases they deviate with large forecasts errors if not checked might have irreversible effects to the distribution network that might lead to uncontrollable voltage margin [10], check Figure 1.2 below.

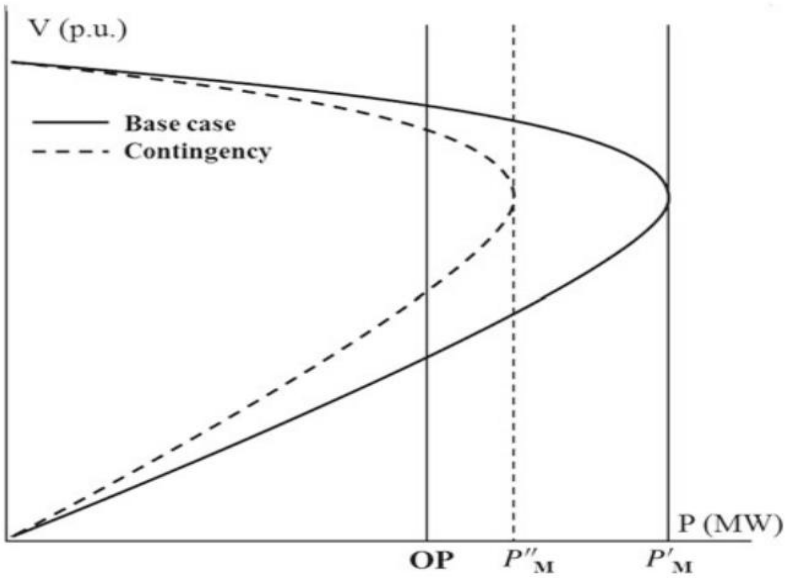

Figure 1. 2 PV Curve [10]

Subsequently, Figure 1.2 attests reliability as a challenge in distribution or transmission networks, the system is vulnerable to voltage imbalances attributed to unpredictability of outages, as mentioned earlier failure of one or two generation units has an overall effect on the whole system , zonal networks for instance are hugely

accepted to mitigate complete shutdown of distribution networks [11], multi-agent method has been applied in that regard with zonal agents and strategically located reclosers to counter propagation of electrical hitches to other zones.

The core motivation of this work is to ensure reliability of DN at the same time profit maximization in the upper level using strategic VPP approach, in that a DRO approach termed as DR-JCCO in this work will be applied to manage uncertainties that emanate from renewables supply and demand in a bi-level framework, Figure 1.3.

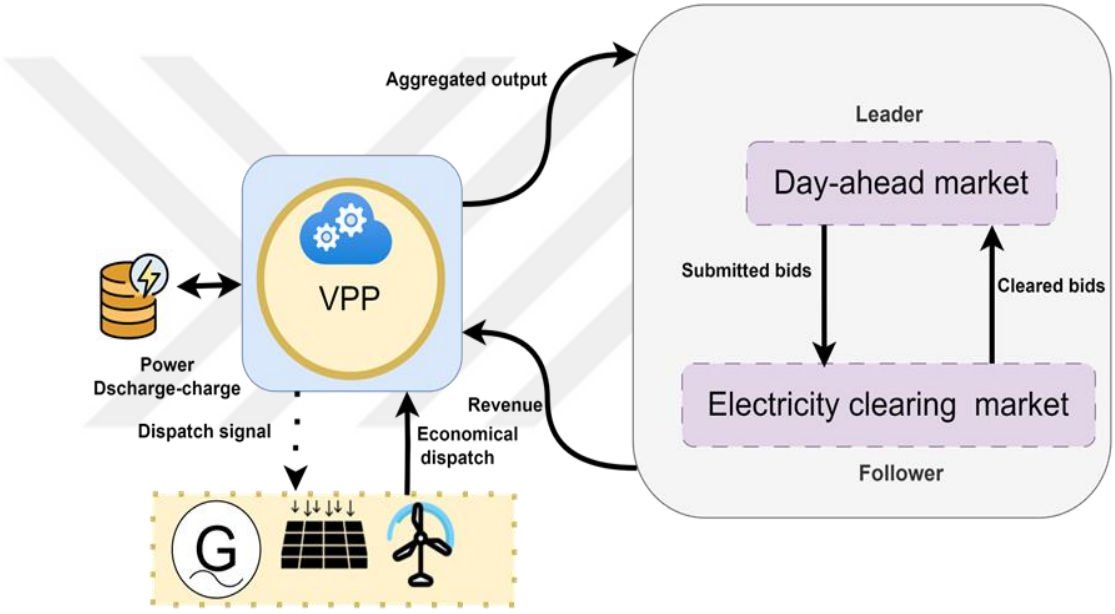

Figure 1. 3 Simple VPP Bi-level Model Integration

Conclusively, a probabilistic constraint will be approximated and solved as part of the operational constraints in a lower objective problem, the approximation of the joint chance constraint will be done using the H-X algorithm a variant of CVaR approximation method.

1.3 Research Scope

The research seeks to address the following questions,

1. How to integrate more renewables into the grid networks with limited curtailment planning?

2. How to manage uncertainties using considerable confidence intervals?

3. Can reliability threshold studies imply cost reduction?

4. Is it possible to decisively formulate a conduit for market studies?

The output of the research will determine how accurate the responses will be, and way forward regarding the adoption of the research for the distribution network operators and value addition for consumers.

1.4 Objectives of the Research

- To promote diversification of energy sources in the distribution network, especially renewable energy sources that are highly preferred for clean energy.

- To apply VPP in the distribution network for distributed generation management and reliability studies.

- To use VPP to mitigate uncertainties that result from renewable energy sources and other extreme contingencies.

- To facilitate the development and application of DR-JCCO approach in the management of uncertainties that emanate from renewables, demand and market prices specific to this work.

- To apply DR-JCCO to coordinate the participation of the energy storage system in the Day-ahead Market (DM)

- To study and propose approximation methods for joint chance-constrained programming, such as the use of CVaR and H-X methods that are known to have tractable solutions, with the target of reducing the computational burden and minimal information loss.

1.5 Research Contribution

The core objective of this PhD thesis is to assess, analyze, and manage distribution level reliability technicalities using uncertainty modeling approach. A VPP concept will be applied to investigate potential network risk in terms of security of supply, with the aim of effectively managing associated reliability threshold and economical benefit of a VPP. Other objectives are as follows:

• **Extensively applying VPP to assess and analyze the distribution network to manage reliability-related issues.**

Distribution networks suffer from component level failure, which impedes daily operation and more often causes delays in the physical delivery of energy. This usually results in financial losses for consumers, and production delays, especially in industries, with the application of VPP system, voltage and power from generational sources can be monitored for optimal performance.

• **Applying VPP as an energy multi-carrier system at the distribution network level, e.g., Diesel generator, Battery storage, Wind Energy and analyzing various use cases.**

Distributed generation has gained traction in research and development, through immense support of achieving clean energy, fossil fuel funding has slightly decreased due to affirmative action that has seen governments hail this noble cause, more renewables are equal to a guaranteed clean energy for posterity, and attractively addition of storage becomes even better, as renewables have intermittent power output.

- **Advancing reliability studies for future state-of-the-art distribution networks, to provide maximum security for system-level components and loss curtailment plan strategies.**

Power system security cannot be overlooked and negligence always result in extremely high prices, which mostly entail loss of life, and as population increases so as power demand and addition of more renewables into the grid network, according to the UN's sustainable development goal (SDG7), a more sustainable, reliable energy for all is the mantra that spearheads adoption of renewables implying supply and demand of power has to balance out, with storage helping achieve the balance as surplus from renewables can be stored and later released for consumption depending on the electricity market prices.

- **Proposing CVaR variant method; H-X to model uncertainties in the system**

The study proposes an H-X solution algorithm in a bi-level framework known to have better performance compared to the traditional CVaR approximation method in the management of uncertainties that emanate from renewables and other external disturbances. The formulations of these methods aim to solve a DR-JCCO, which is an NP-hard problem.

- **Using VPP as a decision-making tool in deregulated electricity wholesale markets to foster customer participation.**

Literature supports commercial VPP to perform its predefined functions, i.e., bidding in wholesale electricity markets such as DM, intraday (ID), and balancing power market (BPM). Within the conceptual development of a strategic VPP, two separate markets will be identified, the electricity clearing market or real-time market and DM market, which form the lower and upper levels of a bi-level framework, respectively.

1.6 Overview of the Thesis Research

1.6.1 Overview of the Thesis Research

The thesis has five chapters, whereby the first chapter serves as an introductory chapter, and presents the problem definition, thesis motivation, the objectives, contribution of the thesis, and the overview of the thesis, with subsequent chapters summarized below:

1.6.2 Chapter 2: Literature Review

The chapter introduces literature studies done on existing reliability issues, power systems optimization methods, uncertainty management, probability forecasting methods, numerical approximation methods and joint chance-constrained programming is given precedence in this chapter.

1.6.3. Chapter 3 Optimal Distribution Network and Electricity Market Design

In this chapter, optimal sizing of distributed generation, optimal power flow analysis is discussed using a 33 bus network system as a case study, then a VPP strategic bidding background with participation in electricity markets is investigated. Finally, the modeling of real-time electricity markets and economic dispatch concepts are introduced.

1.6.4 Chapter 4 VPP Mathematical Modeling

Mathematical formulation of the problem under study, uncertainty incorporation, CVaR and H-X mathematical concepts, followed by application of CVaR and H-X algorithm in solving the DR-JCCO problem, other mathematical concepts such as MPEC and BE are also given.

1.6.5 Chapter 5 Results and Discussion

The chapter discusses the aftermath of the application of the proposed approaches, the analysis is obtained from the VPP model with generation assets such as Wind, Diesel

generators, BESS and system load/demand. Comparison of the methods in solving the DR-JCCO problem is done using appropriate solvers, and then the tradeoff between risk threshold and the VPP profit obtained is examined.

CHAPTER 2

LITERATURE REVIEW

2.1 Network Reliability

The essence of having a steady state power system cannot be underestimated, the benefits and the value of a steady network to a nation can determine the level of growth of that specific nation as human achievements have always revolved around energy for industrialization [12], transmission and distribution networks are the conduits that ensure electricity reaches the end consumer and any delay in transmission or distribution is equivalent to economical loss and more often these delays are as a result of contingencies, which are a common occurrence in electricity distribution networks, they are tedious to deal with if the right approach is not considered, in many countries especially developing ones they suffer from frequent reliability issues that mostly lead to techno-economic losses due to failure of available power supply to cater for the demand. This, in most cases is very devastating to end consumers and for the investors who in turn fail to meet their immediate targets, i.e., low ROI and interruption of consumer comfortability. There are very many studies that have formulated contingency issues as a problem, i.e., N-1, N-2 [13] and N-k, which stands for the variation of the network system from the normal state when failure of one, two and multiple outages occurs, respectively. Outages usually occur when generation units fail due to internal and external factors either in controls or in transmission and distribution lines (T&DL) experiencing electricity overload and then tripping out, which can either be as a result of technical and non-technical losses, research shows that power networks can suffer immensely if continuous supply is done and demand is not competitively accounted for, such losses adversely affect all stages of electricity distribution, therefore it is important to understand how transmission and distribution networks experience losses with reference to developing nations state of affairs. In [14], the study has focused on T&DLs experiencing occasional technical and non-technical losses, technical losses are as a result of electricity dissipated into the

transmission or distribution equipment, i.e., transformers or dielectric losses, while non-technical losses can also be referred as commercial losses that are non-natural, usually occur when electricity is consumed by non-legitimate consumers who are not accurately billed for the right quantity of electricity, this at times can be due to malfunctioning of meters or tampering of electricity meters. According to the world bank report [15], technical and non-technical losses have been highlighted as major issues developing countries face, Sub-Saharan Africa experience losses of up to 50% overtime and Nigeria is one such example, other countries for instance in Latin America and ex-Soviet union regions are also affected. In Latin America, CONDENSA (Bogotà, Colombia) has clearly set its action plan to serve the city, and within its regulatory framework consumers in different regions are served based on their specific needs to facilitate rolling of services to the wider Bogotà. Significantly, curbing non-technical losses raised serious agendas in relation to strategic management improvement plan (SMIP) and use of advanced metering infrastructure (AMI), that ensures sustainable electricity usage and minimization of injected power losses. In [14], solutions to curb T&DLs losses, i.e., theoretical, hardware and non-hardware solutions have been proposed, it was found that there lacks a unified solution to tackle non-technical losses, furthermore non-technical losses can be reduced if customer-utility relationship is enhanced by developing renewable energy hubs within the locality [16], also other measures include pre-paid metering and anti-meter tampering systems for commercial users, which might as well have profound effect and finally improved usage index for customers can benefit utilities on the long run. Non-technical losses are further discussed in [17], with a formula for the distribution price to give monetary valuation of the losses, this can help utility companies access and evaluate non-technical losses and upgrade their systems to minimize such losses and improve their welfare in terms of profit maximization.

2.1.1 Transmission & Distribution Network Security

In literature, outages are defined as occurrences that interrupt continuous power supply and cannot be predicted with certainty, this is signified by abrupt generator shutdowns in certain buses in the grid network [18]. Generally [19], outages are associated with

equipment failure and to some extent natural phenomenon such as lightning, and in other instances overloading of power network lines, which mostly is a frequent occurrence with a high probabilistic level of malfunctioning the whole grid network. The study in [20], has given comprehensive review on traditional methods used to assess power supply interruption for steady security, they include full AC power flow analysis, approximate methods and contingency ranking, these methods can augment each other to reduce computational time and improve accuracy of the results [21], full AC power flow method computes MW and MVA flows together with bus voltage magnitudes of each flows in specific outages, but suffers from computational time and cannot be scaled to accommodate more branches, however, it works well when applied in critical cases to reduce computational time, the usage of specific method highly depends on the speed and accuracy of the results that can support expansion planning and investment efforts by the utility service provider, a method like power flow decoupled method has been proposed [20], and arguably it has better performance in terms of speed and accuracy, but , in any case it has almost similar results when compared to AC full power flow method. Regarding approximate methods such as DC load flow and sensitivity method flow, DC load flow exhibits better performance in calculation of MW flows but is limited as it does not consider reactive power flows and voltage magnitude deviations into its calculations and often results in huge errors, though sensitivity-based voltage security analysis can come in handy. Furthermore, as technology improves calculation of power flow problems becomes progressively simplified with high convergence rate. The presence of high performance parallel computing has facilitated quick solutions for contingency power flow problems.

Lastly, artificial intelligence (AI), i.e., neural networks, fuzzy theory and intelligent algorithms, have been used to obtain faster results without the need of testing the grid network using a specific model [20]. In [12], differential evolution (DE) is used for tuning the controller to achieve a multi-objective purpose, it is compared with genetic algorithm for performance evaluation, additionally, [22] generators have been used to test the response rate of firefly search algorithm , which has shown quick response with more stable eigenvalues for both contingency and the normal cases.

As mentioned before, outages are hard to avoid, and some studies have detailed comprehensive technical studies, from detection to corrective mechanisms which aid in stable grid, that is why understanding preliminary work on grid power analysis will have a positive impact in understanding the reliability assessment of this thesis and the expected outcome, having considered a wide range of literature texts, the capability of the system to overcome outages and maintain power system security, is essentially made up of power system monitoring, contingency analysis and security-constrained power flow, these three aspects are highly sought after by power system engineers and other stakeholders. The authors in [19], examine branch failures whereby outage of generators MVA and violation of voltage are contemplated in the model. The terminal voltages at the grid interface have been determined to vary in the range of 0.95-1.05 per unit in accordance with the input data files. While in [23], how contingency analysis is handled in a grid network has been outlined by firstly prioritizing the essential parts which have a high level risk of causing system failure. Secondly, involving more pronounced stages such as screening-reduction of real-power system to the one that can be simulated and ranking- evaluation of the magnitude of failure or outage of system level components. The ranking can be done using performance, severity and voltage indices, the system level components can be assessed and evaluated to understand general effect of each and every component on the T&DLs, which begs the question on how outage analysis should be carried out?, studies show that outage analysis should be done more careful, in the sense that after identification of outage branches and generators, performance index (PI) of MVA and bus voltages should be applied to assess the severity of the outages, then ranking is done to monitor the most affected branches or buses to reduce the outage impact on the grid network, actions such as optimal placement of FACTS devices [19] can be done by carrying out pre-contingency studies and post-contingency studies and then the performance can be evaluated.

Meanwhile, severity in [24], has been achieved using QV analysis to assess the behavior of voltage after injecting reactive power at a bus, the study exemplary carries out severity studies by switching generators off and on while monitoring the effects on the transmission lines. It is accompanied by identifying the most sensitive generators

using generator shift factor, this operation is done under contingency conditions to prepare the system in case of emergency. Also, screening and ranking of a power system has been studied in [18], the authors analyze screening and ranking of a power system to assess the severity of line outages, performance index is evaluated using active power and voltage performance index, and using the overall performance index, active power and voltage performance index have been combined, enabling the power system to be ranked by obtaining the highest value of performance index. It is imperative to note that, power flow problems are nonlinear set of equations which are generally solved using methods like Newton Raphson Load Flow (NRLF) and Gauss-Seidel Load Flow (GSLF) solution given in [25], there is also Fast Decoupled (FD) method solution that has been used in [26], whereby a single transmission line has been studied, both line and voltage performance indices have been used and later applied on IEEE-14 bus testbed. To handle contingencies more effectively, the nature of contingencies likely to be faced have to be classified, and according to severity index they have to be corrected in line with the governing standards and stipulations to avoid further inconveniences to the power system users and operators , for example in [27], contingency ranking has been applied to identify buses severely affected using performance indices.

Finally, in design and implementation of power systems the whole system infrastructure is taken into consideration and all the constraints both external and internal ones that affect the steady state of the power system are contemplated into the model to effectively simulate unexpected outcomes that might lead to system failure and complete shutdown of the grid network. One of the issue is the scalability of the power system, which raises the question of what will happen if more renewables are added to the grid? and what is expected in case curtailment is not an option? For instance in [28], a robust power system security (RPSS) is investigated through addition of photovoltaic systems into the grid network at the expense of N-1 security-constraint, it is later found that the problem can be less severe by having a storage system to smoothen power and in order to have seamless power output, in addition RPSS was found to be an indispensable tool to the system operators as they could easily visualize regions affected by N-1 failure. Another important element that stands

out is market integration. Generally, the end goal of power producers is to make profits and have an uninterruptible power network to achieve economic goals. By virtue of electricity markets being deregulated, independent power producers (IPP) can participate in various markets such as ID, DM and capacity markets. For this to be achieved, contingencies and their magnitude of power flow distortion have to be looked into. In [29], contingencies are considered in the article, when allocating reserves in the DM, which forms a security-constrained optimal power flow problem. The proposed solution is to obtain an equilibrium between the dispatched energy and the amount to be traded in the DM, with the interest of having an optimal dispatch schedule for the system operator, who oversees control and management of the power network under the nominal ratings and operating limits of T&DLs.

2.2. Virtual Power Plant

VPP is a concept that has gained momentum in power industry, its applicability in the sector has raised appraisal in many fronts. In view of having seamless power flow in the distribution networks with low operational costs, VPP has become a formidable solution engineered to aid grid transactions. As indicated earlier on, unpredictability of outages that delay power delivery have been part of the huge problem of distribution and consumption of power, whereby consumers have to wait for long periods before they get electricity and investors endure losses as a result of multiple failure of T&DLs. On the other hand, renewables make it even more complex as their stochasticity, becomes a challenge based on the uncontrollability of their output in response to the requested demand. For VPP to be applied on a wider grid network, the basics have to be specified and the underlying modules need to be discussed for clarity. The terminologies and composition of such a platform with already applied cases are to be investigated by using literature sources and suitable use cases to cement the understanding of the whole system architecture. The main use cases include application of VPP for assessment of grid reliability and market integration which form TVPP and CVPP, respectively. Figure 2.1 shows VPP architectural design.

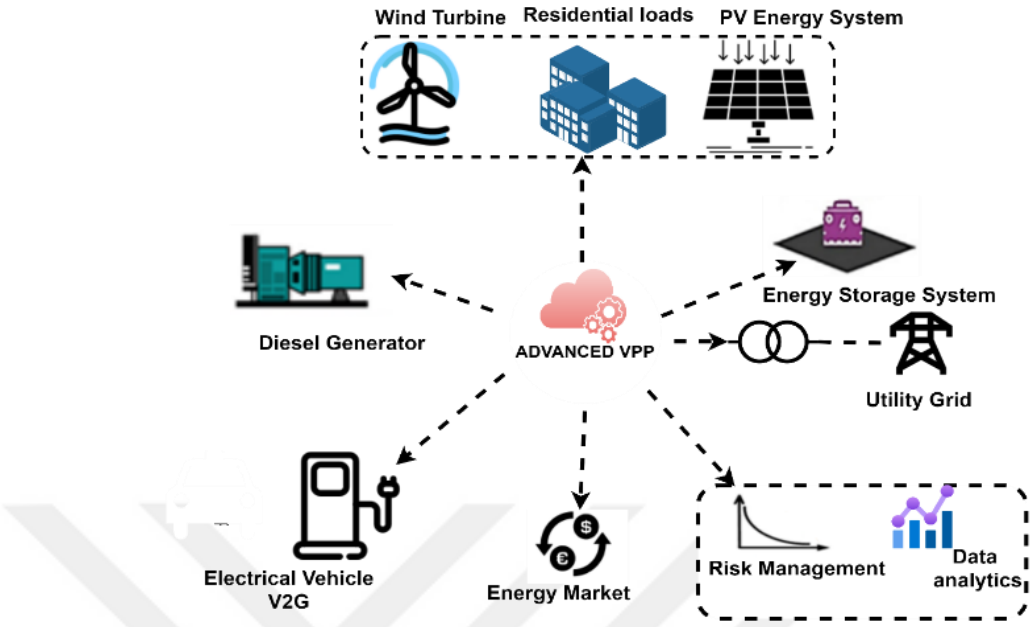

Figure 2. 1 Simplified VPP System Model.

A VPP system according to Fenix project [30], aggregates DERs to provide a unique performance of individual resources. It can incorporate these resources into the wholesale market, similarly, a VPP can be of great asset to system operators in the provision of ancillary services for grid stability. VPP system capabilities can streamline trading activities associated to customers who are strategically enabled to bid in the energy market. In [31], the study explores existing arbitrage opportunities, whereby optimal bidding is solved using the VPP strategy, which involves participation in spinning and reactive power markets. The VPP [32] has PV, WT, DG and ESS, and by extension, Electric Vehicle (EV) parking spots. Further, the model designed contemplates electricity market uncertainties with management of risk that results from scheduling of resources using CVaR. The authors formulate the problem as a mixed-integer non-linear programming (MINLP), which is solved using GAMS.

In developing the VPP, the sole objective is to enable participation of the generating assets in the electricity markets, such as DM, ID, reserve capacity for balancing services or imbalance markets, etc. [33] develops a surrogate model to decrease simulation time and calculate expected VPP profits while keeping network constraints at a pre-defined level as stated in the mid-term policies. In [33], VPP is proposed as a

viable solution to manage energy resources minimize CO_2 and NOx, amongst the DERs , plug-in Hybrid Electrical Vehicle (PHEV) has been factored into the model. A multi-time-scale economic strategy is used as a strategy by the VPP to take part in both reserve and wholesale electricity markets [34]. Table 2.1 shows the difference between VPP and Microgrid, the two concepts vary in their operating levels, while VPP aggregates power-generating units in a wide geographical area and enables them to participate in the wholesale electricity market, microgrids are confined in small geographical locations and are known to participate in retail distribution. Also, Locational Marginal Price (LMP) is essential for VPP, as it is connected to the main grid, whereas a microgrids can operate in standalone mode.

Table 2. 1 Differences between VPP and Microgrid Concept

VPP	Microgrid
Appropriate for large geographical areas	Suitable for small geographical areas
Linked to the national grid of a country and takes part in Wholesale electricity markets	Can operate as a standalone and take part in retail distribution
Affected by available regulatory structures and tariffs	Affected by political and regulatory policies
Largely depends on the national grid stability and economic status of generation units, supports multiple connections of distributed generation	Distributed generation units and loads are limited
Has an economic concept	Has a technical concept
Elements can be controlled remotely.	Ensures steady power supply.

The essence is to aggregate deferrable loads and disaggregate them to meet consumer needs; note that the method is proven to have less computational burden. Next, [35] VPP has been used to maximize economic benefits of DERs owners. VPP takes the capability of ADMM in computational distribution, which effectively eliminates the need of having a central controller. Some VPPs have focused on optimizing and scheduling DERs for financial gain, precisely CVPPs. They do not consider technical specifications of DERs and the impact on the power network system like the TVPP, while [36] studies how DERs owners are allocated benefits using Vickrey-Clarke-

Grove mechanism, the authors develop stochastic MILP model, the results show electric vehicles (EV) having significant contribution margin followed by solar PV. Meanwhile, [37] addresses the scope of CVPP in ensuring reliability of the power system by minimizing the operating costs, scheduling of the DERs according to the forecasted market price. Additionally, the study focused on VPP profit maximization and MG optimal scheduling. The two stages developed enable VPP to increase its profit margin while the MG minimizes its operating costs within its network. Also, [38] studies the effects of TVPP on active and reactive power, a robust capability curve to factor in uncertainties in the model and application of robust optimization to solve a two-stage scheduling problem is proposed. On the other hand, [39] uses VPP for multi-objective scheduling of energy resources, the core objective is to maximize VPP profit while minimizing environmental impact in terms of carbon emissions. Table 2.2 shows studies covering the VPP concept as a management tool. Uncertainty variables in this context include price, RES, and loads. In [40], EVs have been considered due to the impact they have on the grid network and the uncertainty they have as they can act as load, consuming power from the grid network or generation units supplying power to the grid network through utilization of a V2G technological capability.

Optimization has evolved with time, and modern systems have benefited a lot in terms of achieving optimal control of their processes, and to some degree the concept finds application in almost all areas, for instance, power systems, financial planning, combustion engines and expansion planning of investment projects. There are different types of optimization methods, and in this research, stochastic, robust optimization (RO) and chance-constrained programming are investigated. CC and RO technical abilities will be combined for further research and potential application in power systems, the two methods if combined lead to the formation of DRO. To start with, stochastic optimization [50] refers to a mathematical decision-making framework under uncertainties, the concept dates back to 1950s, when George B Dantzig, wrote the famous paper ‘ the origin of linear programming under uncertainty’, earlier works can also be found [51]. Stochastic programming (SP) has evolved over time and it has

Table 2. 2 Existing VPP Literature Sources on Uncertainty Management

Ref. Article	Uncertainty Modeling				Applied Method
	Price	RES	Load	EV	
[30], [31]	✓	✓	✓	-	2-point estimate method
[35]	-	✓	-	-	Weibull function
[41]	-	-	-	-	No uncertainty consideration
[42]	✓	✓	✓	-	Weibull, Beta and Normal distribution function
[43]	✓	-	✓	-	Monte Carlo simulation
[44]	✓	✓	✓	-	Log-normal and Normal PDF
[45], [46]	✓	✓	✓	-	Scenario Generation
[34]	✓	✓	✓	-	Monte Carlo simulation
[47]	✓	✓	✓	✓	Point estimate method
[48]	✓	✓	✓	-	Scenario generation, confidence bounds and intervals
[49]	✓	✓	✓	-	Robust optimization
[40]	✓	✓	✓	✓	Deep bi-directional long short-term memory network
Proposed	✓	✓	✓	-	DR-JCCO

developed into a mathematical programming research field, it has also been applied in various areas, such as financial planning and electricity planning [52]. In short, stochastic programming is a risk-neutral approach, and considers a known probability distribution to optimize the expected outcome. On the other hand, RO is a risk-averse approach and seeks to optimize 'worst-case scenario' over an already defined uncertainty set, the problems associated with this strategy involve min-max operations.

Additionally, chance-constrained optimization, facilitates modeling of flexible systems to mitigate reliability-related issues linked to risk management, as shown by Table 2.3.

Researchers and power system operators have carried out studies to enable simulation of power systems under uncertainties to assess system stability and optimal performance. A number of methods have been researched [53], stochastic and robust methods have traditionally been applied in power systems, the former is a risk neutral

approach and computationally intensive and the latter suffers from conservatism of results. Uncertainties emanating from renewables can be incorporated by use of

Table 2. 3 Differences between the Three Methods [50]

Programming /Approach	Risk aversion	Type of uncertainty
Stochastic	Risk neutral	Probability distribution
Chance-constrained	Risk averse	Probability distribution, risk level
Robust optimization	Worst-case scenario	Uncertainty set

distributionally robust chance-constraint (DRCC) [54], the method guarantees real-time (RT) energy shortfall caused by day-ahead market commitment and unprecedented realization of renewable energy generation, which is kept under predetermined probability threshold regardless of the accuracy of the probability distribution function (PDF). To achieve a more adaptable robust solutions, DRO approach has been used in power systems to obtain secure and reliable optimal power flow. The method guarantees RT energy shortfall caused by day-ahead market commitment and unprecedented realization of renewable energy generation which is kept under predetermined probability threshold regardless of the accuracy of the probability distribution function (PDF). To achieve a more adaptable robust solution, DRO approach has been used in power systems to obtain secure and reliable optimal power flow. Additionally, the approach deals safely with uncertainties contributed by renewables, through mitigation of oversupply and undersupply of power using predetermined thresholds: It is well known that the repercussions of Solar PV and Wind uncertainties can impact the power system negatively, whereby required amount of energy in the market might not be met. In this regard DRO can be adopted to design a risk-aware grid network system using historical error samples.

Furthermore, DRO can be used to coordinate DERs and flexible loads to deliver energy and reserve services to the external grid. Also, DRO coordinates participation of generational units in energy markets, the following literature sources have been investigated and found to align with the scope and objectives of this PhD work [55] [56], the sources contain the following information, distributional locational marginal

prices [57], [58], bilateral matching [59], decentralized [60] and game-theoretical framework [61], [56].

Generally, most problems in power systems optimization are formulated as two-stage problems, a common example is security-constrained OPF problem. The first stage in essence optimizes the system before occurrence of contingencies while the second stage optimizes post-contingency operations. Additionally, the first stage facilitates the decision-making on the available reserves for procurement and the second stage ensures the reserves meet the security of supply requirements to achieve a well-balanced grid network. The equations representing the optimization stages are shown below.

$$\underset{x,\, y_\xi}{\text{Min}}\ f^{s1}(x)+R_{cost}\left[f^{s2}\left(x\,,\, y_\xi,\xi\right)\right] \quad \text{.....(2.1)}$$

$$h^{s1}(x)=0,\ g^{s1}(x)\leq 0 \quad \text{.....(2.1a)}$$

Subject to:

$$R_{sm}\begin{bmatrix} h^{s2}(x\,,y_\xi,\xi)=0 \\ g^{s2}(x\,,y_\xi,\xi)\leq 0 \end{bmatrix} \quad \text{.....(2.2)}$$

$$P_\xi\left(g^{s2}\left(x\,,\, y_\xi,\xi\right)\leq 0\right)\geq 1-\epsilon_i \quad \text{.....(2.3)}$$

$$\underset{P\epsilon A}{\text{Min}}\ P_P\left(g^{s2}\left(x\,,\, y_\xi,\xi\right)\leq 0\right)\geq 1-\epsilon_i \quad \text{.....(2.4)}$$

$$\underset{x,\, y_\xi}{\text{Min}}\ f^{s1}(x)+\ \underset{P\epsilon A}{\text{Max}}\ E_P[f^{s2}\left(x\,,\, y_\xi,\xi\right)] \quad \text{.....(2.5)}$$

$$\underset{x,\, y_\xi}{\text{Min}}\ f^{s1}(x)+\ \underset{\xi\epsilon\Xi}{\text{Max}}\ E_P[f^{s2}\left(x\,,\, y_\xi,\xi\right)] \quad \text{.....(2.6)}$$

The difficulty nature of the above equations is attributed to the unknown value of $\boldsymbol{\xi}$. In defining a well-structured problem, other parameters have to be introduced to conclusively obtain intended results, risk operators such as R_{cost} and R_{sm} are used to quantify the risks associated with observations of $\boldsymbol{\xi}$, the introduced parameters stand

for risk associated with cost and the latter is risk related to breaching of the security measure or operation of the system, respectively.

In reference to equation (2.3), obtaining an accurate representation of P_ξ is challenging as the parameter ξ is unknown and therefore highly intractable and numerically difficult to analyze. It is for this reason; a family of distributions are suggested to help in quantification of the distribution. Application of ambiguity sets have potentially emerged as sure way of establishing tractability of the unknown parameters. The ambiguity sets involve possible representation of the uncertain parameters with all distributions, $P \epsilon A$. Common types of ambiguity sets are metric-based, and moment-based Figure 2.2 depicts the sets and their formation based on historical data.

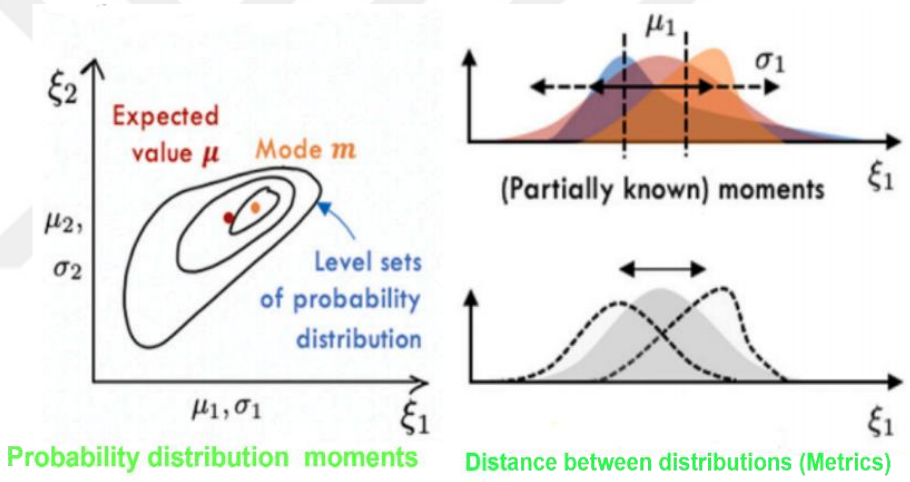

Figure 2. 2 Two-dimensional Vector ξ Uncertainty Representation [53]

The moment-based approach, as shown in Figure 2.2, uses moment information. For example, the mean represents the first-order moment, and the covariance represents the second-order moment. By applying empirical data ambiguity sets, all distributions that share the same moments can be generated [53] [62]. Arguably, given that ambiguity sets are generated using historical data, the DRO can therefore be considered as data- driven. Similarly, using the moment-based concept depending on the information available , ambiguity sets can be enlarged through addition of more distributions with the same moments but not necessarily same to those obtained from empirical data [63].

Also, metric-based strategies make use of Wasserstein distance by measuring the distance between two distributions. A distribution in the ambiguity set is specified, and the distance is measured in reference to the empirical distribution, the closeness of the distance to a positive value, which can be less or equal than the given positive value is used as an evaluation criteria [64]. Figure 2.3 represents power systems optimization techniques under uncertainty.

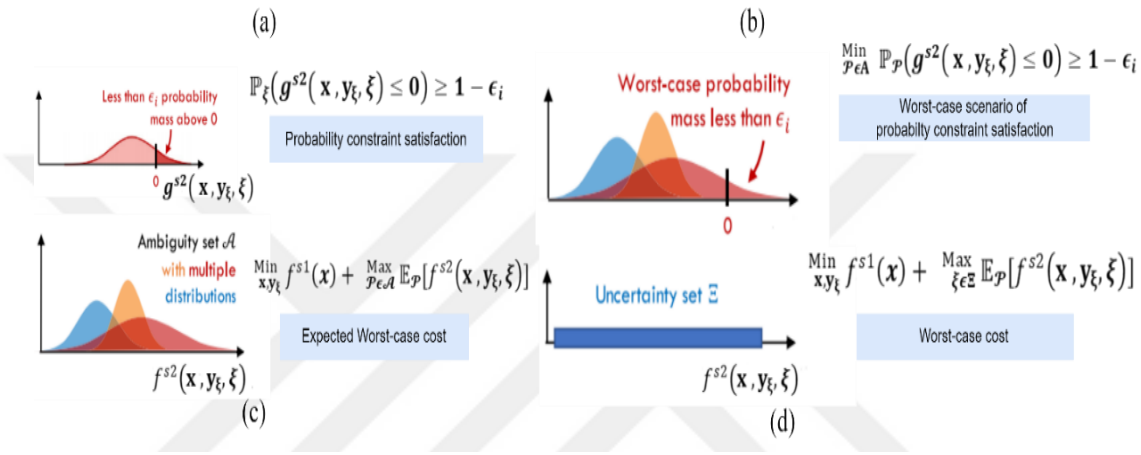

Figure 2. 3 a) Chance Constraint b) DR Chance constraint c) DR Optimization d) Robust Optimization. Probability Constraints Under Uncertainty [53].

Since the value of ξ is not known, the first-stage decisions variables are represented using x , which are referred as here-and-now decisions. The variables have to be decided before ξ is known. The second-stage decision variables are y_ξ , they are known as wait-and-see type of decisions. The decisions are made after the values of ξ are realized.

Additionally, the first and second-stage decisions x and y_ξ are selected with the view of minimizing the first stage (s1) cost function and the second-stage cost function (s2), see equation (2.1). For tractability reasons, both R_{cost} and R_{sm} are defined, leading to application of incumbent optimization programs such as stochastic optimization, DRO, RO and CCO. Application of the specific optimization technique depends on the existing information of the uncertain parameters ξ during the decision-making stage, as well as the chosen solution strategy for handling these uncertainties in the problem at hand.

In [65], DRO approach has been applied, it encompasses ambiguity sets in moments, i.e., first and second, and proposes cutting planes as potential solution. Dynamic line rating concept has been used [66] to develop DRO and both moment-based and Wasserstein metric-based solution approaches have been applied. A moment-based DRO for optimal power flow [67]. The method considers uncertain renewable power and reserves provided by generation units, the output is a semidefinite or second-order cone model. A Wasserstein metric is proposed [68] , under renewable energy uncertainty, [69] applies Wasserstein metric to solve joint chance constraints. Furthermore, [70] studies a multi-stage DRO for optimal power flow and applies a Wasserstein metric . Other studies have reformulated exact solutions to Wasserstein DRO optimal power flow problem [71]. Conditional covariate information can be considered [72] to reduce the size of the ambiguity set to avoid computational burden, which is one of the common challenge when solving optimization-related problems. Depending on the nature of the problem and expected results, it is advisable to keep the size of the ambiguity set as minimal as possible. Scenario-based approach can also be applied to generate independent scenarios of power profiles, whose accuracy depends on the size of the sample size, though the results can vary significantly when different samples are used.

Notably, the scenario-based approximation solutions cannot be improved further when the size of the samples increases exponentially; in fact, the performance slows down as computational burden increases. In some instances the solutions could be very conservative and even deteriorate. Besides, scenario-based approximation would require ad hoc methods to reduce the number of scenarios for application reasons, in which case expert knowledge would be required to identify suitable methods.

2.4 Uncertainty Management

Natural events cannot be determined with absolute certainty, when they occur the ability to recreate similar chain of events can be very challenging. Generally, quite a number of sectors suffer from unpredictability of key variables that can be used in decision-making processes, e.g., stock markets, energy sector dealing with RES,

electricity markets and network dynamic systems, which are advanced systems for transport sectors. In all these sectors, energy sectors and electricity markets are of great importance for this study. RESs have gained exemplary utilization globally, supported by affirmative action that aims to achieve net zero emissions by 2050, an obligation financed and adopted by countries that have subscribed to Paris Climate Accords (2015). However, the setback of RES is stochasticity of their output, for instance Wind and PV have high levels of intermittency which is challenging to control, this unreliability makes grid networks vulnerable and susceptible to unexpected shutdowns. Electricity markets are also engulfed with a great deal of uncertainty, whereby market prices for DA and intraday cannot be determined in advance. Therefore, uncertainty becomes a stochastic optimal problem, which can be solved using statistical means by proper setting of parameters and decision variables to formulate appropriate methods for solutions that can easily converge to optimality. Solutions such as information gap decision theory (IGDT) [46], has been used to simulate market price-related uncertainties Figure 2.4 shows modeling approach of uncertainties respective to the problem being solved, different challenges require unique solutions, and various studies have modeled uncertainties with the aim of attaining maximum efficiency with less complexity. Similarly, probabilistic models have emerged to be very effective in power network systems, as they have contributed hugely in the management of RESs into the grid, though computational burden has been a drawback.

Here and now and wait and see, is an often-used phrase that summarizes a stochastic problem solution. It constitutes first and second stages in stochastic programming. In short, the process forms the basis of making decisions using a sequence of deterministic and scenario generated stages. Next, uncertainty modeling plays a crucial role in the management of renewables and other DGs that take part in electricity markets, at the same time helps to maintain the stability of the grid network.

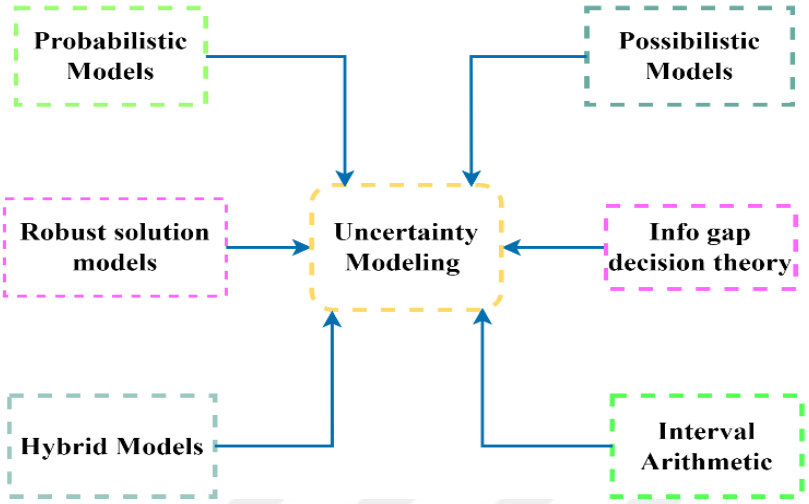

Figure 2. 4 Uncertainty Modeling and Associated Models

In [40], bi-directional long short-term memory (BLSTM) is applied as solution method to solve uncertainties associated with electricity prices and wind speed. The approach used a temporal horizon for previous and future states to give an accurate estimate of stochastic parameters. Also, the authors claim , BLSTM outperformed other methods in terms of error reduction and profit margin, and in [46], authors have used scenario trees for market prices uncertainties, wind generation, up and down regulation by considering binding probabilities. In [44], a backward reduction method has been used to obtain a good measure of scenarios, which have been objectively used for the study.

In [42], CVaR and degree theory have been used to develop a scheduling model for a VPP system that connects various DGs and incentive-based demand response (IBDR), additionally, Latin hypercube sampling methods (LHS) and Kantorovich distance have been applied to build uncertainty analysis model, with the objective of having a minimum CVaR that considers maximum operation revenue of a VPP. Meanwhile [43], considers uncertainties that emanate from the bidding of a CVPP in DAM . In the DAM, prices together with DER generation and consumption form the basis for modeling uncertainties. Also significant are competitors' price curves and real-time balancing prices.

Quantification of these uncertainties, constitute a bi-level optimization approach that the authors have applied in their research. In [73], PDFs are used to model market prices , electrical load consumption and renewable generation using Weibull and beta distributions to model wind speed and solar radiation, respectively. Concerning normal PDF, the applicable case is with electrical demand and prices for reserve or spinning markets.

2.4.1 Probability Forecasting Under Uncertainty

Probability is a fundamental concept in power systems, which is used particularly in analyzing and managing uncertainties. Control systems often experience significant deviations between actual measurements and expected values, which emanate from system errors and unpredictable variations. Such deviations can complicate the operation of plants and, in extreme cases, makes control nearly impossible if external disturbances are not thoroughly examined and accounted for. Unlike dynamic systems in control theory, probability helps to model uncertainties using PDF, which can hint on the level of control required. In power network systems, given the prevalence of having more renewables into the grid network, probability modeling can come in handy. There is a substantial body of literature that extensively explores the application of probabilistic and statistical concepts to model power generation and address challenges of instability in power networks, which are often caused by imbalances between supply and demand. Probabilistic forecasting is generally categorized into four main approaches: interval prediction, quantile prediction, scenario-based prediction, and density prediction [74]. Figure 2.5 shows the probability energy forecasting methods using UK national demand data. The four types of modeling approaches have found their applications in transmission and distribution network levels. Also, these four probabilistic forecast methods have certainly gained prominence in uncertainty application, especially in areas dealing with PV power, Wind power, load and market electricity price forecasts.

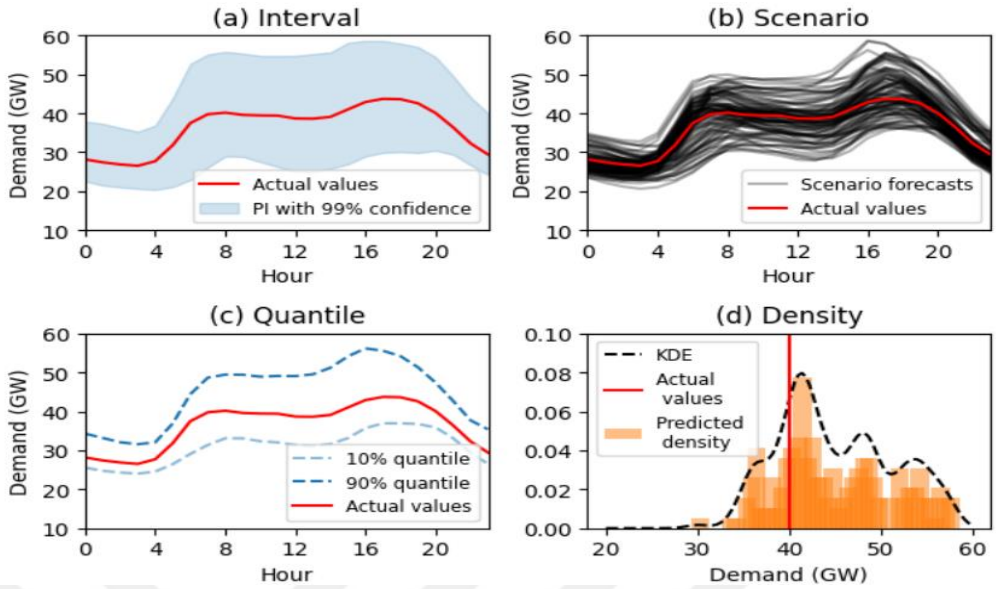

Figure 2. 5 Presentation of Probability Forecasting Using (a) Interval (b) Scenario (c) Quantile (d) Density [74]

Research topics have emerged recently in application of probabilistic energy forecasting in the areas dealing with provision of system inertia and grid states. Ref.[75] and Ref.[55], used density forecasting for system inertia and developed a quantile machine learning model, respectively. The developed models found application in distribution network, whereby node voltages were predicted successfully. The research was further extended to tackle power flow problem, whereby variation of EV charging scenarios were used to effectively avoid voltage violations with the objective of having reduced costs.

Probabilistic programming approach is used in a market competition setting [76], it considers demand and water inflows in hydro power plant, they constitute the uncertainty factors that are not congruently correlated or statistically independent, a mixed complementarily programming (MCP) is applied as a solution strategy. Next, identification of how much electricity the retailer can purchase from the long-term market [77] and the amount that can be purchased from each generator is investigated.

In addition, the graphic methodology can generate more than one optimal solution for the retailer. Also, an optimal bidding strategy framework is established on the basis of

the uniform price spot market [78], whereby competing generators place their bids which are modeled using PDF. PDFs are obtained from past market data analysis. A risk factor ensures the profit of generating power and the bidding risk are well balanced for a more logical bidding price. In [79], the stochastic dispatch (SD) is expanded to optimize two objective functions: 1) the combined operating cost , 2) the thermal units' emissions. The formulation applies the concept of Pareto front, the identification of the Pareto-optimal solutions is enhanced through multi-objective particle swarm optimization (MO-PSO). Several simulation runs are done under conditions such as total load, cost coefficients of reserves, and the coefficient values of the penalty cost.

Stochastic programming and hybrid intelligent approaches are applied in generating price-wind power scenarios [80] to enable wind energy trading under uncertainty. Risk aversion strategy is incorporated by using CVaR methodology, which limits the volatile nature of the expected profit. [81] considers a set of probable forecasted loads, and in stage one, a three-component function is put into use as an object of the algorithm which minimizes the expected total market payment. The three components include reactive power payment, costs of transmission losses as well as transmission charges. Furthermore, the algorithm maximizes the expected voltage stability margin and the required local reactive power reserve in voltage control areas within the network.

Strategy for trading wind power in deregulated energy market is studied in [82]. The findings show that the strategy maximizes the value of the market revenues, with the assumption that the wind power producer becomes the price-taker, additionally, the use of the expected utility maximization (EUM) formulation requires probabilistic forecasts of wind power generation and point forecasts of day-ahead, real-time market prices and the imbalance sign probabilities.

Next, accurate quantification of the uncertainties of wind generation forecasts by use of interval forecasting approach is proposed [83], it has a high potential to support various operation and planning activities in power network systems, for example providing reliable information during dispatch, e.g., the hourly Nord pool market. Importantly, the interval forecasting findings can be applied to develop new operation

and planning tools, which can probabilistically help TSO operators acquire reserves in advance. Also, it can support strategic bidding and risk mitigation for GenCos. Under uncertain load and RES generation, microgrid reconfiguration problem [84] is identified. The set up seeks to establish an optimal configuration within a well-defined criterion, at the same time ensure satisfaction of the system load with arbitrarily high probability adhering to maximum current limits on the distribution lines.

In [85], chance-constrained model is utilized by energy storage (ES) in power systems with high wind power generation, the strategy considers both the load forecast error and wind power forecast error as variables. The p-efficient point method is applied to facilitate the conversion of the constraints from stochastic to deterministic. [86]Probabilistic optimal power flow (POPF) is very essential in modern power network analysis, the framework involves probabilistic modeling for power networks under loading and renewable power penetration. The probabilistic methods are evaluated on the basis of computational time and accuracy and compared to monte carlo simulation (MCS) method. [87]Wind power forecasting error is modeled using beta PDF and incorporated in the economical dispatch (ED) problem to obtain PDF of generated power, energy not supplied (ENS), and generation cost, etc. Also, some representative values obtained from the PDF in the previous time steps are considered to model the effects of ramp constraints on power production. [88]Wind speed data points are input into an economic dispatch model, which then produces data for estimating the probability distributions of optimal fossil fuel generation outputs, transmission loss, and total cost of power production. [89] The development of a stochastic model predictive control (SMPC) and the analytical calculation of chance constraints are emphasized under a combined effect of set-based and probabilistic uncertainties. Uncertainties from changes in load demand and intermittent power from renewables are incorporated in the stochastic optimization problem.

[90] Proposes a probabilistic method which manages wind power sources alongside other producers and takes into account the uncertain behavior of wind power in specified intervals. [91] Uses probabilistic forecasting by the maintenance engineers to make rational decisions and create risk awareness scenarios. It is shown that, in

terms of minimizing expected cost, the decision to send or not to send a service vessel depends on how far the probability of the wave height value is below the safe limit. Next, [92] quantile regression has been compared to ARMA model; it is realized that quantile regression model possesses several advantages. The results signify the importance in application of quantile regression in optimization models for submission of bids in the energy reserve markets. Generally, an optimization model used for the bidding relies on good density forecasts of the capacity marginal prices to assess the conditional probability of acceptance. [93] Probabilistic spatio-temporal forecasting model is proposed, it predicts the wind speed in a region by making use of multi-site historical information. The model derives its functionality from deep learning model and variational Bayesian inference. The proposed deep learning model benefits from the abilities of ConvGRU and 3D CNN by use of an encoding-forecasting framework, suitable for spatio-temporal prediction challenges.

From [94], an LSTM framework is implemented in three fundamental stages: Data preparation, Model training and probabilistic forecasting. Figure 2.6 shows the performance of various methods used in probabilistic forecasting of wind speed (m/s).

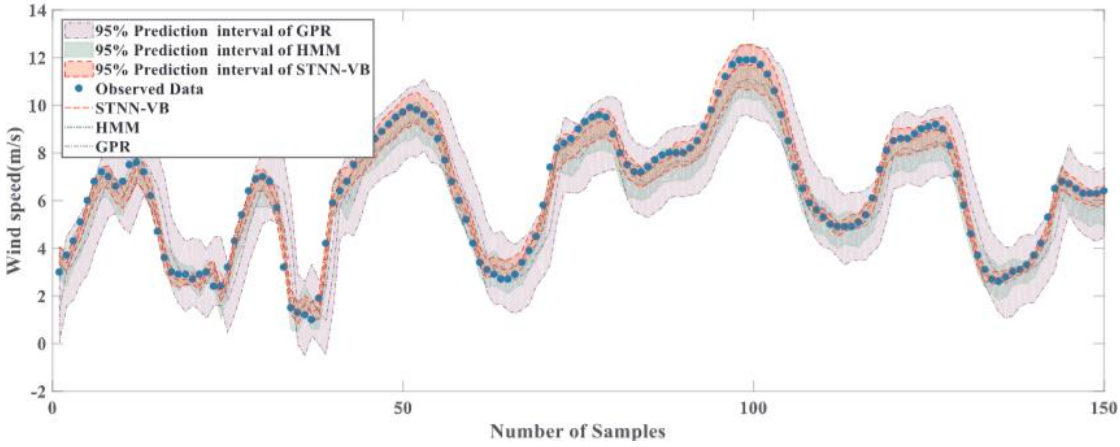

Figure 2. 6 Hourly Forecasts of Gaussian Process Regression (GPR), and Hidden Markov Model (HMM) Using 150 Samples as of March 2014 [93].

In [95], the work combines point prediction and interval prediction. The efficacy of the results show improvement in the prediction accuracy of photovoltaic power forecasting, which can greatly enable grid planning, reliability assessment and risk

analysis. Likewise, accurate photovoltaic power forecast support effective scheduling and management of photovoltaic power plants.[96] Two phase engagement/control problem within the context of capacity firming is addressed. Another contribution by the authors is to use a recent deep learning technique known as Normalizing Flows, to calculate PV quantiles and compared to long short-term memory (LSTM). Further, an integrated forecast-driven strategy is modeled as a min-max-min robust optimization problem with recourse which is solved using Benders decomposition algorithm.

[97]The given model herein can provide reliable wind speed probability forecast results for an entire specified zonal area by use of a one-time forecast under meteorological information from a targeted area. The proposed model, employs the multi-network deep ensemble strategy to get accurate spatio-temporal wind speed predictions through integration of multiple state-of-the-art convolutional recurrent neural networks by assigning weight to each network using intelligent optimization algorithm. [98]A framework that enables the creation of personalized standard load profiles (PSLPs) for the electricity, heat, and PV sectors, and the generation of a non-parametric probabilistic forecast from them using QR was developed. A question on how to use PSLP and quantile personalized standard load profile (QPSLP) can be transferred from the electricity sector to heat and PV generation was answered, also probabilistic forecasting was found to give detailed outlook on uncertainty compared to deterministic forecasting.

An analog ensemble (AnEn) method is evaluated [99], the method originally was designed for meteorological probabilistic forecasting and later tested for wind power forecasting, solar power probabilistic and deterministic forecasting, and wind resource assessment applications. Temporal discretization is used to rate transmission lines [100], the process involves ensuring a constant rating that is safe to use throughout the specified time . The rating needs to be lower than the actual rating with high probability to guarantee the safe operation of the transmission line. This could be done by using dynamic thermal line rating (DTLR) which basically optimizes the utility of overhead power transmission lines by adjusting the rating according to acceptable

ampacity limits. Table 2.4 provides an overview of research work in application of probabilistic statistical information in management of uncertainties.

Table 2. 4 Overview of Probabilistic Management Approaches for Uncertainties

Ref #	Year	Uncertainty	Techniques	DERs	Solution Method	Concept
[77]	2005	local load forecast	Total Time on Test Transform	Gen	Cost probability comparison	Bidding Strategy
[78]	2010	load and supply	Probability distribution function (PDF)	Gen (owned by GENCO)	adaptive particle swarm optimization (APSO)	MCP
[79]	2010	Wind	CPDFs	Thermal and WP units	Multi-objective particle swarm optimization (MO-PSO)	SD
[80]	2011	market price and Wind	SP	WP	Scenarios	Energy Trading
[81]	2012	Load	Probabilistic /six-stage multi-objective algorithm	Gen	Monte Carlo Simulation	Reactive power trading
[82]	2013	Wind, Market prices and system Imbalances	Optimal quantile strategy	WP	Two constraining techniques (In both decision space and probability space)	Participation of WP producers in trading
[83]	2014	Wind	Probabilistic interval forecasting	WP	Extreme learning machine and particle swarm optimization	Impact of WP generation on the power system
[85]	2014	Wind and load	Chance-Constrained optimization	WP and Thermal	Kernel estimation by using p-efficient theory to convert CC into deterministic model	Sizing of ESS that can accommodate WP production
[86]	2014	RES	Probabilistic optimal power flow	RES	First order second moment, cumulant based, two-point estimation, and PPE	Reliability of the power system network
[87]	2015	Wind	Convolution of the PDF and ENS other failure events	WP and Thermal	Proposed Economic Dispatch approach vs MCS (Monte Carlo Simulation)	Economical dispatch problem for WP

[88]	2016	Wind	Statistical analysis of WP generation	WP	Stochastic-Economic Dispatch	Determining optimal dispatch of the corresponding fossil power plants
[89]	2016	Load and RES	SMPC	PV	Integrating the PDF over the set	Optimal dispatch of fossil power plants given RES
[90]	2017	Wind	two-level optimization	WP	TLBO, PSO-GSA, ALO	Lowering operational costs
[92]	2019	Marginal Market prices	quantile regression		Natural cubic splines	German reserve power markets bidding using PD .
[93]	2020	Wind	Probabilistic spatiotemporal deep learning	WP	STNN and variational Bayesian inference (STNN-VB)	Accurate probabilistic forecasting of wind speed .
[95]	2021	PV	Probabilistic ensemble prediction	PV	A stacking- long-short-term memory neural network BAYES neural network: NSGA-II	VPP is proposed as a new concept with PV prediction.
[96]	2022	PV	Probabilistic modeling min-max-min ROP	RES (PV)+BATTERY	Benders-dual cutting plane algorithm and a C&CGA	Promoting renewable generating facilities.
[97]	2023	Wind forecasts	Probabilistic forecasting	Wind	Truncated negative log-likelihood scoring rule	Probabilistic spatiotemporal forecasting problem of Wind
[98]	2024	load	PNLFF	Thermal and PV	Quantile regression	Forecasting problem of photovoltaic
Propo-sed		RES and Load	Bilevel-DRO	RES + Thermal	CVaR +H-X	Profit Maximization in DAM

2.5 Chance Constrained Optimization

Chance constrained optimization approaches is one of the many probabilistic methods formulated using random parameters to solve optimization problems [101]. There are many areas of application, i.e., engineering and finance, they deal with product demand, meteorological conditions and foreign exchange rates involving different national currencies. These categories in optimization problems constitute the uncertainties expressed as critical system constraints. The challenge is to make decisions before random parameters are observed, meaning there is a high chance the

decisions would not lead to optimal solutions. The decisions taken at the initial stage might be difficult to track implying the constraints violated would not be easy to trace due to unprecedented randomness of parameters. There are examples such as purchasing energy from deregulated electricity markets and pumped storage plants that show violated constraints can be determined at the second stage, in this case uncertainty emanates from unpredictable or inaccurate electrical demand forecasts, or violation in terms of power supplied and amount of power bought from the market. The generation unit will be penalized as per the set conditions or bilateral agreements between the supplier and the utility provider. Various studies show that DRO can be used to collectively dispatch energy resources in the market and when combined with theoretical game theory such as Stackelberg game, it can substantially achieve remarkable perfomance in coordinating participation of DERs in electricity markets with the view that more than one player can participate in power trading, therefore the modeling approach entails formulating the problem as JCCP. JCCP involve collective optimization of more than one constraint under a probability threshold, there are various methods of formulating JCCP and applying probability chance constraints as a solution is a research area that has gained great attention.

Chance constrained programming solutions and mathematical formulation progress to include stochastic programs which form categories of problems to be solved in two stage and multistage approaches [23]. Multiple constraints can be estimated using probability threshold, for instance battery and renewable power from Wind and Solar can be formulated as a JCCP problem, which was first mentioned in [69] [70], there are several difficulties encountered when solving JCCP problem among them the intractability of the resultant distribution function and tight approximations which lead to conservative results, some studies limit uncertainties to large probability interval to ensure they fall under a predetermined probability interval, [104] studies convex approximations with the aim of having Karush-Kuhn-Tucker (KKT) convergence. JCCP [105], is noted to have the best performance compared to individual or single chance constraint , the method provides a better metric in regards to achieving cost and robustness, it is claimed to be tractable for advanced models.

Optimization problem is shown by equation (2.7),

$$\text{Min } f(x) \quad \text{.....(2.7)}$$

Subject to:

$$c_i(x,\xi)\leq 0,\ldots\ldots c_m(x,\xi)\leq 0 \quad \text{.....(2.7a)}$$

After addition of a probability constraint equation (2.7a) becomes equation (2.8).

$$P\{c_i(x,\xi)\leq 0,\ldots\ldots c_m(x,\xi)\leq 0\}\geq 1-\alpha \quad \text{.....(2.8)}$$

Equation (2.8) can be simplified into equation (2.9).

$$Y(x)=1-P\{c_i(x,\xi)\leq 0,\ldots\ldots c_m(x,\xi)\leq 0\} \quad \text{.....(2.9)}$$

$$x\epsilon\chi \quad \text{.....(2.9a)}$$

$$\chi \text{ subset of } R^N\rightarrow R \quad \text{.....(2.9b)}$$

$$f: R^N\rightarrow R \quad \text{.....(2.9c)}$$

$$c_i: R^{N+k} \text{subset of } R^N\rightarrow R \quad i=1\ldots, m \quad \text{.....(2.9d)}$$

c_m : m stands for the number of constraints required and $1-\alpha$ is the conditional value given to ensure the probability constraint holds and $Y(x)$, equation (2.9) indicates the probability the constraint is not enforced, and usually α is set between [0 , 1] and normally 0.01, 0.05 and 0.05 or even 0.1 are preferred values of α [104].There are chances that $Y(x)$ might not be verified directly or $Y(x)$ ends up being quasi-convex, in this case conventional methods can be used such as quadratic method [106], also CVaR in [107], Bernstein approximation [108], the approximations are suitable for single chance constraints and though they find feasible solutions easily they can also be sub-optimal [104], the solved individual chance constraints can further be used to approximate joint chance constraint, whereby in other studies it has been solved using Boole's inequality [108], the shortcoming of the approach is solution conservatism. Without the closed form of $Y(x)$, then Monte Carlo technique can be used, and in case

In literature, Monte Carlo methods are known to be very slow when compared to other approximation methods. Relative to deterministic methods, Monte Carlo have high computational burden and depends on the function to be approximated and the size of the sample set. Most studies limit the sample size to less than 100 dimensions for quick solutions and optimal performance [104]. It was found that utilizing a large sample set of parameters to solve a joint distribution function is challenging in practice and when ξ is inexact the approach cannot be used.

Another method suggested is gradient approach, which solves the JCC problem without decomposing it into individual chance constraint problems and employs Boole's inequality to avoid severe conservativeness, though it has high computational burden.

Finally, [66] has succinctly applied robust optimization to solve inexact or ambiguous distributions.

2.5.1 Convex Optimization Problems

Convex optimization is a class of mathematical problems, which are integral in formulation of efficient systems and have a wide range of applications especially in power systems, [114] areas such as optimal dispatch of generation units, expansion planning and nodal pricing leverage on convex optimization for simplicity of models, additionally, most solvers are readily available for solution of convex problems. Convexification of non-convex problems is ideal in optimization and guarantees optimal solutions. Generally, non-linear problems are difficult to solve and require high computation. It is for this reason, convex problems are preferred as they can be computationally tractable. The concept is applied in [115] to upgrade and design gas and electrical systems jointly.

In [27], convex optimization is applied and when benchmarked with dynamic programming (DP) it performs better with significant drop-in evaluation time, subsequently global optimal results are obtained by using convex vehicle model. Integrated energy systems (IES) [116] uses convex hull with a polyhedral approach,

which has better performance compared to hyperplane-based linear method. In [117], semidefinite relaxation of chance-constrained AC-OPF is applied to ensure global optimal solution. Ref. [118], applies second order cone programming (SOCP) to convexify non-convex problems which are NP-hard. Further, SOCP relaxation has found applications in optimization of distributed energy storage (DES) problems in power systems. Common standard convex problems can be represented by notations shown by equation (2.10).

$$\text{Min } f_0(x) \leq 0,\ i=1,\ldots, m \quad \text{.....(2.10)}$$

$$f_i(x) \leq 0,\ i=1,\ldots, m \quad \text{.....(2.10a)}$$

$$a_i^T x = b_i,\ i=1,\ldots,p \quad \text{.....(2.10b)}$$

Whereby, the objectives and the inequality constraints are convex [119], the equality constraints are usually affine as indicated by equation (2.10). Similarly, both feasible and optimal sets are convex. Further definition of a convex function is as follows,

$f: S \rightarrow R$, S Being the domain containing the convex set belonging to vector R. equation (2.11) ensures the convexity of functions holds as shown in Figure 2.7.

$$f(\lambda x_1+(1-\lambda)x_2 \leq \lambda f(x_1)+(1-\lambda)f(x_2) \quad \text{.....(2.11)}$$

x_1 and x_2 are in S and $\lambda \in [0,1]$. In case of one-dimensional functions, the second derivative of f''has to be greater or equal to 0 to be regarded as convex otherwise $f'' \leq 0$ is concave.

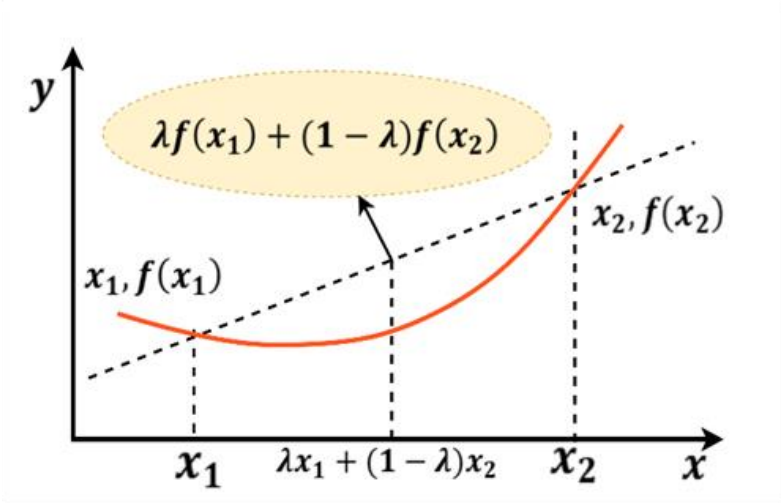

Figure 2. 7 Convexity Condition

It is imperative to understand the characterization of models based on nature of the functions, which also determines the convergence of the algorithms or numerical methods dealt with in section 2.5.2. Figure 2.8 shows convex functions and their derivatives.

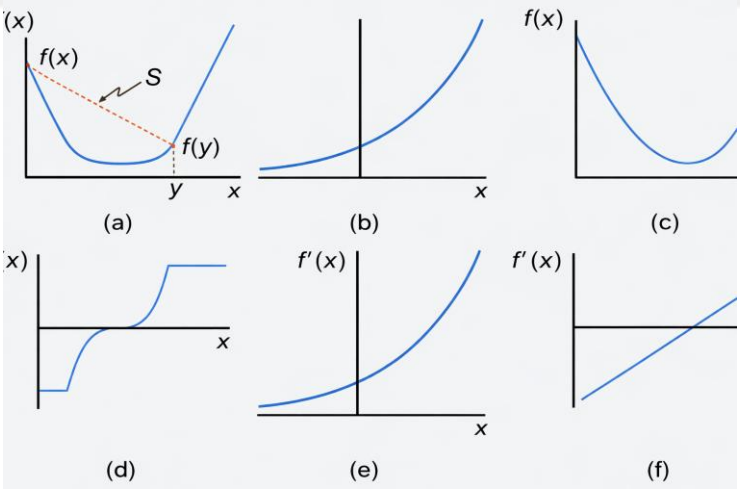

Figure 2. 8 a) Convex function b) Strictly Convex c) Strongly Convex d) Monotone Function (First Derivative of (a)) e) Strictly Monotone (First Derivative of b) f) Strongly Monotone (First Derivative of (c)) [120].

2.5.2 Numerical Approximation Methods

There are several methods used in approximating JCC, section 2.4.1 has dealt with some of the methods used in operational research to solve JCC problem, it has been realized that ambiguous distribution functions have to be properly approximated using special-designed algorithms or approximation methods to enhance tractability, which is the difficulty nature of JCC. In power systems some of the methods have been put into practice to solve OPF problem. To understand the challenging nature of JCC [121] and resulting distributions, there should be conditions that will facilitate tractability of the functions , the first condition states; the coefficients of the decision variables should be deterministic, the second condition; the cone nature of the uncertain parameters and the dispersion function should be homogenous and be in first order. In literature some studies have used scenario-based and approximation methods to tackle JCC an NP-hard problem. [122] explores JCC-OPF to integrate wind energy into the transmission network while [70] [71] suggest droop control function to act as a vector responsible for the management of wind forecast errors .

Usually application of scenario technique is effective when large samples are involved, the shortcoming is its reliant on statistical methods such as sample average approximation (SAA) which requires high-level knowledge in implementation to obtain accuracy, Sℓ1QP-type trust-region algorithm has been proposed [123], the algorithm scales effectively large problems and reduces computational time by using sample-based technique. Approximation methods are also preferred in decomposing JCC problem into individual chance constraints, set as violation rates. Bonferroni approximation works under the assumption that individual violation rates are equal to joint violation rate divided by the number of individual violation rates [108], the method has not been extensively researched though it is known to apply thresholds for all constraints and does not consider intersection of individual constraints. Subsequently, [80] [112] CVaR approximation has been applied to approximate JCC, a scaling vector is introduced to relax the solution and avoid conservatism. Later, the method was compared to Bonferroni approximation, it was realized that CVaR method had 8-12% improvement. Importantly [124], the authors have carried simulation

studies using symmetrical, unimodal and combined sets of uncertainties to investigate the cases which pass the violation criteria, meanwhile [125], claims that literature sources have not exhaustively investigated individual constraints violation rates owed to the difficulty of determining violation rates for each individual constraint. This work has proposed a framework to approximate JCC problem as illustrated in Figure 2.9.

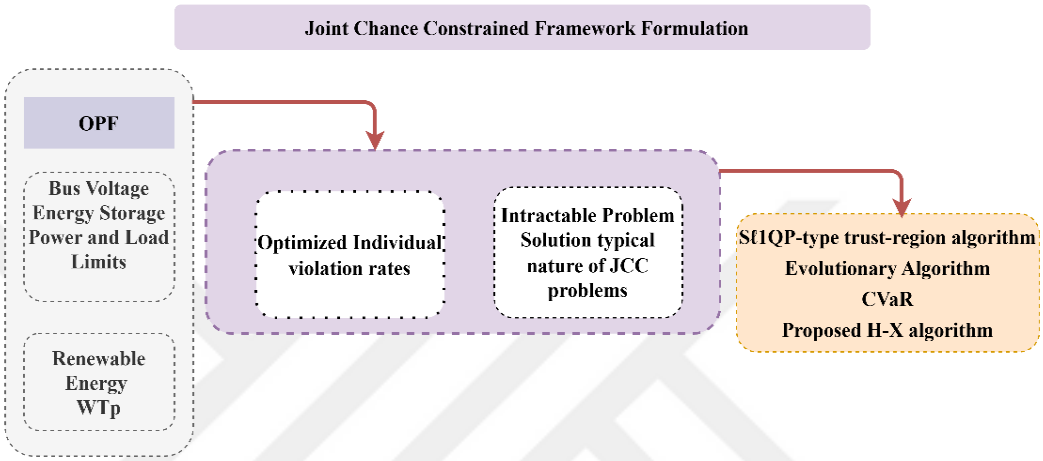

Figure 2. 9 Generalized JCC Formulation and Tractable Solution Approaches

2.5 Conclusions

Power network systems are vulnerable to disturbances, which can either be internal or external, the possibility of having a permanent solution for power interruptions is the most sought-after by power engineers and stakeholders, the thesis has highlighted reliability issues that occur in power systems and the contribution they make in power delivery, technical and non-technical losses have been identified, which are the root causes of unsteady power supply and overloading of supply lines, various solutions have been proposed such as hardware, theoretical and software solutions. In all these solutions, understanding the process of identification of contingencies has been given critical emphasis, i.e., contingency ranking by use of performance, severity and voltage magnitude, critical buses or outage lines can be identified and corrective actions can be taken. The methods used to carry out power flow analysis have been identified from both numerical and technological aspects, VPP is given as a tool that can continuously monitor changes in the power system and supports the transformation agenda in

curbing carbon emissions through the integration of renewable energy sources. In management of uncertainties, probabilistic forecasting is identified as quantification strategy of market prices and RES-related uncertainties, given the success the method has achieved so far in regard to combination with heuristic methods, the procedure can be used to model stochasticity in RES by statistically defining PDFs that are appropriate for integration of DERs into the grid network. Additionally, the optimization strategy is covered, and DRO programming is proposed whereby in comparison to other methods such as scenario-based and robust methods, it has better out-of-sample performance, a distinction has been made between single chance constraint and joint chance constraint which is a NP-hard problem. Convexification of non-convex problems is briefly introduced to suggest ways of enabling tractability of functions to reduce loss of information and less computational burden of optimization processes, and through contextual literature sources various key algorithms have been suggested to make the problem less conservative, and then H-X algorithm a variant of CVaR approximation method is proposed.

CHAPTER 3

OPTIMAL DISTRIBUTION NETWORK AND ELECTRICITY MARKET

This chapter highlights the introductory modeling approach of DERs and will not delve into comprehensive mathematical modeling approaches. In that case, significance and assessment of DERs will be the main focus.

Chapter 2 critically dealt with incumbent optimization strategies eminent in uncertainty management. Having identified the focal optimization strategy DR-JCCO. Then optimal sizing of DERs is paramount, as the point of connection plays a huge role in ensuring optimal power flow in the network. Given the urgency of connecting renewables and storage systems into the grid network, security of supply and resilience of the grid-network are pivotal in facilitating trading of power as a commodity in electricity markets, and end-point consumption through residential and commercial connections.

The interaction between DERs and the grid network is paramount in understanding how network resources participate in the electricity market. Conventional DGs are dispatchable whereas renewables are non-dispatchable as shown in Figure 3.1, both Wind and Solar PV vary significantly throughout, Solar PV (SPV) is available during early morning hours depending on the region while maximum SPV output is at midday, and the output becomes zero again at the evenings, likewise Wind generation output depends on the intensity of the speed of wind, and the terrain where the turbines are installed.

Currently, [126] gives an assessment of future projections of Wind and Solar PV, similarly World Economic Forum (WEF) has provided a future perspective in relation to costs reductions. In the study done, the costs of Solar PV will likey decrease by 50% and that of Wind constituting both onshore and offshore will fall by 25% and 50%, respectively. Additionally, the adoption of renewables will likey continue in the

coming years due to high module efficiency and improved cell production techniques (IRENA,2019). Further, The European Green Deal (EGD) estimates that greenhouse gas emissions will be reduced by 55% by 2030 compared to 1990, partly due to the cost-competitiveness of renewable energy sources (RESs), which has remarkably attracted investments and conducive policy frameworks structured to promote green energy generation unlike fossil-fuel-based resources [127]. For instance, the renewable energy directive of 2018/2021 got revised to project new renewable energy targets to 40% by 2030 [128]. The trend will be partly due to technological advancement and high cash flow opportunities. Comparatively, the growth of renewables across the globe has tremendously reduced the cost of energy production vis-à-vis coal and gas plants.

Although RESs are naturally available, they are complex to integrate directly into the grid, and even if incorporated into the energy mix, their unpredictability could potentially destabilize the grid network. In retrospect, this chapter presents the architectures and tools necessary for the integration and participation of DERs in the market. The optimization of these resources will be addressed in the fourth chapter.

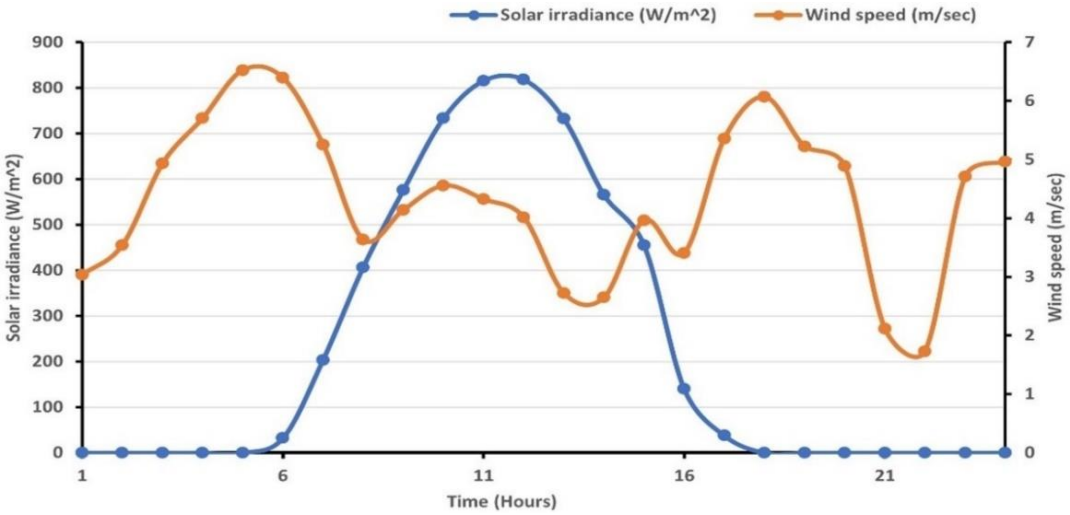

Figure 3. 1 Solar PV and WT Intermittent Generation Profiles

3.1. Distributed Energy Resources (DERs)

The increasing level of renewables and decentralized control of energy resources are fundamentally altering the existing power system infrastructure. Utilization of DERs is one way of installing and operating various energy resources independent of the location, given the persisting issues such as climate change caused by extreme carbon emissions, widespread adoption of renewables are important as well as energy storage systems (ESS) such as battery energy storage system (BESS), flow batteries and compressed air energy storage (CAES), etc. A significant amount of effort has previously been made to promote the integration of DERs into the power system. Studies have been conducted to develop standards for uniformly integrating diverse inverters into mainstream power system networks.

The IEEE Standard 1547™ has been used to certify a wide range of inverters, ensuring they meet the requirements for accurate performance in DER applications. OpenDER, released by the Electric Power Research Institute (EPRI), has been used as an assessment tool to evaluate the impact of DERs on power systems. Figure 3.2 shows an intractive Open-source distributed energy resource (OpenDER) appropriate for power stakeholders and applicable for modeling of inverters whose impact on the power systems can be assessed.

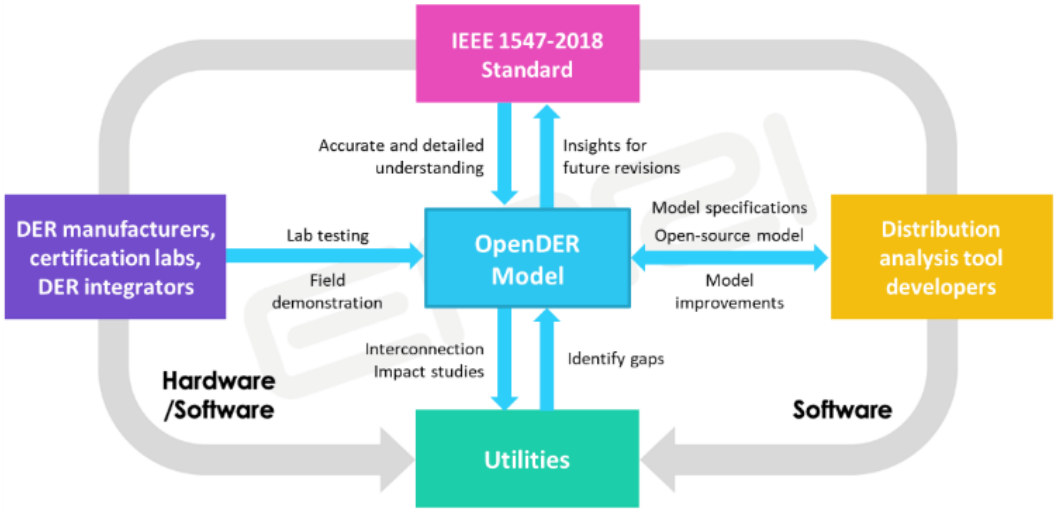

Figure 3. 2 OpenDER Model for Power System Network Stakeholders [129]

Ideally, conventional generators meet grid network requirements as they are often used for baseload.They can provide continuos power supply for a long period, when compared to RESs they are very costly to maintain and operate.

When Wind power is added into the energy mix the supply curve shifts indicating the conventional generators are only started in case the Wind power plant cannot meet the demand required for a stable grid network Figure 3.3.

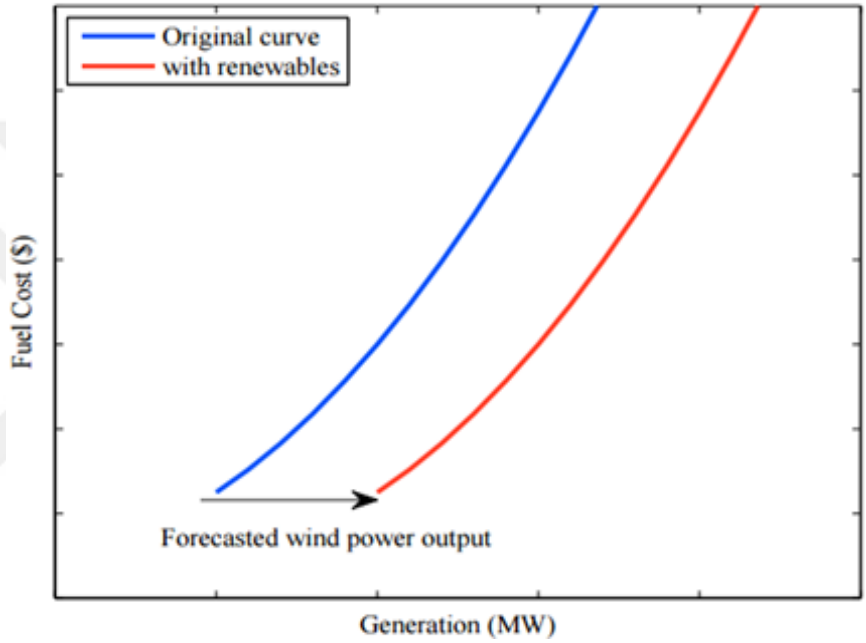

Figure 3. 3 Power Generation Cost Curve [130]

3.1.1 Gas Plants

As part of the DERs, gas plants are commonly used to provid stable power fort he grid over long periods. CHP and gas-fired turbines can be used a Peaker plants to provide ancillary services to the grid network. In combination with other generation units, a unit commitment algorithm has to be used to dispatch them in an economical manner. The costs of maintanance and operation is high when compared to the maintainance of non-dispatchable power generation resources.

A case study has been developed in [131] to evaluate a microgrid which is grid-tied or off-grid under electrical and thermal load profiles .The costs associated with

conventional power plants emanate from fuel consumption and other variable costs. Table 3.1 identifies diesel generators from G1 to G3 and the respective nodes they are located on. The minimum and maximum active power together with maximum and minimum reactive power are indicated.

Table 3. 1 Diesel Generator Production Costs

#Node	DG ID	P^{Min} (MW)	P^{Max} (MW)	Ramp rate (MW/h)	Q^{Min} $(MVar)$	Q^{Max} $(MVar$	$a(\frac{\$}{MWh}$	$b(\$ /MWh)$	$c\left(\frac{\$}{(MW)^2}\right)h$
16	G1	0	0.6	0.6	-0.2	1.2	0.02	2	0
20	G2	0	0.6	0.6	-0.2	1.2	0.06	1.75	0
30	G3	0	0.6	0.6	-0.2	1.2	0.06	1.75	0

The production costs of the generators can be formulated as a quadratic function (3.1).

$$C_j^G(P^G_j)=a_j(P^G_j)^2+b_j(P^G_j)+c \quad \text{.....(3.1)}$$

IEEE 30 bus system as shown by Figure 3.4 can be used as a radial testbed for analysis of optimal power flow in the grid network, the cost data for the generators can be the same. In radial bus systems, arrows indicate direction of power flow from the first bus up to the last bus, the dotted tie lines represent switching from and to different zones. The 33-bus testbed can be used to identify voltage swell or sag and critically affected lines due to external disturbances, and overloading or faults during OPF analysis.

Generally, the power system of the future will ensure distribution network and transmission system interactively coordinate RESs to stabilize the grid network all the time, which brings the idea of applying the VPP in optimal scheduling of dispatchable and non-dispatchable energy resources, respectively.

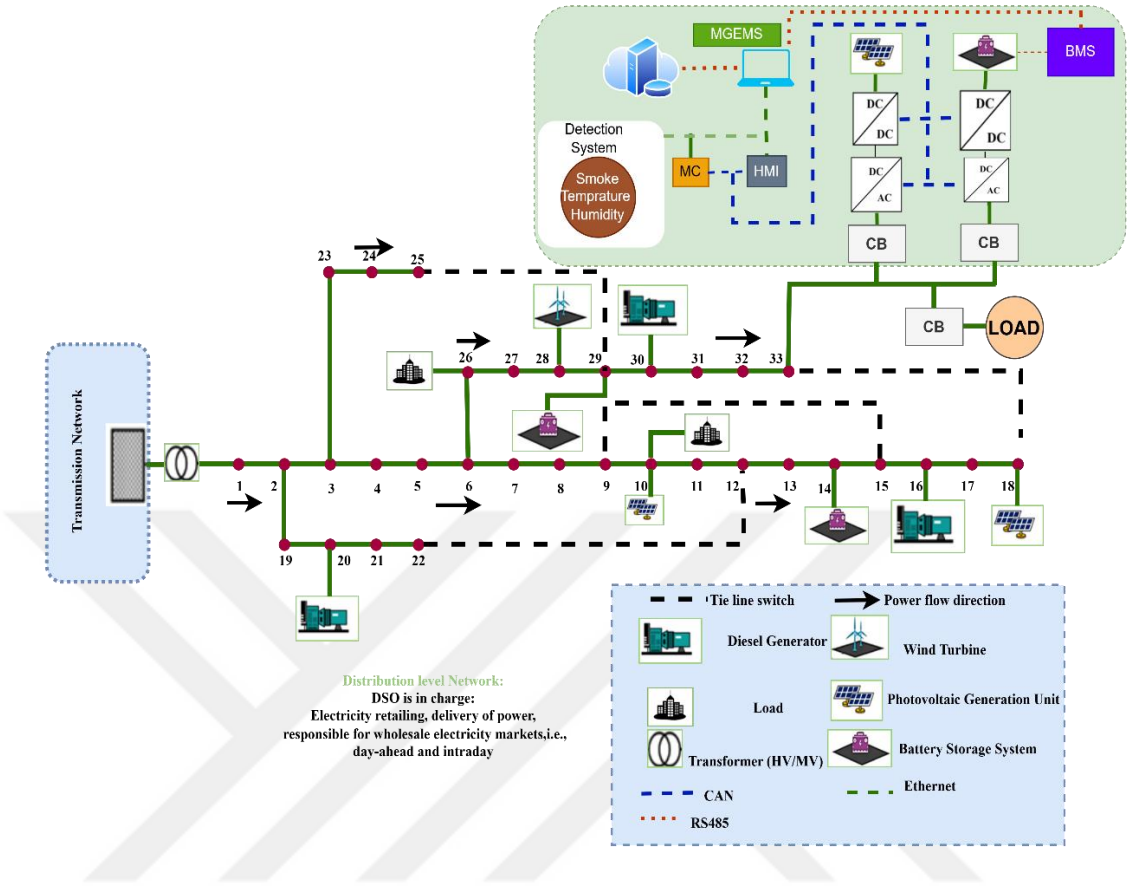

Figure 3. 4 DERs and Microgrid Connection on IEEE 33 Radial Bus Network

3.1.2 Solar Energy

RES forms part of distributed generation, and unlike conventional generators, their advantages are linked to the impact they have on the environment. Coupled with low costs and availability, this makes them easily deployable. In a more general sense, the advantages of RES are quantifiable on the basis of being environmentally friendly and can generate a reasonable amount of power when irradiance and high wind speeds are present. Additionally, low costs and high ROI make them attractive for long-term investment plans. Besides their advantages, they also require auxiliary support systems, such as storage systems to meet the capacity to incorporate excess power generated during periods of maximum solar irradiance and high wind speeds. Other challenges could include the high costs of installation and material acquisition, and usually, vast pieces of land are required to generate MW-GW scale of energy. The

selection of a solar PV system requires expertise in identifying architectures appropriate for the application area.

Generally, Solar PV systems come in a wide range of sizes, and the system must be properly sized to meet power requirements [132], as a result, a thorough feasibility study should be conducted, considering factors such as location, costs, and the type of control and monitoring strategy to be used.

Table 3.2 highlights PV inverters and existing configurations or architectures that require scrutiny before application.

Table 3. 2 PV Inverters and Available Configurations Adapted from [133]

Solar PV Inverters	Configuration	Application area	Generation range (Power)
Central	PV modules are connected in series to form a string, and the strings are connected in parallel to the central inverter (DC/AC).	○ Small (grid-scale systems) ○ Medium (grid-scale systems ○ Large (grid-scale systems	○ 500 kW-1 MW ○ 1-5 MW ○ 5-20 MW
String	PV modules connected in series to form strings and each string is connected to independent inverter (DC/AC) integrated into the grid.	Residential Commercial/grid-scale	○ 1-10 kW ○ 10-500 kW
Multi-string	Similar to string inverter, they are connected to a single inverter	Large-scale	3-10 kW
AC module	The inverter is integrated into the PV module and generates AC from the available PV modules	Small-scale	50-500 W
Hybrid-BESS	Leverages on the core functionalities of an inverter and a BESS, common in RES: supports self-consumption and enables low energy costs	small-scale applications, ○ Industrial settings,community and residential areas.	3-10 kW

In addition, the choice of inverter is critical due to variations in existing inverter models and their associated PV architectures. As much as Solar energy is on high demand, its limitation is related to availability of irradiance or the local weather conditions of given region, and uncertainties that are usually related to the solar radiation intensity, which can lead to under production and over supply. Usually, the

solar radiation intensity follows β-distribution, and the standard expected Solar PV output $\{P_{spv,t}:t\in T\}$ is given by equation (3.2).

$$f(P_{spv}|\alpha,\beta)=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left(\frac{P_{spv}}{P_{spv,max}}\right)^{\alpha-1}\left(1-\frac{P_{spv}}{P_{spv,max}}\right)^{\beta-1} \quad \text{.....(3.2)}$$

Since empirical equations are used, the error can be represented as $\varepsilon_{spv} \sim N(0,\sigma_w^2)$ [134], also a random number $\xi_{pv} \sim U(0,1)$, can be used to determine the generation status of the Solar PV and similar logic can be used for the WT.

3.1.3 Wind Energy

Wind power output intermittency depends on the wind speed and other parameters, which are related to the geography and the weather conditions of the local area [134]. Research has studied the variance using mathematical models to specifically model the aerodynamic characteristics of the wind turbine.

In literature, the most commonly used mathematical approach entails applying Weibull distributions, which are represented as probability distribution functions (see Figure 3.5). In [135], wind speed has been studied, it is found that wind speed can be modeled using more than one PDF, and in that case two-parameter Weibull distribution is commonly used to model wind speed frequency distribution. In some cases, two-paremeter weibull might not give expected results and in that regard three-parameter Weibull distrubution is used as a remedy though it is not commonly used in the wind industry. Note, there can be considerable measurements differences between the two PDFs caused by null wind speed, in order to calculate wind energy output, key assumptions are required.

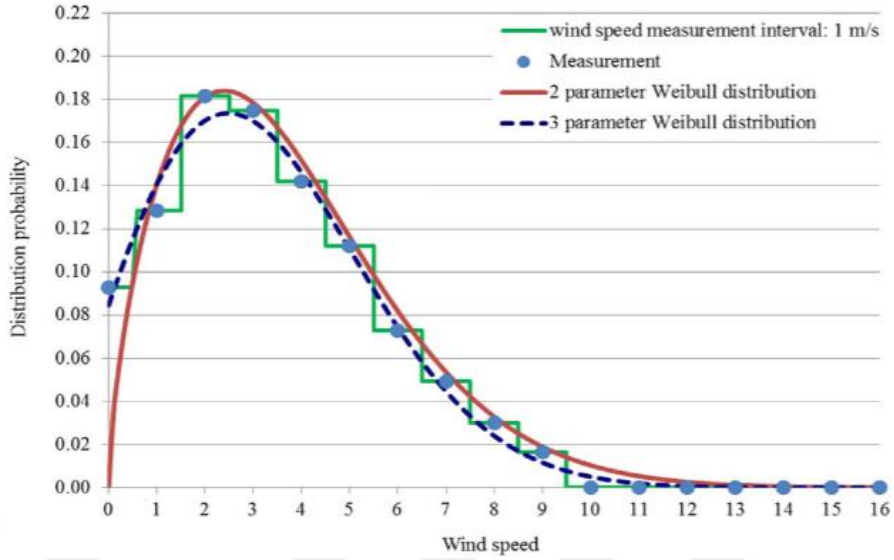

Figure 3. 5 Weibull Probability Distribution Functions [135]

Meanwhile, equation (3.3) represents a Weibull distribution function, which is a standard empirical equation used to quantify power output of a wind turbine (WT).

$$f(v|c,k)=\frac{k}{s}\left(\frac{v}{s}\right)^{k-1} e^{-\left(\frac{v}{s}\right)^{k}} \quad \text{.....(3.3)}$$

Additionally, the existing correlation between wind speed and the WT output $\{P_{wT,t}: t \in T\}$ is represented by empirical equation (3.4).

$$P_{WT}=\begin{cases} P_{wT,r} & v_r \leq v \leq v_{co} \\ P_{wT,r}\frac{v-v_{ci}}{v_r-v_{ci}} & v_{ci} \leq v \leq v_r \\ 0 & v<v_{ci} \text{ or } v>v_{co} \end{cases} \quad \text{.....(3.4)}$$

The empirical statistical error ε_{wT} follows a standard distribution $N(0, \sigma_w^2)$ [134], there are other parameters that are included in the modeling of WT such as forced outage rate of WT, δ_w, which play a crucial role in power output test analysis. To simulate an outage event of a WT, a random number ξ_w can be used in a uniform distribution $\xi_{wT} \sim U(0,1)$.

3.1.4 Energy Storage System (ESS)

The improvement of technology has facilitated the roll out of ESS in the power sector. These advancements have supported the efforts to integrate renewables into the grid using different types of ES technologies. It is well known that solar PV and wind energy are stochastic in nature and are characterized by unprecedented variability in power output. Such inconsistencies in power production render them unreliable. In the field of power systems, research has developed methods and key solutions to enhance renewable integration into grid networks [136].

Over the past decades, extensive studies have investigated the complexities of incorporating storage systems into the generation mix, evaluating options such as renewable curtailment and other methods for storing excess supply. The central issue is having a clear understanding of types of objectives or goals to be accomplished, constraints to be factored in optimization techniques, renewable energy sources, and lastly available storage technologies.

In regard to having rapid solutions and immediate dispatch of grid-coupled energy resources, some studies have formulate unit commitment problem with the intention of using storage to adopt renewable energy into the grid [136], the solution technique is to develop a decision-making model that utilizes charge-discharge four-stage-novel co-optimization strategy, which is generally accepted as a unit commitment formulation, as it leverages on robust methodologies. Other studies such as in [137], Wind power is converted into a dispatchable asset using BESS, the idea is to trade energy directly into spot DA, balancing and ancillary markets.

Initially, the power markets were traditionally served by dispatchable assets such as CHP and diesel generators, which rely heavily on fossil fuels. The study progressed to use multi-stage stochastic programming to model a VPP participating in DAM, equally, storage can participate in the electricity market using VPP platform to transfer electrical energy at different periods or for future use, and support balancing of generation and demand in the electrical grid network.

To navigate the complexities associated with storage technologies in optimal control, [138] adds details to the existing research with the view of improving storage model's accuracy at the expense of computational burden. The short-comings are identified to be inadequate open source data for research, experts knowledgeable in cell balancing and incomplete full-fledge uncertainty models associated with risk-averse and control methods. Another aspect is limited knowledge in cooling and thermal management approaches, lastly the research identified models that lack right combination of measured degradation stress factors, which originate from the failure to identify accurate models.

[139] identifies two important parameters for ESS: depth of discharge (DOD) and depth of charge (DOC), they are directly related to the lifespan and operational status of the ESS. The cyclic nature of charge-discharge of ESS negatively impact the lifespan of ESSs, implying that such parameters have to be carefully chosen to minimize degradation rate of ESS [140]. The use of BMS can guarantee optimal performance of ESS during operation through tracking of continuous state of charge (SoC) to avoid overcharging or deep discharge of the ESS [141].

Therefore, when choosing an ESS for the wind and solar power plants. It is necessary to review Table 3.3, the models shown can help guide engineers, researchers and energy stakeholders to assess the specified battery models in terms of attaining economical value, and gauging the performance of various models to configure, recommend and make the right investment decisions, at the initial stages of selecting the right RES technology and a properly sized ESS technology.

Table 3. 3 Battery Models Applicable for PV and Wind Power Plants [133]

Battery	Merits	Shortcomings
Equivalent Circuit Model (ECM)	○ Easy to implement does not require high-level skills ○ Appropriate for real-time applications ○ Voltage and current are accurate and precise	○ The accuracy for complex chemistries diminishes ○ Complete coverage of all the electrochemical processes is not available ○ Continuous calibration
Two-Point Model	○ Simple when compared to ECM ○ Appropriate for real-time applications ○ Can effectively estimate SoC	○ Inaccurate coverage of battery dynamics ○ Temperatures ○ Continuous calibration
Electrochemical Impedance Spectroscopy (EIS)	○ Granular information on electrochemical processes can be obtained ○ Battery aging studies can be conducted easily ○ Can effectively estimate SoC	○ High-level skill is required (Expertise) ○ Analyzing model data is complex and time-consuming ○ Low accuracy under changing conditions
Diffusion Model	○ Specifically, lithium-ion dynamics can be well presented ○ Battery behavior can be predicted more effectively ○ Appropriate for studying thermal effects	○ Complex and computationally challenging ○ Vast battery parameters are required ○ Degraded performance under extreme temperatures
Electro-Thermal Model	○ Electrical and thermal properties of the batteries are well presented ○ Thermal management studies can be conducted ○ Battery performance under wide range of load conditions can be predicted.	○ Vast consideration of thermal and electrical parameters ○ Computationally challenging ○ Need calibration continuously

Figure 3.6 shows different type of storage technologies , and each technology can be chosen depending on the scale of application and the performance required.

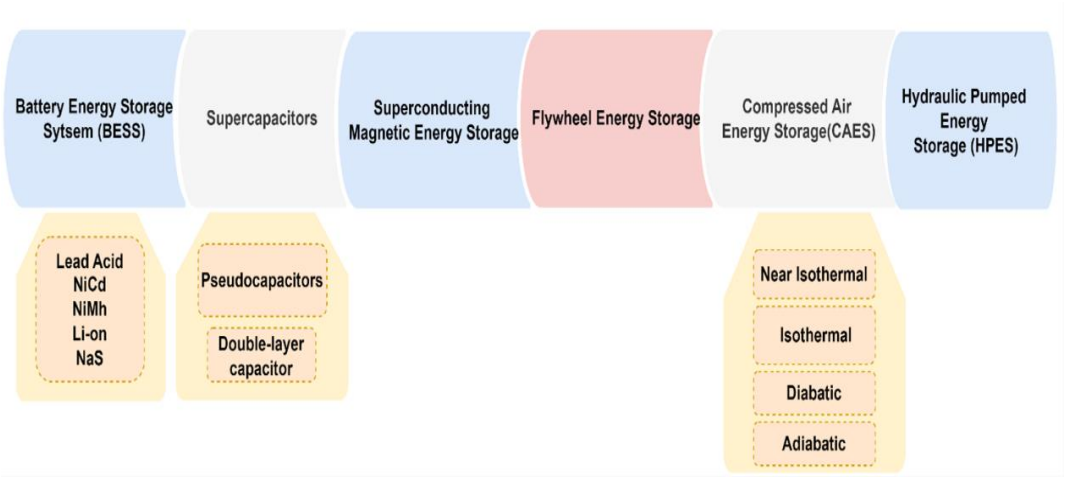

Figure 3. 6 Energy Storage Technologies

Table 3.4 illustrates features and characteristics of storage technologies, efficiency, and application area, which determines the capacity of the BESS required.

Table 3. 4 Features for Different BESSs [142]

Type	Energy Density (Wh/kg)	Life (Cycle)	Cost ($/kWh)	Efficiency (%)	Applications
Lead Acid	25–45	200–1800	150–500	65–80	Peak shaving, Spinning reserve, Frequency regulation
Nickel Cadmium	50–75	2000–2500	800–1500	60-70	Frequency regulation
Nikel Metal Hidride	170–420 Wh/L	----------	----------	65-70	Peak shaving
Sodium Sulfide	150–240	2500–4500	300-500	75-90	Peak shaving RES integration Power Quality
Lithium Ion	80–200	1000–10,000	600–2500	90-97	Arbitrage Peak shaving Frequency regulation Power Quality
Vanadium Redox Flow	10–50	12,000–14,000	150-1000	75-85	Peak shaving Arbitrage Frequency regulation Power Quality

Grid scale application entails deployment of BESS to provide steady power supply and a channel to integrate more renewables into the grid. On the long run, the benefits of

BESS for the grid network are immense as the ISO can use the technology to defer expansion of transmission lines and manage congestion in a more efficient way as shown by Figure 3.7.

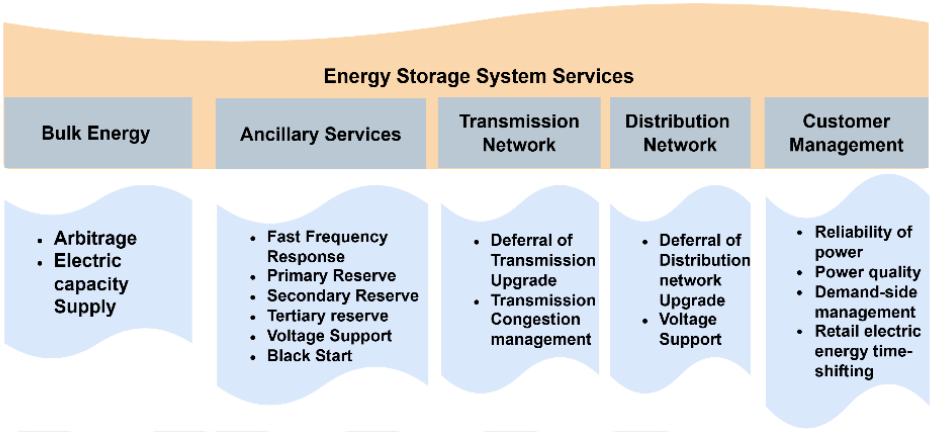

Figure 3. 7 Grid-Scale Energy Storage Services [143]

BESS plays a very significant role in stabilization efforts of the grid network, Figure 3.8 shows how power smoothening is achieved by deploying BESS.

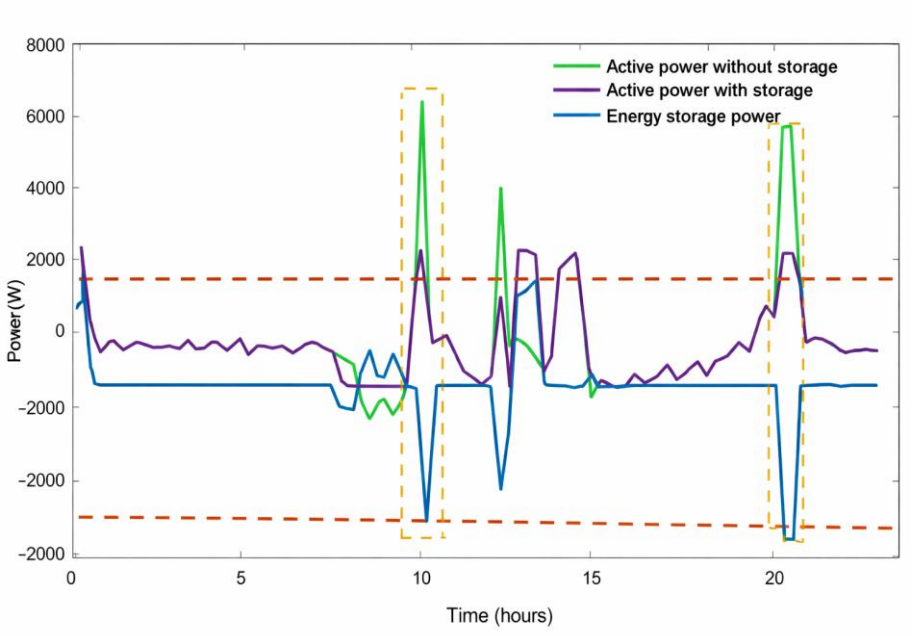

Figure 3. 8 BESS Peak Demand Absorption

The green line represents the peaks when BESS is not in use, and the purple line is power with BESS, which implies the power peaks are absorbed by the storage system and then discharged approximately at hour 13 as shown by Figure 3.8, and then the discharge-charge cycle continues. The BESS operates within the upper and lower bounds as shown by the dotted red lines.

The impact of storage can be represented by use of a duck curve as shown in Figure 3.9. Storage has significantly reduced the peak load and ramp rate has gone low compared to when storage is not applied. During the peak hours the renewables are unavailable to cater for the demand, and Peaker plants are then deployed to cover for power deficit at an extra cost, implying storage can compensate for extra power demand required at peak hours.

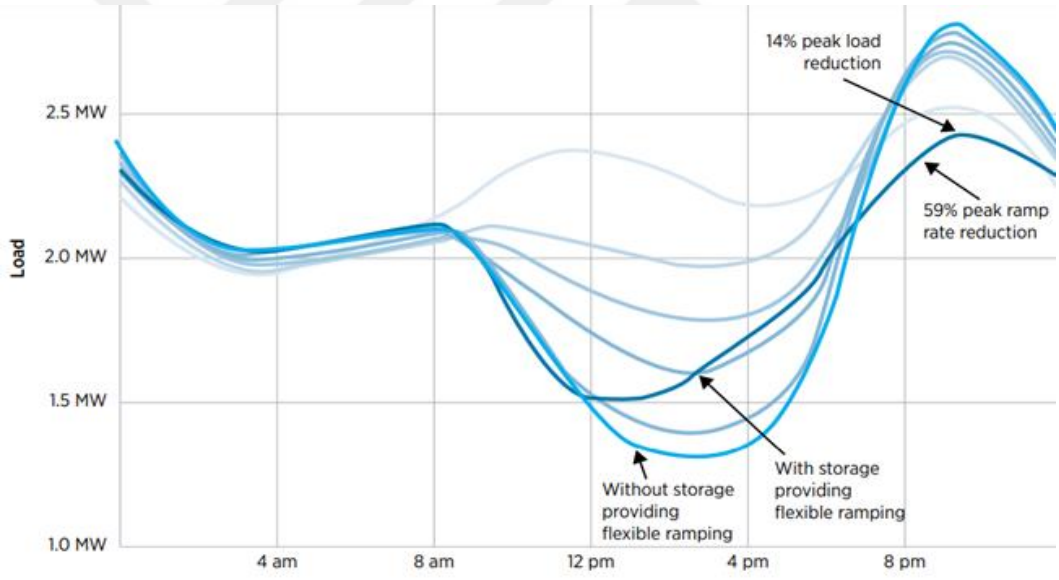

Figure 3. 9 Storage Impact on Peak load. Source: Sunverge (2015)

There are factors that determine the type of storage to use and can be classified into various categories depending on the ESS technology available as indicated by Table 3.5, they include costs, lifespan, scalability, power density, energy capacity and environmental impact.

Some ESS can literary be used for all application cases, but some are better left for large-scale application, as they require vast pieces of land and high-level engineering

skills to install and operate such as PHES, Hydrogen fuel cells, etc. There are also electrochemical properties that are linked to the overall ESS properties mentioned, for instance SoC, voltage and current waveforms [133].

Table 3. 5 ESS Merits and Demerits

Ref#	Energy Storage Technology	Main Features	Merits	Demerits
[144]	Lead-acid Batteries	Affordable: signified with low costs	Easy to use and maintain	Low energy density with shorter lifespan
[145]	Lithium-ion Batteries	High energy density	High efficiency in charging and discharging modes	Explodes easily and can cause fire
[146]	Flow Batteries	Easily scalable	Discharge-charges effectively without limits	Low energy density
[147]	Redox Flow Batteries	Scalable and durable(several months to years)	Discharge for long periods	Regular maintenance makes it expensive
[148]	Sodium-Sulfur Batteries	High energy density	High durability compared to other batteries	Expensive when compared to lead-acid battery
[149]	Supercapacitors	High power density	High discharge-charge rate which lasts for long period	Low energy density and circuit control are a requirement
[150]	Hydrogen Fuel Cells	High energy density	No eminent emissions	High installation cost
[151]	CAES	Affordable when compared to existing technologies	Large energy storage capacity	Not appropriate for small-scale projects
[152]	Flywheel Systems	Fast response to changing energy demand	Environmentally friendly with negligible emissions	Expensive and needs high-level engineering skills
[153]	Pumped Hydro Energy Storage (PHES)	Established technology	High Durability(several months to years)	Suitable for large scale projects(Vast piece of land)
[154]	Thermal Energy Storage (TES)	Established technology	High energy density and easy to integrate with cooling and heating systems	Suitable for large-scale applications
[155]	Capacitor Banks	Fast response to changing energy demand	Easy to maintain	Low energy storage capacity
[156]	Gravity Storage systems	High efficiency and low cost in comparison to existing technologies	No emissions	Limited storage potential

3.3 Power System Network

The electrical grid network is a critical infrastructure in the power transmission and distribution industry. It is designed in a way that it can accommodate diverse power generation sources and loads. Power grid network has slowly progressed to accommodate RESs, with this advancement the network is required to be flexible all the time to facilitate grid stability and management of RESs at required thresholds [157]. In that regard, transmission and distribution of power has to be continuous to gurantee security of supply and delivery of quality power. Power hugely depends on market price and demand, and the prices can change to reflect the quantity of power needed for delivery.

The higher the price implies less power will be required and the lower the price the higher the demand, though it might not be the case all the time due to complex nature of technicalities required when operating the grid network . RESs contribute to this complexity, their power output being unpredictable is a setback to grid system management. If power output is not monitored, they can have a nagative impact on the network , also the fact there are deregulated markets the number of participants has increased such as IPPs, market and regulatory agents overally complicating the trading and compensation of asset owners when they incur losses.

In addition , to effectively interact with the various systems in the network, defined levels are used and each level has specific functions , which are configured to achieve a particular set purpose, the primary level as shown in Figure 3.10 ensures the safety of the physical power components through frequency and volt/var control, these approaches ensures the microgrid can be connected or disconnected without voltage violations. In the secondary level, optimization techniques are applied to effectively manage blackstart process and RESs forecasting. The secondary level involves monitoring of field components and incoming data, establishing communication with distribution management system (DMS) and energy market.

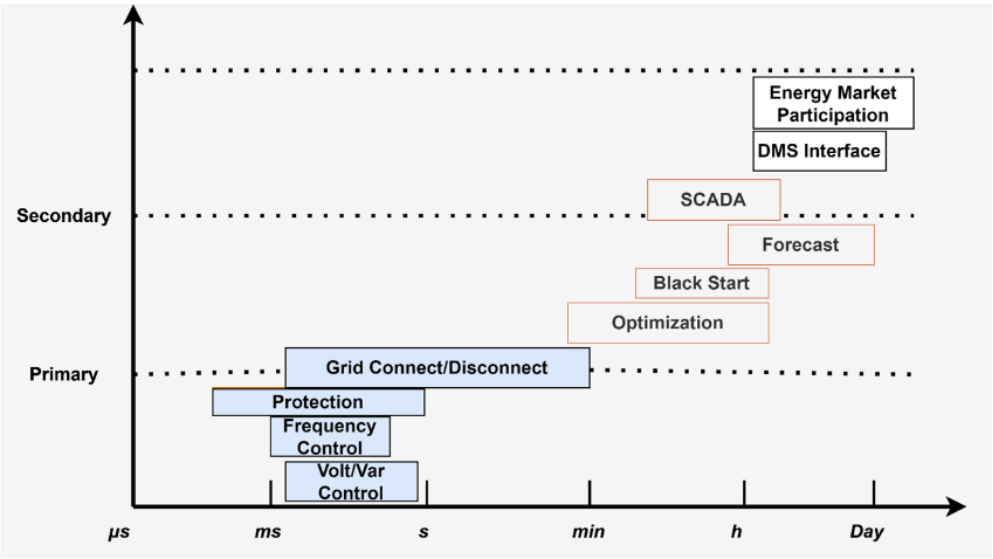

Figure 3. 10 Microgrid Hierarchical Control Levels

Subsequently, for smooth power flow to be realized at all periods, certain aspects of the grid network have to be considered in full effect. The design criteria of power network systems, entails paying attention to voltage levels in the network, and research has shown extensive work in understanding modeling of power systems under penetration of renewables and storage systems in line with the concept of static operating envelope (SOE) technical limits, which ensure DERs or CERs operate within the specified limits to guarantee secure, reliable and quality power. Most studies carry out power flow analysis or load flow to assess the impact of DER on the grid network, by solving a power balance equation so as to obtain bus voltages, also assess whether there is capacity violation of line ratings and the extent at which power losses could occur.

Generally, the balancing equation is non-linear and requires iteration methods such as Newton-Raphson, the fast-decoupled and the Gauss-Seidel solution methods. In case of DC power flow, the problem becomes linear implying linear solution methods are used. Figure 3.11 shows general OPF objective functions that have been used in previous works. It provides clarity in understanding power system networks under simulations, which augment the assessment of flexibility capabilities of distribution systems and microgrid networks emphasizing the importance of smart-grid concept [158].

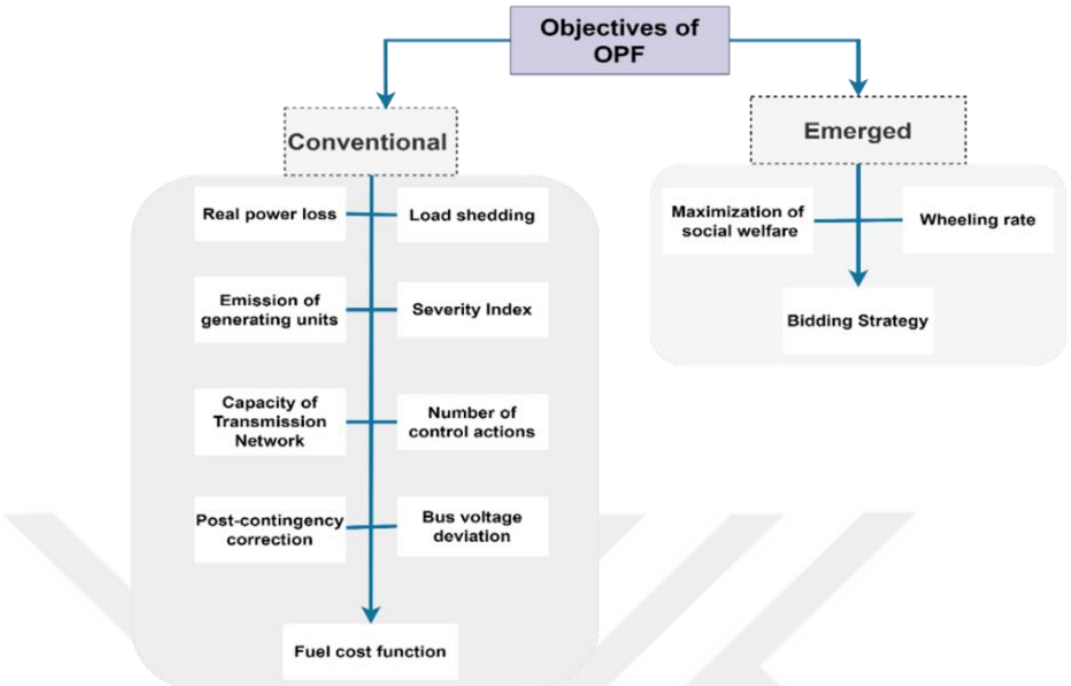

Figure 3. 11 General OPF Objective Functions, Adapted from [159]

Table 3.6 shows the load and generation buses. The slack bus represents power mismatches between planned generation and the total generation and can be quantified as total load and losses in the system. The slack bus also known as Swing bus can be referred as a reference bus with specified voltage and phase angles.

Table 3. 6 Real Power and Reactive Power Specification in Power System Buses [160]

Type of Bus	**Voltage** $(\lvert V_i \rvert \angle \delta_i)$		**Real Power**			**Reactive Power**		
	Magnitude	Angle	Generation	Load	Net real power	Generation	Load	Net reactive power
Slack	Specified	Specified	Unknown	specified	unknown	Unknown	specified	unknown
PV	Specified	Unknown	Specified	specified	Specified	Unknown	Specified	unknown
PQ	Unknown	Unknown	Specified	specified	Specified	Specified	Specified	Specified

Furthermore, Table 3.6 has a PV bus also known as a regulated/generator bus and it specifies net real power and the regulated voltage magnitude .on the other hand, load buses are known as PQ buses and their voltage magnitude and angles are not known, and only voltage angle is not known for PV bus [161], at the slack bus both voltage and angel magnitudes are specified and the variables are not solved. To determine the

number of unknows, 2(n-1) (g-1) is applied, whereby n is the number of buses and g the number of generators, also real and reactive power balance equations are used to solve the unknowns. In addition, admittance matrix is applied to determine the unknowns and has admittance values for all lines and buses. It enables power flow studies to be carried out and assessment of safe operation of the power network system. In [160], Pandas power library has been used to perform optimal power flow studies, by modeling an IEEE 33-bus network with DERs such as PV, Wind, BESS and DGs.

The use cases are modified and implemented as follows: Case 3 includes PV, wind, and BESS; Case 6 includes PV, wind, BESS, and DGs; and Case 7 includes PV, wind, BESS, and DGs with an additional 10 MW load added to bus 26. In Case 7, the robustness of the grid network is tested by injecting a 10 MW load at bus 26, while all other parameters remain unchanged, such as base power at 20 MVA, substation voltage at 12.66 kV, and HV at 20 kV. The upper and lower voltage limits are set to 0.85 and 1.15 pu, respectively. DG values are used and connected to buses 16, 20, and 30, as indicated earlier in Table 3.1. Additionally, PV and wind turbines are connected to buses 18 and 27, with 2 MW and 0.012 MW, respectively. Two BESS units, each with a capacity of 4 MWh, are connected to buses 26 and 28.

Figure 3.12 displays the variation in voltage when different cases are applied. The addition of 10 MW implies higher demand compared to generation. The voltage sag can be corrected by adding a 3 MW DG to compensate for the high demand at nodes 26 and 28. Otherwise, Case 3 does not show large voltage deviations because the DERs are optimally placed. Compared to Case 6, the addition of DGs provides greater stability to the power system network, highlighting a tradeoff between the use of fossil-based generators and RES. Therefore, further research is needed to strike the right balance between the use of conventional generators and RES in order to enhance grid stability while protecting the environment.

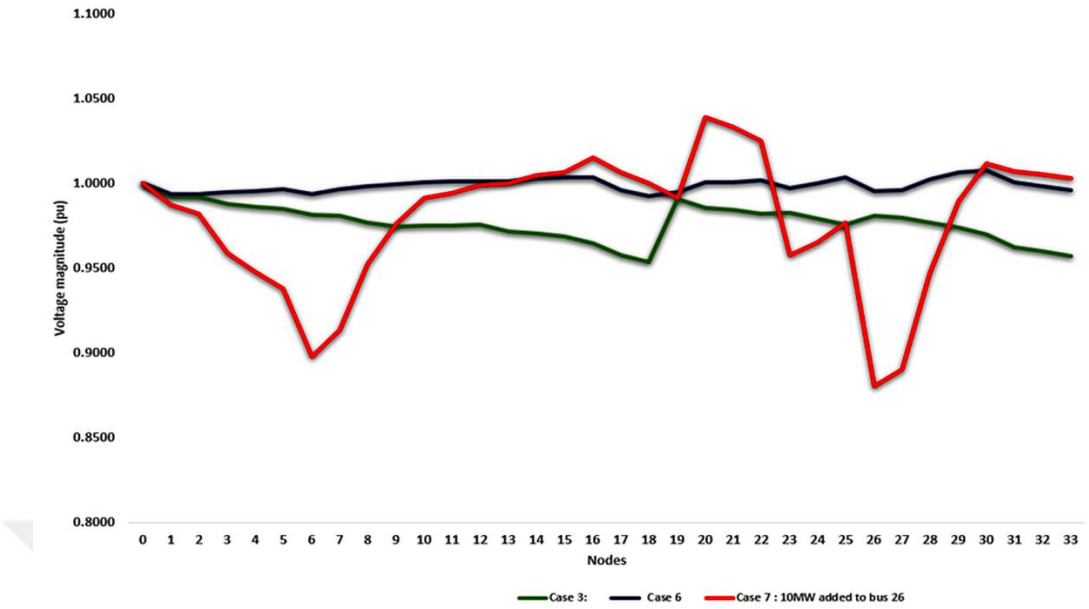

Figure 3. 12 Comparison of Voltage Deviations Under Different DERs Cases

3.4 Electricity Market

Power markets are designed in a way that multiple electricity stakeholders can interact in selling and buying of energy at specific clearing price. For the whole process to be conducted, security and stable generation of electricity must be ensured and the distribution process should meet the requirements set by the ISO, this involves power supply and demand should be able to meet required thresholds every time. The suppliers or generating companies (GenCos) should also have necessary permits to operate their power plants and be licensed to participate in power markets by market operators or designated agents. Generally, market operators and agents are involved in the energy trading process.

The agents are responsible for selling and buying of electricity, they can be GenCos who can supply electricity as IPPs or wholesale electricity consumers. Operators are public companies that are responsible for economic and technical management of the power system network, i.e., independent market operator (IMO) and ISO, respectively [137].

Figure 3.13 shows the electricity market stucture demarcated into various stages, from the negotiation stage untill settlement stage showing the negotiaition stage, clearing, delivery and then settlement. All these stages comply to power supply and demand requirements. D-1 is when the purchase and sale offers are made and cleared. In day D, electricity is physically delivered using the matched offers. Lastly in D+1, market imbalances are settled by the ISO.

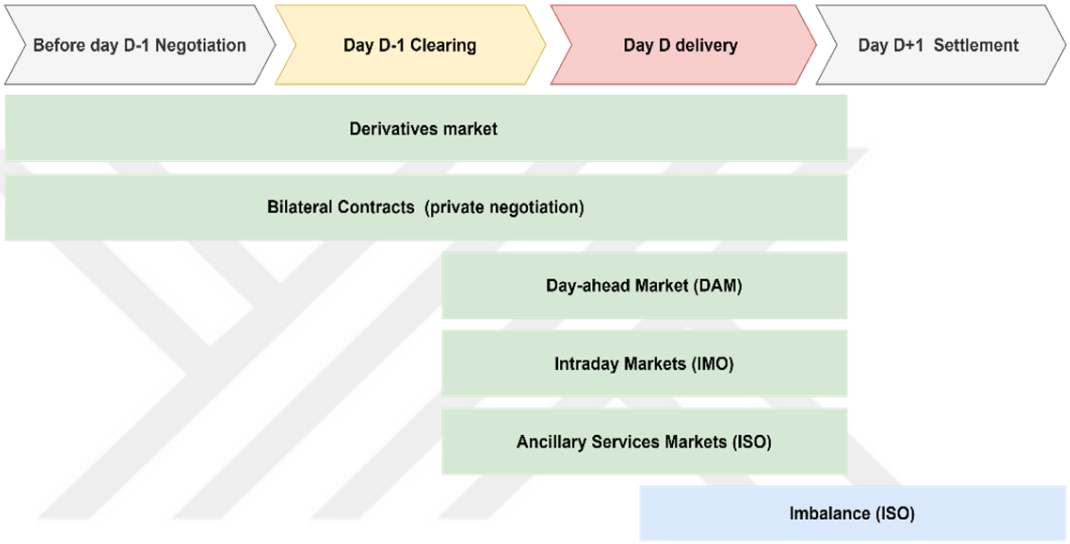

Figure 3. 13 Electricity Market Structure , Adapted from [137]

ISO ensures grid code compliance of all the GenCos, in terms of power capacity required at various connection points and the IMO receives orders and matches them with respective prices and quantities for settlement purposes.

The IMO is in charge of wholesale electricity markets such as day-ahead and intraday markets, and the ISO negotiates power to be used for balancing of the grid network termed as ancillary service market (ASM). [137] notes that grid system operators are monopolistic, non-competitive, and focus primarily on regulating the grid network to provide stable power supply across the network structure. For instance, the IMO can formulate a price clearing procedure to objectively clear the market.

Figure 3.14 shows the Iberian Electricity Market (MIBEL) market clearing using price mechanism. The electricity purchase offers, and sale offers equally get the same price

after the market is cleared, the matching sale and purchase offers for hour 5 are on the left of the market clearing price.

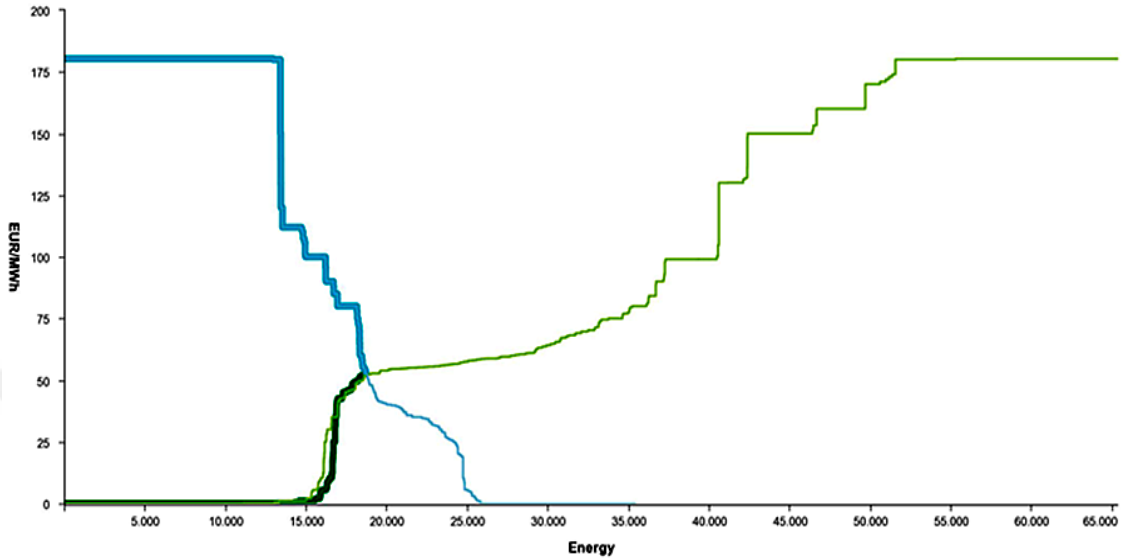

Figure 3. 14 Supply and Demand Curves (MIBEL, Hour 5-05/03/2019) [162]

Additionally, there are derivative and future markets, which are used to supply power during unexpected shutdowns of key generation units, fluctuations risks, and significant voltage imbalances. Mitigation of these shortcomings is the focus of the ISO, and through the intervention of the IMO all power markets such as DAM, IM, and ASM get optimally cleared to comply with the dispatch regulations set by the ISO. Figure 3.15 shows the research progress in power markets from the year 2011 to 2020 using a VPP set-up [163].

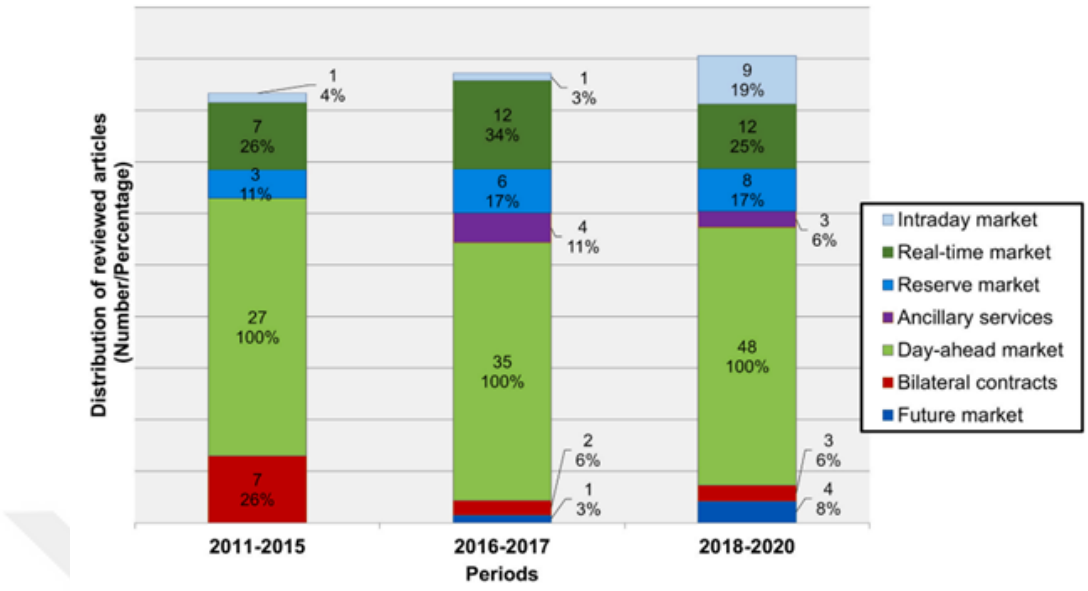

Figure 3. 15 Power Market Types (2011-2020) [163]

3.4.1 Day-ahead Market (DM)

DM handles electricity transaction in the next 24 hours, the purchase and sale offers are made in the day before then the results can be adjusted by the ISO to meet the grid code requirements.

Figure 3.16 shows the trading schematic of the day-ahead process flow, the dynamic nature of the grid network entails such a keen and precise stages, the process is in easily determinable stages with market operator being strategic on how supply and demand is met. Virtual net load is obtained from the difference between the renewable energy potentially supplied and the conventional energy supplied to the load.

The order book contains quantities and prices constituting offers and bids, respectively. The next instant, day-ahead clearing is achieved shortly after the market clearing price is determined and then followed by day-ahead settlement period. In this stage, the cleared orders and forecasted errors are input into the update trade schedule module, which adjusts the orders in relation to the forecasts errors, and then the stages that follow are the set assets constraints and the updated trade schedule which aligns with the market consistency that states the requirements of the market to avoid

violations of any form, the constraints available govern the operations of the specified assets, and ensures their optimal dispatch and availability at the same time. The two bifurcated sections end up in the market consistency and day-ahead closure, respectively. The day-ahead market has predetermined opening and closing hours and the bids or offers are given a timeline, if the necessary conditions of the day-ahead closure are met and the optimal operational costs are evaluated the system goes into congestion management mode, otherwise new orders are made. In addition, market consistency can be assessed using the cleared orders which are also input into the redispatch demand orders, for redispatch to take place the redispatch market operator checks the cleared orders and then carries out redispatch clearing and settlement to meet the system requirements, and satisfaction of both the buyers and suppliers.

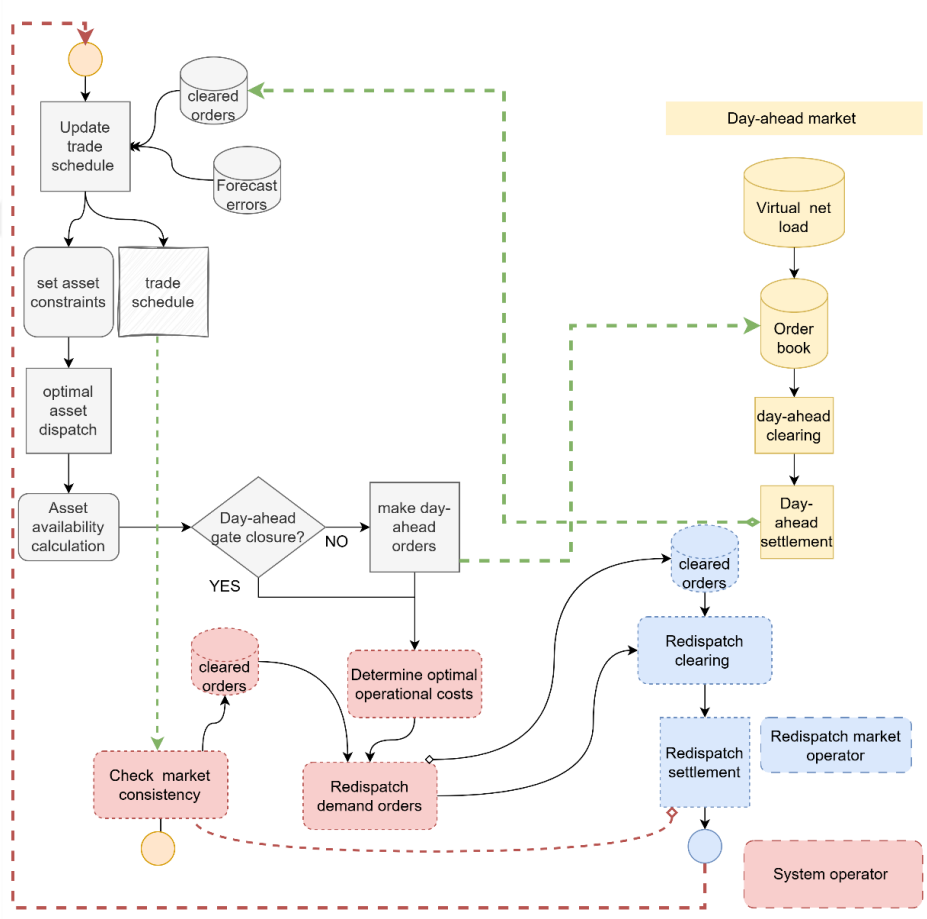

Figure 3. 16 Day-ahead Order Placement and Clearance , Adapted from [164]

3.4.2 Intraday Market

The market is structured in a 24 h period, hourly bids are submitted into the market and the operator makes adjustments using the ISO incoming signals. Power purchases and sales are matched hourly and the ISO responds to the deviations by limiting the dispatch from the generational units or cuts down demand to stabilize the power grid network.

3.4.3 Ancillary Service Market

The aim of the ancillary service market is to provide frequency support for the grid network by balancing demand and supply fluctuations. The predicted and actual power mismatches are corrected using ancillary services. Market agents can submit their up and down regulation reserve bids covering 24 h, and the ISO can clear them respectively based on the condition of the grid network.

3.4.4 Imbalance Settlement (IS)

In the IS, after the sales and purchase are cleared in day D, the actual deviations between real-time generation and the cleared energy in the DAM and IM are calculated. The owners of the supply units and consumption units are settled with respect to these deviations. According to the bilateral agreements, the owners can receive compensation for the energy they produced and was not bought or pay penalties for not producing the required amout of energy.

Therefore, the trading agent such as VPP owner should be privy to market information and adjust power according to the current grid requirements to avoid being penalzed or oversupplying energy. VPP agent can apply price mark up model to determine his bidding price or calculate risks involved when determining the price of the energy quantity to be dispatched.

Overall, the VPP can strategize its bidding approach to obtain maximum benefits depending on the marginal costs and the market type, as will be discussed in subsection 3.5.

3.5. VPP Strategic Bidding

Electricity markets are very competitive, and the participants need to develop bidding strategies that will help them maximize profit by adhering to the measures set by the regulators to uphold compliance in regard to possible abuse of power market regulations. A properly designed electricity market is expected to have zero tolerance to abuse, and be immune to violations and loopholes from outsiders who have the intention to alter market prices for their own advantage. There are two markets which are of interest, real market and perfect market, and the notable difference between the two markets is that real market is inefficient as it operates lower than maximum social welfare, unlike perfect electricity market which aims at maximizing social welfare.

A power supplier becomes a price taker meaning the supplier cannot determine the market price or change the prices as set. In regard to microeconomic theory, the supplier is encouraged to optimally bid marginal cost to stand high chances of being cleared. Note, strategic bidding problem was first addressed in [165], and its defined as an approach that the generator owner uses to bid without considering marginal cost to take advantage of market imperfections to increase profit [2]. In case a generator bids without lowering generation costs and becomes successful, then it is clear that the generator has market power. However, in new electricity market models the aspect of being perfectly competitive is not hugely factored in, and the supplier can exercise market power by bidding strategically to increase profit. Next, the problem of strategically bidding is common in pool trading whereby suppliers and at times large consumers use sealed auction to make offer prices and quantity bids, which are then decided upon by the market operatör who uses merit order dispatch criteria to determine the winning bid and market clearing price (MCP). Usually, for contracted trading, bilateral type of arrangements and step-by-step negotiation process involving the seller and the buyer can be used [2].

The bidding problem commonly involves suppliers though demand side bidding has gained substantive attention, there are three ways used to formulate bidding strategies,

- MCP approximation in the next trading phase
- Estimation of behavioral pattern of rival partcipants
- Utilization of game theories

There are also emphirical market simulation methods that can assess strategic bidding behaviour, though they often do not lead to satisfiable systematic approaches that can help create efficient bidding strategies. In the bidding space, other supportive tools are required, such as forecasting tools that can help predict electricity prices in pool trading, also, additional analytical trading tools can utilize demand forecasts to investigate partcipant's bidding curves and transmission congestion. Realistically, bidding strategies are continuous and an equilibrium electricity market price existing is not certain, Figure 3.17 summarises bidding strategies.

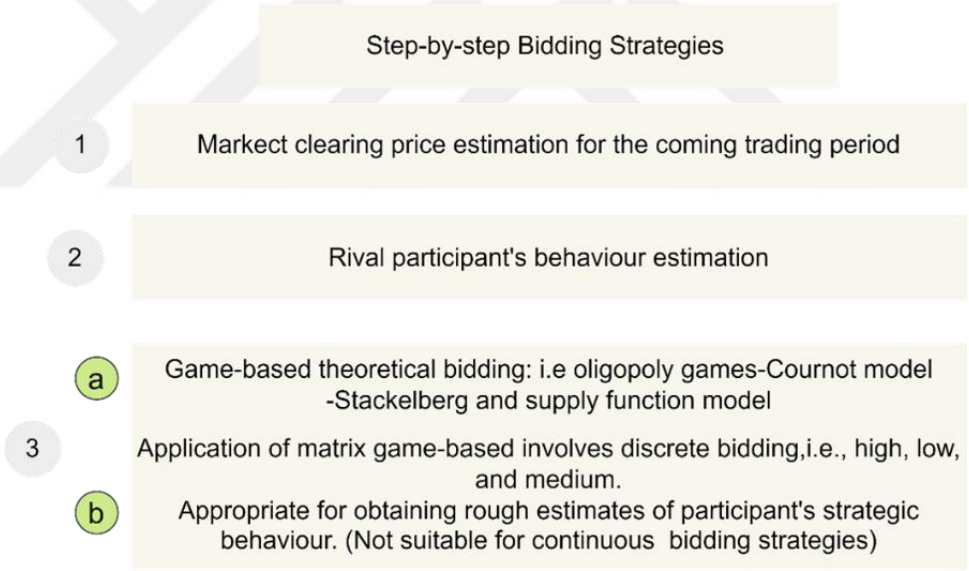

Figure 3. 17 Bidding Strategies

Electricity market clearing prices might not be realistic on the long run, due to intense simplification, and application of assumptions to represent optimal bidding for suppliers and consumers. Therefore, MCP is just an estimation for analyzing power market using uniform pricing mechanism to reduce transmission congestion and offer satisfiable social welfare in competitive electricity market. Furthermore, to understand

the process of bidding, comprehensive market models, auction rules and bidding protocols have to be considered as shown Figure 3.18.

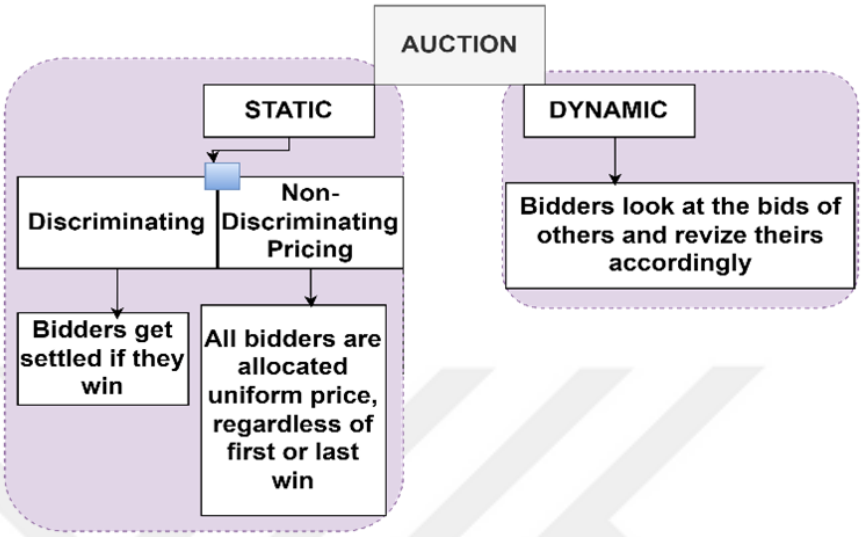

Figure 3. 18 Categorization of Auction rules

Auctions can further be classified as sealed or open. A sealed auction is a descending bid, while an open auction is an ascending bid. Their nature is country-specific. Moreover, sealed bid is regarded as first price and second price auction, usually referred as non-discriminating auctions. Uniform pricing mechanism is used depending on whether it was set to the first winning or the last winning bid. Also, auction can be submitted by both the buyer and seller when explicitly required, in which case they are referred as double, almost all the countries globally make use of sealed bid auction to carry out their bidding process using uniform pricing. In determing the nature of bidding protoccols, we have to look at the existing market designs, which defines the terms of engagement and the characteristic of the bids, the bids might be submitted in two forms multipart bid or single-part bid [166]. In regard to energy bid, placement of bids is done in relation to the energy price segments and the amount of energy supply available, i.e., the price of each energy block can be from the unit or group of units.

Ref.[167], details several market designs with diverse energy-bids, which can be categorized into multipart bid or single-part bid. Multipart-bid is described to have

independent prices for start-up units, no-load operation and energy, common in England-Wales electricity market. Also, for multipart bid the market operator is required to clear the market using unit commitment approach, while a single-part bid is common in Carlifornia electricity market and tends to offer energy price with fixed or variable costs, distinctly, separate prices can be given for different energy blocks in a unit. It is noted that single-part bids can be cleared using the normal market clearing process, whereby an equilibrium is found between supply and demand to reveal the winning bid of the day used to schedule power supply and demand for 24h trading period. In [168], simple-part bidding process is suboptimal as two buyers can compete for the same energy block under the premise that none of them is privy of each other's information, hindering its application for multiple suppliers. [169] studies a radial basis function neural network, which enables suppliers to review and check their bids one more time after submission using a sequential bidding strategy.

Overall, multiple period auctions need more research, and a thorough unit commitment program has to be developed for the supplier despite the fact that the program requires consideration of start-ups costs, operating constraints and inter-temporal dependencies which might not be strategical for the supplier to maximize total benefits in power markets such as day-ahead market. So, the supplier faces two major challenges: first, identifying the best unit commitment status; second, selecting the proper coefficients for the 24-hour energy supply or bid functions, which will help in scheduling energy for each hour in the given period while concurrently maximizing benefits. These two challenges must be carefully considered to find the best solution.

3.6 Conclusions

ESS is fundamental when RESs are involved, the existing BESS models can guide researchers and engineers in selecting the best models for RESs. The application criteria of ESS has been presented and application cases are highligted respective to they type of ESS available. ESS are known to reduce peak load which can interfere with power flow in the grid network if unchecked. Combination of storage with RESs also plays a significant role in integrating renewables into the grid network. Also, the

importance of the power system network is highlighted through optimal network design and the integration of DERs, which is crucial for understanding the impact of adding more DERs into the grid. The study of OPF has enabled researchers and engineers to conduct power system simulation studies to determine the optimal placement of DERs, thereby avoiding voltage imbalances. Meanwhile, electricity markets determine whether power will be deilvered or not, by using specific market clearing algorithms such as EUPHEMIA [170] to facilitate physical delivery of energy, then the IMO and ISO can ensure the supply and demand are at balance all the time. Similarly, energy deviations are dealt with in the IS stage and any further penalties or compensation are then calculated according to real-time generated energy and the amount cleared.

Finally, Bidding process has been dealt with using precise examples in power markets. The complicated part is attested in literature using auctions divided into static and dynamic, and given the complexity of bid placement and clearing, new electricity market models have emerged which are competitıve in nature and most of them use uniform pricing mechanism irrespective of the quantity or price offered or bidded.

CHAPTER 4

VPP MATHEMATICAL MODELING

NOMENCLATURE

Abbreviations

ISO	Independent System Operator
WPP	Wind Power Plant
DG	Distributed Generation
CHP	Combined Heat and Power
DGs	Diesel Generators
DAM	Day-ahead Market
EPEC	Equilibrium Problem with Equilibrium Constraints
KKT	Karush-Kuhn-Tucker
SP	Stochastic Programming
CDF	Cumulative Distribution Function

Sets & indices

i	Number of BESS index
J, g	Number of generator index
T	24 h

System Parameters

U_t	Total generated power from generators
$C_{i^B,t}^{BESS}$	Battery energy storage systems

b_t	Total power difference between demand and renewable output
λ_t	Price per unit storage energy
P_s^{VPP}	Maximum quantity VPP provides (electricity)
P_s^{DB}	Maximum quantity VPP purchases (electricity)
ξ_s	Submitted bid price
χ_s	Submitted offer price
ξ^{op}	ISO offering price
λ_t^{inC}	Cost incurred by VPP in DA
γ_t^g	Generator fuel cost
χ^{Bp}	VPP buying price
$C_{i,t}^G$	Generator cost function
$SUC_{i,g}^{VPP}$	Generator Start-up cost in VPP setup
$MUP_{i,g}^{vpp}$	Minimum up time for unit g in VPP
$MDN_{i,g}^{vpp}$	Minimum down time for unit g in VPP

Variables

P_t^{VPP}	VPP power committed (aggregated output) in electricity market
P_t^{BD}	Purchased power from the electricity market(consumed by VPP)
P^G	Generator power
P^{ED}	Discharged battery power
P^{EC}	Battery charging power
P_t^{VPP}	VPP power in DA in period t
P_t^{DB}	Cleared VPP demand in period t

$P_{j,t}^{G}$	Optimal Generator output in DA
ξ_{t}^{c}	Clearing market price
$\beta_{g,t}^{VPP}$	Binary variable if 1, the generator starts u
$\gamma_{g,t}^{GB}$	Binary variable if 0, the generator shuts down

Chapter 4 introduces all the decision variables and parameters used in the optimization of DR-JCCO. The parameters and decision variables are defined in order to obtain feasible results. To develop an optimization strategy for the problem at hand. A bilevel framework is proposed, the structure allows design of VPP that is able to participate in two electricity markets, DM and electricity clearing market operated by the ISO. As studied in chapter 3, under strategic bidding, the bids are submitted for clearing in consideration of the DM prices. If they pass clearance, then the VPP can calculate its profits made or expected with minimal operational costs. The technical aspects are represented by the ability of the ISO to reduce congestion and secure the system at all costs by ramping up and down generation units, checking compliance to capacity limits and charge-discharge of BESSs. Ideally, the VPP contemplates all operational constraints and optimally schedules its resources to meet the flexible demand. The bids are submitted by the VPP and using forecasting capabilities, renewable generation scenarios are generated, then the generation is constrained to avoid violation of the predefined probabilistic constraint. This chapter mathematically models a VPP in a bilevel approach and formulates a joint chance-constrained (JCC) problem using distributionally robust optimization (DRO). Renewable energy scenarios of Wind power are used to factor in Wind power plant uncertainty, Figure 4.1. The collective modeling approach is presented as a DR-JCCO approach.

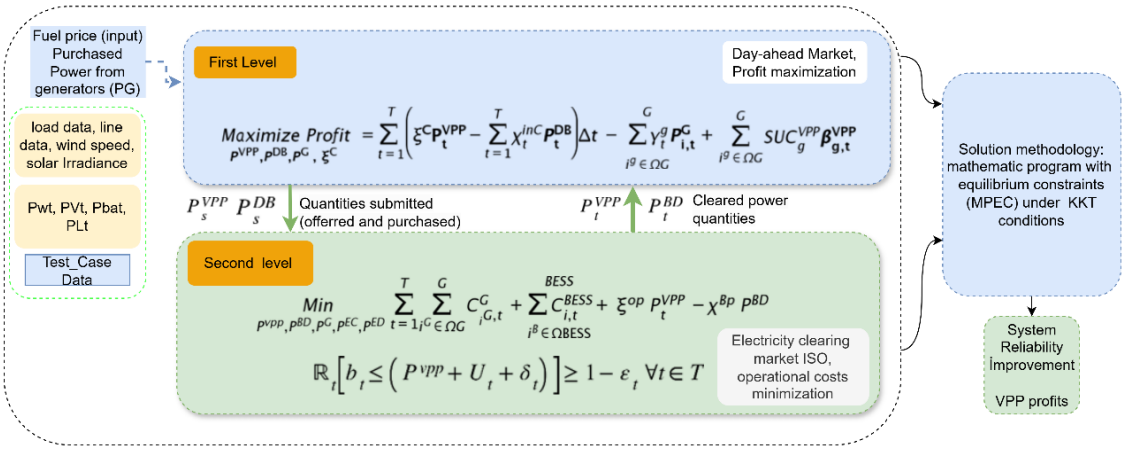

Figure 4. 1 Bilevel VPP Mathematical Model

From Figure 4.1 it can be deduced that the two level objective functions are used with key assumptions: the ISO clears the market based on the submitted bids from the VPP operator by aiming at keeping operational costs at a minimum. Once the prices are cleared the VPP operator tries to maximize the revenue using cleared quantities, characterized by the amount of power purchased and sold by the VPP. The study of bilevel programming and its application areas are introduced in section 4.1 to form the basis of developing the solution for this research.

4.1 Bilevel Programming

Bilevel Programming (BP) is a field that is progressively growing. In literature , the method has gained attention with other optimization methods such as stochastic and robust since 1990s [171]. Bilevel problems are complicated in nature and require specialized solutions in practice, especially when uncertainty is included in the optimization model. Moreover, it provides an easy way to model two distinct agents using leader and follower semantics. The agents use binding and non-binding constraints to facilitate decision-making under uncertainty. The origin of bilevel modeling is identified and known to have been formulated by H.v. Stackelberg in 1934 [172], and then Bracken and McGill applied the concept in mathematics in 1973 [173]. The approach as mentioned, uses two players or agents to make decisions that are acceptable to both parties under well-defined set of constraints. The BP has received

attention of late and various applications have emerged, when uncertainties are factored into single-level optimization, stochastic optimization is usually applied [50]. Equation (4.1) shows a linear problem formulated as single level optimization.

$$\mathrm{Min}_x\{c^T x : Ax \geq b\} \quad (4.1)$$

Uncertainties in bilevel optimization arise due to unknown information between the decision makers. The leader is unaware of the follower's decision, and same applies to the follower at the time of decision-making. Consider equation (4.3) and equation (4.4), $Z(x)$ represents optimal x values, in case there is no feasible solution for the lower problem then the whole bilevel problem has to be reformulated to check for optimality. When there is no optimal solution the problem is said to be ill-posed [174], and in this case both optimistic and pessimistic approaches can be used to reformulate the bilevel problem.

$$\min_{x \in X} F(x,y) \quad (4.2)$$

Subject to:

$$g(x,y) \geq 0 \quad (4.2a)$$

$$y \in Z(x) \quad (4.2b)$$

$$\min_{y \in Y} F(x,y) \quad (4.3)$$

Subject to:

$$g(x,y) \geq 0 \quad (4.3a)$$

The optimistic approach ensures the leader selects the follower's response in a number of optimal solutions in the lower-level problem for his own benefit by minimizing variable y equation (4.3).

The focus of optimistic approach is to solve the lower-level problem without coupling constraints that depend on y . In pessimistic setting, the leader expects the follower to

select the worst possible response according to the upper-level objective function using the multiple optimal solutions available to the follower. Equation (4.4) shows a bilevel problem under data uncertainty, which occurs when the leader and the follower access incomplete or inaccurate data. Uncertainty sets are generally modeled using polyhedral, ellipsoids, boxes or cones [175] [176].

$$\min_{x\in\bar{X}} \min_{y\in Z(x)} F(x,y \quad (4.4)$$

$$\min_{x\in\bar{X}} \max_{u\in U} F(x,u \quad (4.5)$$

Whereby $F: R^{n_x} \times R^{n_u} \rightarrow R$ is continuous with sets $U \subseteq R^{n_u}$ and $\bar{X}$. In respect to single-level robust optimization, uncertainties can be dealt with under the assumption that the coefficients of the objective function are uncertain and the optimal solution found satisfies worst-case parameters [171], or assuming that uncertainties can be linked to the coefficients of the constraints and the solution to be obtained is feasible for all. Uncertainty can be represented using uncertainty set U equation (4.6).

$$\min_{x\in X} F(x) \text{ s.t. } G(x,u)\geq 0 \text{ for all } u\in U \quad (4.6)$$

The objective function $F: R^{n_x} \rightarrow R$ and the constraint equation $G: R^{n_x} \times R^{n_u} \rightarrow R^m$ are continuous [171]. Unlike single-level optimization where decisions are made here and now, bilevel optimization decisions are made after uncertainty is realized or before the follower makes a decision. Wait-and-see is a case whereby the leader makes a here-and-now decision without uncertainty consideration, then the follower takes into account the revealed uncertainty and the leader's decision. The follower can hedge against uncertainty which causes ambiguous optimal solutions by using optimistic approach commonly used by regulating agents in energy markets. In [177], two-stage distributionally robust stochastic bilevel optimization problem is studied (TDRBO) and solved using moment uncertainty. The problem is complicated and often intractable, as per the bilevel programming both robust optimistic and pessimistic models are applied as bounds for the overall problem. The authors apply fixed and random recourse for the decision rule approach to obtain a tractable bounded optimization problem. The approaches applied are attested to be reasonable and

effective in this regard. In the first stage, the decisions are made without considering uncertainties, and in the second stage the decisions are made by considering uncertainties from renewables, i.e., Wind and Solar PV. These decisions are made with recourse and ensure tractability of the problem. The bilevel approach breaks down the objective functions into two, maximum and minimum in game theoretic framework, whereby the lower level minimizes the operational costs, and the upper level maximizes the profit. Equation (4.7) denotes a typical two-stage problem.

$$\underset{x \in X}{\text{Min}} \quad c^{\top}x + E\left[v(\xi)^{\top} y_x(\xi)\right] \quad \text{.....(4.7)}$$

$$\underset{x \in X}{\text{Min}} \sup_{P \in P} E_P[c(x,\xi)] \quad \text{.....(4.8)}$$

The decision variables are represented by the following vector $x \in X \subset R^n$, which focuses on the upper-level problem, $\xi: \Omega \rightarrow R^k$ represents a vector of random variables in a probability space (Ω, F, P) and an uncertainty set Ξ, the decision at the lower-level in the bilevel optimization is indicated by $y_x(\dots) \in R^m$ as an integral part of the second stage. Equation (4.5) represents the general structure of a DRO problem, and in this case $R^n \times R^k \rightarrow R$ is continuous and P is a set of probability distributions of ξ and $E_P[\dots]$ is the expected outcome under the probability distribution/measure $P \in P$.

VPP in literature is considered as an aggregator; implying various DERs are traded as a block in DM, intra-day or ancillary markets. Table 4.1 presents some of the existing problems that have deployed BP in formulating objective functions.

Application of BP in VPP is novel in this study, the VPP will maximize profits in the DM and the second level is presumed to be the ISO responsible for electricity market clearing by ensuring minimal operational costs to manage congestion and deliver electricity at low prices to the consumers.

Table 4. 1 Overview of Problems Utilizing BP in Literature

Ref #	Problem structure	Modeling Levels		Uncertainty	Solution algorithms
		Upper level	Lower level		
[178]	Bilevel	Energy hub	EVs	SP	—
[179]	Bilevel	Energy hub	Users	Two-stage RO	C&CG
[180]	Single level	—	—	KL-based DRO	Outer approximation
[181]	Single level	—	—	KL-based DRO	Benders decomposition
[182]	Single level	—	—	KL-based DRO	C&CG
[183]	Bilevel	DN	MG	—	Stackelberg game
[184]	Bilevel	DN	MG	RO	ADMM
[185]	Bilevel	DN	MG	—	Noncooperative game
[186]	Bilevel	DN	MG	—	KKT
[187]	Bilevel	DN	MG	RO	ADMM
[188]	Bilevel	DN	MG	DRO	KKT
[189]	Bilevel	TN	DN	IGDT	KKT
[190]	Bilevel	TN	DN	RO	Iterative method (Two steps)
[191]	Single level	TN	MG	IGDT-SP	—
[192]	Bilevel	TN	MG	RO-SP	Dantzig-Wolfe
[193][194]	Single level	—	—	Moment-based DRO	Delayed constraint generation
[195]	Energy Hub	Energy hub	Users and EVs	KL-based DRO	Crafted C&CG (Linearization of USP)
Proposed	Bilevel-VPP	Day-ahead Market	Electricity clearing Market	DR-JCCO	CVaR&H-X

4.2 Solution Methodology

The scenarios will be generated using Normalizing Flows (NFs), a probabilistic -driven forecasting method that considers multivariate interdependencies in the model structure to generate accurate forecasts. Then, DR-JCCO framework that utilizes a bilevel structure will be investigated using approximating algorithms, both the CVaR and H-X will be applied to facilitate tractability.

The proposed solution methodology applies two-level solutions known as bilevel approach. The ISO usually tries to minimize operational costs in power systems, which is formulated as minimization problem and the second objective function is for the VPP operator to solve. In this problem, the operator tries to maximize the social benefit of DERs. Now, after the above stages have been identified, chance-constraints regarded as joint are kept below a specified threshold. This largely considers a probability level, and the trade-off between making profits at the expense of reliability.

Usually, DR-JCCO problems in nature are difficult to solve and most studies simplify the solution using the probability constraint expressed in terms of probability distributions. Wasserstein has been used in literature to find optimal distance between two distributions, and similarly it has successfully been used for out-of-sample performance studies.

There are quite a lot of methods used, in this regard review chapter 2. In this chapter, CVaR is used for approximation of the DR-JCCO to enhance tractability, Bonferroni is also a potential method but only considers individual chance-constraints and then estimates overall joint-constraint using the individual chance-constraints.

CVaR and H-X will be applied, and they will be compared in terms of conservativeness of solutions and speed in managing uncertainities in the grid network and overall participation of VPP in electricity market . CVaR and H-X application will be demonstrated using wind scenarios and their effectiveness in charge-discharge of the BESS will be investigated.

Figure 4.2 shows the workflow that will be used to obtain the results, DR-JCCO in its pure form will be applied and then the approximating algorithms will be tested for convergence.

In this research, DR-JCCO formulation and tractability using CVaR approximation and H-X algorithm will be the first of its kind focusing on storage, diesel generators and generated WP uncertainties.

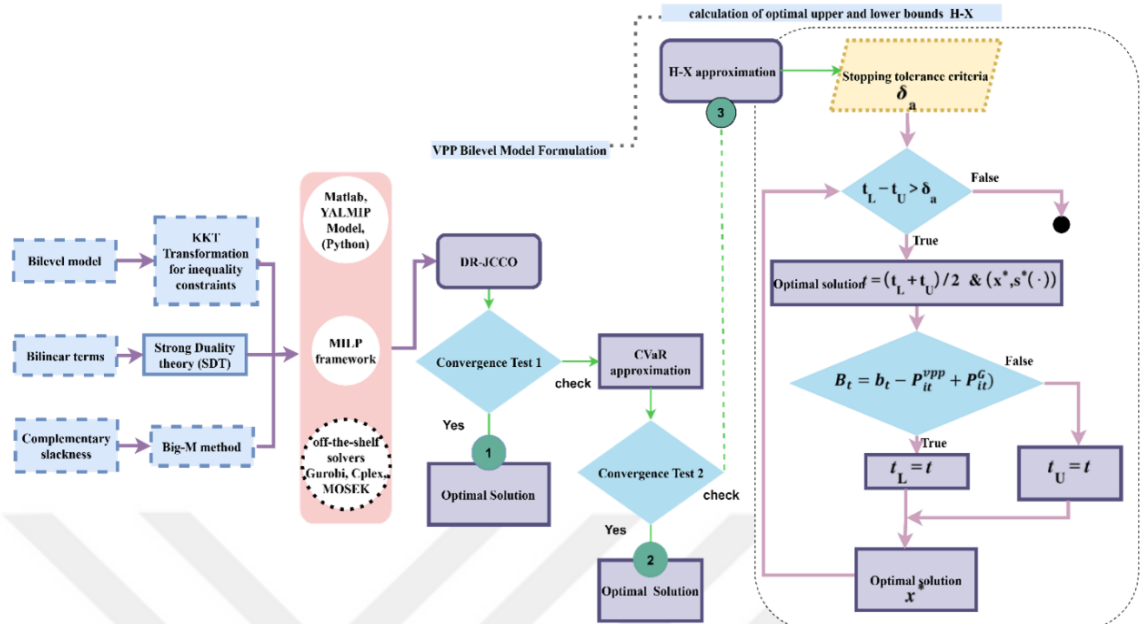

Figure 4. 2 Problem Modeling and the Algorithmic Flow Chart

The core aim of DR-JCCO is to integrate renewable energy into the grid, with the formulation designed to facilitate trading by exporting power to the grid while ensuring that the VPP remains profitable. To apply DR-JCCO, two areas have been explored:

1. The adoption of a data-driven approach that directly applies the method for profit maximization.
2. The use of a bi-level optimization approach where a minimization problem (operational costs) is solved first, followed by a maximization problem.

The above steps are evidenced in robust optimization problem that has progressively been formulated into two stages that are challenging to solve. Research shows the possibility of approximating probability constraints to obtain tractable distributions, and in applying H-X approximation method, a more robust performance can be realized compared to the conventional CVaR approximation method.

4.3 Distributed Generation Modeling

4.3 1 Fuel Generator

Active power of the fuel generator and the demand supplied is shown by equation (4.9).

$$P_{ij}+P_j^G=\sum_{k\in\pi(j)}P_{jk}+P_j^d \quad \text{.....(4.9)}$$

P_{it}^G dispatched power from the fuel generators as in [54], can be applied as total p_j^g which then can be multiplied by incremental generation cost of conventional DGs (USD/MWh) γ, and further be considered as a cost the VPP operator incurs when DGs are used. Generally the VPP submits the cost curve which is similar to the conventional generators' curve and in case of any deviations it can only shift depending on whether the available renewable energy caters for the available load, otherwise the conventional power generation units will suffice the demand [130]. Power flow problem can be estimated using a branch linearized flow model of a radial network. P_{ij} stands for active power and Q_{ij} is distribution network's reactive power equation (4.10), and P_j^g active power, P_j^ddemand, q_j^greactive power generated and q_j^d reactive power demanded at bus j. equation (4.11) V_j bus j voltage magnitude, V_o slack bus, R_{ij} resistance, and X_{ij} reactance.

$$Q_{ij}+q_j^g=\sum_{k\in\pi(j)}Q_{jk}+q_j^d \quad \text{.....(4.10)}$$

$$V_j=V_j-\frac{R_{ij}P_{ij}+X_{ij}Q_{ij}}{V_o} \quad \text{.....(4.11)}$$

In power systems linearized flow models are preferred compared to DC power flow model, which is usually applied in transmission networks, partly because it avoids factoring in reactive power and takes on constant bus voltage magnitude equation (4.10) and equation (4.11), respectively. The general cost function of generators is indicated equation (4.12), whereby a_j and b_j are quadratic cost function coefficients.

$$C_{j^G,t}^G=a_j\left(p_j^G\right)^2+b_jp_j^G \quad \text{.....(4.12)}$$

The total generated power from conventional sources can be indicated by $C_{i^G,t}^G$ which can further be approximated into equation (4.14), and then power output from the fuel generator is limited by equation (4.15).

$$p_j^G \sum_{j\in\pi(0)} p_{0j} \quad (4.13)$$

$$C_{i^G,t}^G \approx \gamma \sum_{\Omega_G} P_{it}^G \quad (4.14)$$

$$0 \leq P_{it}^G \leq P_{max} \; \forall t \in T \quad (4.15)$$

Linearized branch model finds it application mostly in voltage control and dispatch of renewable energy sources, [196] [197] , and since it does not account for losses in the system, it is not appropriate for calculation of locational marginal prices (LMPs), but in terms of performing power flow calculations for the VPP, it is highly preferred as the VPP operator gets paid according to the bids submitted to the ISO.

4.3.2 Battery Energy Storage System

ESS are ideally used to smoothen the generation scheduled to be submitted to the ISO, through charging when the demand is low and discharging power when there is peak demand, it has low impact on the cost curve [130]. Equation (4.16) shows a battery cost function the k_1 and k_2 are coefficients of the utility degradation function which can be neglected in the optimization calculations. Meanwhile, Minimum discharging and charging power is shown by equation (4.17).

$$\sum_{i^B\in\Omega BESS}^{BESS} C_{,t}^{BESS} = \sum_{t=1}^{T} \lambda_t P_t^{EC} - P_t^{ED} + k_1 d_t + k_2 d_t^2 \quad (4.16)$$

$$P_{min}^{ED} \leq P_t^{ED}, P_t^{EC} \leq P_{max}^{EC} \quad (4.17)$$

$$SOC_{it} = E_{i,t}^{BESS} / E_{i,R}^{BESS} \quad (4.18)$$

$$SOC_{min} \leq SOC_{it} \leq SOC_{max} \quad (4.19)$$

$$E_{i,t+1}^{BESS} = E_{i,t}^{BESS} - P_{i,t}^{BESS} \Delta t - E_{i,t}^{BESS} \eta \Delta t \quad (4.20)$$

$$P_{i,t}^{BESS} \leq \bar{P}_i^{BESS,Dis} \chi_{i,t}^{Dis} \quad (4.21)$$

$$P_{i,t}^{BESS} \geq \bar{P}_i^{BESS,Chr} \chi_{i,t}^{Chr} \quad (4.22)$$

$$\chi_{i,t}^{Dis}+\chi_{i,t}^{Chr}\leq 1 \quad (4.23)$$

4.4 Uncertainty Formulation

4.4.1 Probabilistic Forecasting

Forecasting is integral in having a robust energy management system, it contributes to integration process of RESs. The methods used in forecasting can be in two forms, statistical and machine learning methods. The method of interest is use of Normalizing flows (NFs) a deep generative method that has shown great performance when compared to other methods such as GAN, VAN, etc.

The authors in [198], seek to establish performance differences in existing deep generative models, the models are investigated using key performance metrics such as continuous rank probability score (CRPS), quantile score, reliability diagram, etc. Later, quality metrics and profits are also used to compare the models (NFS, GANS, VAEs). The study focuses on a comparative assessment of performance, concluding that NFs demonstrate superior performance.

Furthermore, it highlights application cases of NFs in power systems [96] to generate PV quantile forecasts for the robust planner then by using encoder-decoder type of architecture ,.i.e., forecasting model, the intra-day point forecasts are calculated for the controller. Similarly, the controller uses real-time receding horizon from point t to T to calculate PV generation according to both renewable forecasts and daily contracts to charge-discharge BESS.

In modeling of renewable energy systems NF can be used, the technique is part of generative models applicable for sampling and density estimation. They transform a basic distribution into a complex distribution by use of invertible transformations Figure 4.3, this capability of generating complex transformation facilitate modeling of enhanced data distributions.

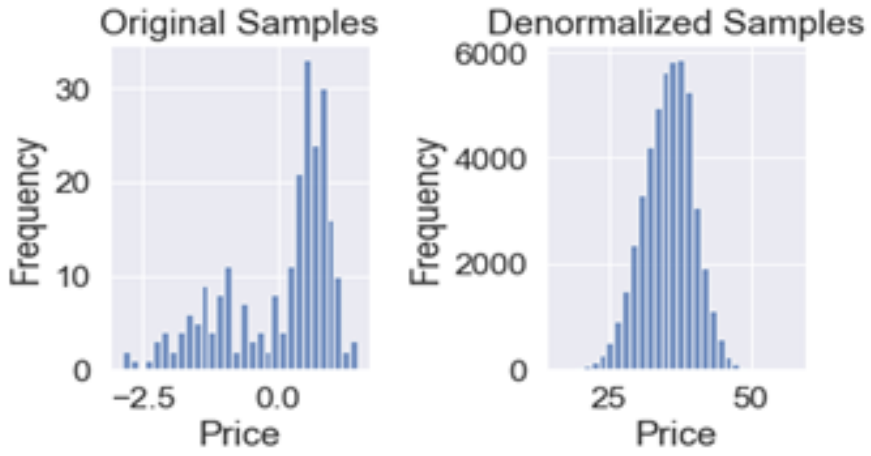

Figure 4. 3 Denormalized Electricity Market prices

Largely, in Energy Management Systems (EMSs), forecasting has been used to predict stochastic energy resources such as PV and Wind playing a role in stabilizing grid network systems by enabling system operators manage uncertainties more effectively.

Also, when demand and market prices are known the system operators or market operators will be able to provide bids that meet system requirements and avoid incurring extreme penalties, especially when there is undersupply or oversupply.

Additionally, security of supply is a concern and the need to have high fidelity models will enable participants to trade freely and get settled with minimal financial losses. As this work progresses, NF is suggested as a forecasting method in this work, it will be used to generate scenarios that will be integrated into the optimization module Figure 4.4 and Figure 4.5, respectively.

Figure 4.5 illustrates the application of NFs and Linear Regression (LR). Wind quantiles are derived using NFs, while market price predictions are achieved through LR. The NFs are essential for representing confidence levels, with the 10th quantile providing a conservative estimate and the 90th quantile representing a more optimistic scenario.

Moreover, the day-ahead scenarios generated by NFs are utilized to compute excess loss in the optimization phase. Simultaneously, LR is used to forecast market prices,

ensuring a close-to-real market clearing scenario and evaluating the robustness of the VPP for trading in the DAM.

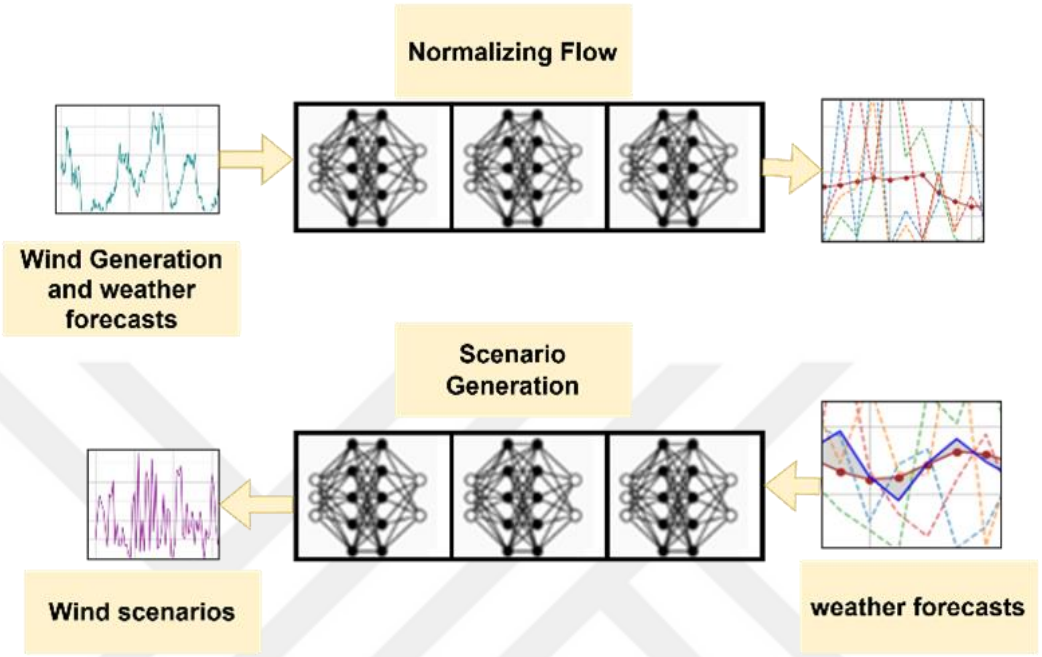

Figure 4. 4 NF Implementation Stages

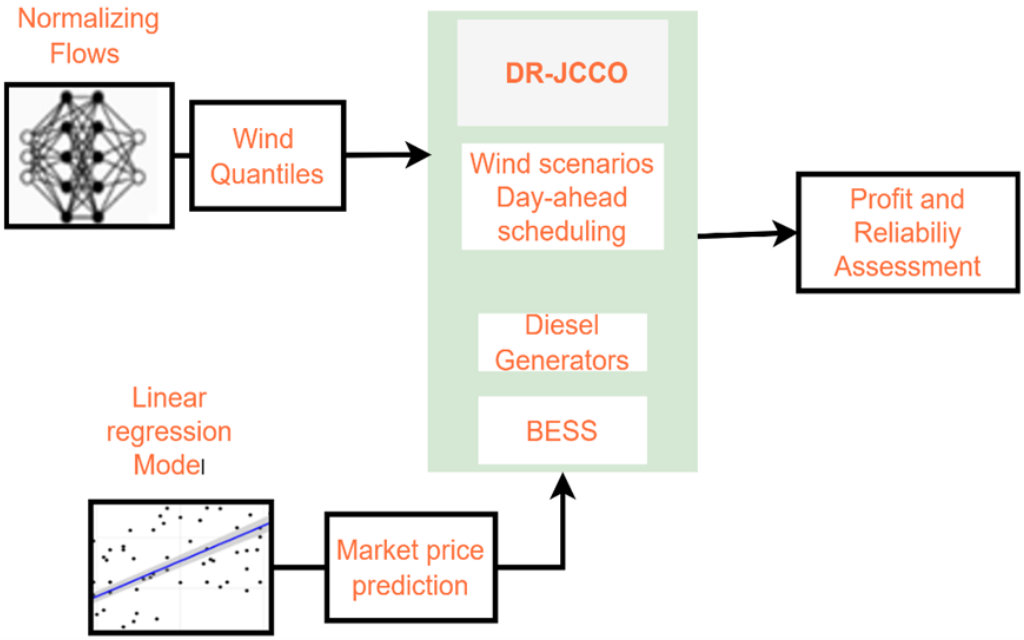

Figure 4. 5 Generation of Scenarios and Optimization Strategy

4.2 Renewable Uncertainty Modeling

Modeling renewable uncertainty is challenging. In this section, a step-by-step mathematical approach is used to model the variability of RES. Of particular importance is the estimation of chance constraints using well-established mathematical models that are widely applied in operations research. The subsequent equations demonstrate the stages and the transformation of a DR optimization problem to illustrate a power-systems use case.

$$B_t=b_t-(P^{vpp}+U_t),\ \forall t\in T \quad \text{.....(4.24)}$$

From equation (4.24) the net energy shortfall is indicated using b_tVPP's net RT demand (MW), it is the difference between endogenous demand of the VPP and the total renewable energy output, b_t and the expected true probability P_t; might not be known in advance, and it is for this reason a reference distribution R_t is introduced. It is obtained using historical samples of b_t [199] and the expectation is that the two distributions will be symmetrical about the mean. This divergence can be solved by applying variety of techniques,i.e., Wasserstain distance and kullback-leibler (KL) as probabilistic divergence measuring methods ($\varnothing$ -divergence measure). In literature, it represents a generic family as exemplified in [200] and [201], it finds its application in power systems [199] while KL is defined by equation (4.26).

$$R_t[B_t\leq\delta_t]\geq 1-\varepsilon_t\ \forall t\in T \quad \text{.....(4.25)}$$

$$v(P_t)=\int_{b_t\in T}([\ln P_t-\ln R_t]P_t)\,db_t\ \forall t\in T \quad \text{.....(4.26)}$$

Then, ambiguity set Z_t is given (4.27), and therefore JRCC can be associated to b_t by equation (4.28).

$$Z_t=\{P_t|v_t(P_t)\leq V_t\},\ \forall t\in T \quad \text{.....(4.27)}$$

$$\inf_{P_t\in Z_t} P_t[B_t\leq\delta_t]\geq 1-\varepsilon_t,\ \forall t\in T \quad \text{.....(4.28)}$$

DR-JCC captures probability distributions in the ambiguity set equation (4.28), VPP's net energy shortfall B_t is compared to δ_t which is a given constant with a probability threshold $1-\varepsilon_t$ at all t . It is significant to note, the VPP operator specifies threshold risk and the constant to show the impact of risk towards profit making. Studies have indicated, lower threshold values result in conservative solutions and the VPP operator is inclined towards taking low risks. Equation (4.30) is gotten by substituting equation (4.24) into equation (4.28).

$$R_t\ [b_t \leq (P^{vpp}+U_t+\delta_t)] \geq 1-\varepsilon_t\ \forall t \in T \quad \text{.....(4.29)}$$

Since JCC problems are non-convex and direct solutions are difficult to obtain then with this perspective the VPP robust decision can be reached using CDF of the reference distribution equation (4.30).

$$R_t\left[b_t \leq b^{11}{}_t\right] \geq 1-\varepsilon_t\ \forall t \in T \quad \text{.....(4.30)}$$

Equation (4.29) can therefore be approximated by equation (4.31).

$$X \cong P^{vpp}+U_t+\delta_t \geq b_t^{11}\ \forall t \in T \quad \text{.....(4.31)}$$

The question of interest is what happens when the VPP operator encounters energy shortfalls when trading in DM? Certainly, the shortfalls will create mismatches, and the strategy that need to be taken entails the VPP operator buying energy in real-time at a slightly higher price to offset the imbalances in case the committed bids do not match [43] [202]. The DR-JCCO will allow the VPP operator to make decisions between expected costs equation (4.32) in the DM and the risk associated without paying high penalties in the RT market.

$$\underset{P^{vpp},P^{BD},P^{G},P^{EC},P^{ED}}{\text{Min}} \sum_{t=1}^{T} \sum_{i^G \in \Omega G}^{G} C_{,t}^{G} + \sum_{i^B \in \Omega BESS}^{BESS} C_{i,t}^{BESS} + \xi^{op}\ P_t^{VPP} \quad \text{.....(4.32)}$$

The following constraints govern the ISO in keeping the operational cost of the power system at minimum, power balancing equation (4.33), and the subsequent operational constraints equation (4.33-4.43). Note that equation (4.34) and equation (4.35) will not

be utilized as the study does not factor in power flow study contraints in terms of active and reactive power.

$$P_t^{VPP}=\sum_{i,g} P_{it}^{G}+\sum_{i,BESS} P_{it}^{BESS}+\sum_{i,w} P_{it}^{W}+\sum_{i,pv} P_{i,pv}^{pv}+P_{it}^{BD} \quad (4.33)$$

$$V_{min}\leq V_j\leq V_{max} \quad (4.34)$$

$$V_{-i}\leq V_j\leq \bar{V}_i \quad (4.35)$$

$$P_{min}^{vpp}\leq P_{t,s}^{vpp}\leq P_{max}^{vpp}\ ,\forall t \quad (4.36)$$

$$P_{min}^{BD}\leq P_{t,s}^{BD}\leq P_{max}^{BD}\ ,\forall t \quad (4.37)$$

$$B_t=b_t-\left(P_{it}^{vpp}+P_{it}^{G}\right),\forall t\in T \quad (4.38)$$

$$\inf_{P_{t\in Z}} P_t\ [B_t\leq\delta_t]\geq 1-\varepsilon_t,\ \forall t\in T \quad (4.39)$$

$$\sum_{i,g} P_{g,t+1}^{G}-\sum P_{g,t}^{G}\leq R_{i,g}^{GU},\ \forall t<T,\ \forall g \quad (4.40)$$

$$\sum_{i,g} P_{g,t}^{G}-\sum P_{g,t+1}^{G}\leq R_{i,g}^{GD},\ \forall t<T,\ \forall g \quad (4.41)$$

$$\sum_{t=1}^{MUP} \alpha_{g,t+1}^{G}-1\geq MUP_g^{G},\forall \beta_{g,t}^{G}=1 \quad (4.42)$$

$$\sum_{t=1}^{MUP} 1-\alpha_{g,t+1}^{G}\geq MDN_g^{G},\forall \gamma_{g,t}^{GB}=1 \quad (4.43)$$

$$\underset{P^{VPP},P^{DB},P^{G},\xi^{C}}{\text{Max Profit}}=\sum_{t=1}^{T}\xi^{C}P_t^{VPP}-\sum_{t=1}^{T}\chi_t^{inC}P_t^{DB}\Delta t-\sum_{i^g\in\Omega G}^{G}\gamma_t^{g}P_{i,t}^{G}+\sum_{i^g\in\Omega G}^{G} SUC_g^{VPP}\beta_{g,t}^{VPP} \quad (4.44)$$

Subject to:

VPP Operational constraints equation (4.33-4.45) (4.45)

Electricity market clearing equation (4.32) (4.46)

4.5 Approximating Algorithms

In chapter 2, various approximation algorithms were investigated and literature sources elaborating on the application part was also given. The nature of JCC is complex and computationally intensive for the available solvers and due to the shortcomings such as a conservativeness of results, convex approximations can be very handy in tracking DRO problems, CVaR is known to be the best approximation of DRO problem and can enable tractability of JCC problems, however it can vary from case to case. This work applies CVaR in the context of energy systems such as BESS in a bilevel model. The approach is further formulated to include H-X algorithm, a new convex approximation algorithm, which according to the study in [203], is the best so far in approximating JCC problems. The application will be the first of its kind in power systems.

4.5.1 CVaR

CVaR approach estimates the risk beyound the value at risk (VaR) and it is known to have the best performance in approximation of JCC problems, the approach factors in all the distribution losses which are given in a defined threshold, it also referred as expected shortfall. In [204], CVaR is applied to approximate the reliability of the system using stochastic and fuzzy uncertainties, which ideally adjusts the conservatiness of solutions against the expected worst-case scenarios. In literature, VaR is uniquely applied to approximate investments by applying predetermined threshold level, but in case of CVaR such an investment can be formulated beyound VaR through computation of expected shortfall. VaR and CVaR is given by equation (4.47) and equation (4.48), respectively.

Given that $\widetilde{X}$ is a random variable let P and $Q_{\widetilde{X}}(\cdot)$ be its probability distribution and CDF respectively, under a defined risk level of $(1-\varepsilon)$ then VaR of $\widetilde{X}$ can be expressed by equation (4.47).

$$\mathrm{VaR}_{1-\varepsilon}(\widetilde{X}) := \min_{s}\{s : Q_{\widetilde{X}}(s) \geq 1-\varepsilon\} \quad \text{.....(4.47)}$$

$$\mathrm{CVaR}_{1-\varepsilon}(\widetilde{X}):=\min_{\beta}\left\{\beta+\frac{1}{\varepsilon}E_P[\widetilde{X}-\beta]_+\right\}\text{.....(4.48)}$$

The first approximate of the chance constraints considers replacement of the probability threshold using the CVaR bound, and second bonferroni's inquality approach of estimating individual constraints and a third step, ensuring safety conditions are not violated by satisfying chance constraints. Usually, CVaR is regarded as a tight convext optimization and depending on the problem formulation the approximating methods for DR-JCCO can vary in performance and others can emerge superiour based on speed of convergence, meaning that comparison of the methods is vague [205]. However, in this work the case studies built using DERs will be tested to indentify strengths CVaR over H-X algorithm. CVaR can be expressed in terms of VaR as shown by equation (4.49), which is finally equalized to equation (4.51). Reference distribution shown in equation (4.31) can be input into equation equation (4.50).

$$\mathrm{CVaR}_{1-\varepsilon}=E^P\left[Q(\widetilde{X})|Q(\widetilde{X})\geq \mathrm{VaR}_{1-\varepsilon}\right]\text{.....(4.49)}$$

Equation (4.49) is equivalent to equation (4.49a)

$$\mathrm{VaR}_{1-\varepsilon}+E^P\left[Q(\widetilde{X})-\mathrm{VaR}_{1-\varepsilon}|Q(\widetilde{X})\geq \mathrm{VaR}_{1-\varepsilon}\right]\text{.....(4.49a)}$$

$$\mathrm{CVaR}_{1-\varepsilon}=\inf_{\tau\in R}E^P\left[\tau+\frac{1}{1-\varepsilon}\max\{Q(\widetilde{X})-\tau,0\}\right]\text{.....(4.50)}$$

Equation (4.49) gives a quantile function $Q(\widetilde{X})$specified within a confidence interval $1-\varepsilon$. Commonly, CVaR estimates the value beyound VaR such as $Q(\widetilde{X}) \geq \mathrm{VaR}_{1-\varepsilon}$ making CVaR to be applied as a risk metric to quantify the tail of the probability distribution P of $Q(\widetilde{X})$.Probability distribution of the quantile function is uncertain, and ambiguity sets are often used to formulate the distribution, and it is for this reason the DR-JCCO applies CVaR, known as the best among the convex approximations which is classified as low-parametric, applicable for to assessment of the level of impact of worst-case distribution on the trading aspect of the VPP.

4.5.2 Heuristic-X

In [206] , the authors have proposed H-X approximation, they claim the method can provide efficient solutions and easily track the objective value and the expected violation level of safety constraints. Furthermore authors in [203], suggest a reformed formulation of the heuristic-X algorithm as ALSO-X , citing that it has the best peformance compared to the traditional CVaR method [203] when solving chance-constrained problems over known distributions and by extension type-∞ wasserstein ambiguity sets, which utilizes wasserstein balls to quantify worst-case scenarious with a given radius over several distributions. The solutions are a bit robust as the distance is almost constant regardless of the distance exhibited by different distributions.

Also, Type-q wassertein ambiguity sets are a possible fit when considering worst-case scenarios over several distributions, though the approach quantifies the possible deviations solely between the nominal distribution and a group of alternative distributions, the approach somehow is flexible in managing uncertainty as it does not rely on worst-case scenarios. The challenging part is determining robustness of solutions without affecting flexibility of solutions, the latter is mostly preferred as the results gotten are less conservative unlike type-∞ ambiguity sets formulated using wasserstein approach. Authors in [176] and [121], equally study the approximating algorithms and conclude that at times the methods could result in sub-optimal solutions under similar conditions , which takes work presented herein a few steps ahead by formulating the methods using the same logic and applying diverse solvers to obtain optimal solutions. Modeling H-X algorithm is not different from CVaR, the difference is in the iteration loop , which tries to find optimal t by using the lower bound and upper bound, the smallest value is then assigned to t ensuring the problem becomes tractable and feasible equation (4.51).

$$X^{*}(t) := \min_{x \in X, s(\cdot) \geq 0} t \left\{ E\left[s\left(\tilde{\xi}\right)\right] : \text{equation } (4.33), c^{\top}x \leq t \right\} \quad \text{.....(4.51)}$$

4.6 MPEC Approach

To apply MPEC, an overview of existing studies could be outlined as follows, first the classification of diverse literature sources have to be investigated by considering papers that have worked on optimal bidding strategy, which involves conventional generation units or RESs constituting a VPP, which can bid strategically as a price maker or price taker as was discussed in chapter 3 under stategic bidding.

Second overview could be based on bi-level models, which contemplate VPPs in their models, and the last overview can be based on potential application of game theory to achieve an equilibrium point [30], the authors have also provided studies that delve into multi-objective bidding.

Work in [207], represent optimal bidding strategy using two-stage MILP model in DM and RT electricity markets. In short, the overviews if examined further could provide a body of literature that has applied MPEC and EPEC mathematical approaches to model VPPs bidding strategies, i.e., in [208] a multi-carrier energy system is modeled in the electricity market. EPEC model is appropriate where there are multiple VPPs [209], which are competitive in nature, the model considers a fair price for all the rivals or participants while MPEC applies a single-level modeling approach and assumes bids from other participants are deterministic. Apparently, integer programming has been used as one of the solutions for MPEC problems [210] [211], binary solution has been used in [210] to solve MPEC problem by discretely approximating continuous decision variables that contain non-linear terms, auxiliary variables are also introduced to keep binary variables within the expected range to avoid unboundedness and infeasibility issues.

In addition, KKT conditions and complementarity constraints are factored into the mathematical model to relax the constrainsts and ensure the soulution converges. MPEC is suitable for single-level problem and in this work it will be applied to obtain one single-level objective function for optimal dispatch of the VPP.

4.6.1 MPEC Formulation

The MPEC approach can help reformulate the two-objective function into a single objective function for quick solutions using available solvers. Equation (4.32) and equation (4.44) are modeled further using binary expansion technique to obtain single-level objective function that considers all the necessary constraints. Complementarity contraints and big-M notation are taken into consideration when applying MPEC approach. VPP output and prices are both variables as shown in equation (4.44) and their computation results in a non-linear function which is challenging to solve with the existing solvers.

To obtain a linear function that is solvable by existing solvers such as gurobi, etc. The problem will have to be formulated as MILP problem using the appropriate mathematical notations. Big-M parameter b^M has to be large enough to allow for the transformation to be exact and avoid loss of information. The bilinear terms are indicated using $x= P^{VPP}$ and $y= \xi^{op}$. To linearize the problem, first 2^n discrete points are used within a precise interval demarcated by upper and lower bound of y $[y^l, y^m]$ leading to equation (4.52).

$$y=y^l+\Delta y \sum_{n=1}^{n} 2^{n-1} z_n \quad \text{.....(4.52)}$$

z_n is noted, with n being a binary variable and Δy is a step size which is given by equation (4.53).

$$\Delta y=\frac{y^m-y^l}{2^n} \quad \text{.....(4.53)}$$

When n increases Δy decreases implying the step size decreases with increasing n. Introducing x variable into equation (4.53) results in equation (4.54), also $v_n = xz_n$ can be substitued into equation (4.55).

$$xy=xy^l+\Delta y \sum_{n=1}^{n} 2^{n-1} xz_n \quad \text{.....(4.54)}$$

$$xy=xy^l+\Delta y \sum_{n=1}^{n} 2^{n-1} v_n \quad \text{.....(4.55)}$$

Big-M notation relaxes the constraints as shown by equation (4.56).

$$0 \leq x - v_n \leq b^M(1 - z_n), \forall_n \quad (4.56)$$

$$0 \leq v_n \leq b^M z_n, \forall_n \quad (4.57)$$

Applying the logic of v_n, equation (4.56) is forced by $z_n = 0$ and $v_n = 0$. In the case of $z_n = 1$, $v_n = x$ is forced into equation (4.57). In short, equation (4.55**)** is the best approximating equation of a non-linear equation with bilinear terms subject to the $v_n = xz_n$ relationship, additionally, the loss of information can be controlled by using precise number of segments and applying $O\log_2 n$, n being the number of segments needed to express a linear function that can give outcomes that are relatively accurate. In formulating VPP bidding mechanism, $\xi^{op} P^{vpp}$ needs to be expanded by linearizng objective function indicated by equation (4.44) into equation (4.58).

$$\text{Maximize Profit} = \left[\xi^{op}{}_t \, P^{vpp}{}_{t,n} + \Delta\xi \sum_{n=1}^{n} z^{n-1} \, z^{vpp}{}_{t,n}\right] - \sum_{ig \in \Omega G}^{G} \gamma_t^g \, P^G{}_{i,t} + \sum_{ig \in \Omega G}^{G} SUC_g^{vpp} \, \beta^{vpp}{}_{g,t} \quad (4.58)$$

The objective function is subject to the constraints represented by equation (4.45), (4.46), (4.56) and equation (4.57).

4.7 Conclusions

BP has been introduced and mathematically modeled focusing on its application to VPPs, with key literature sources referenced, giving particular attention to the DR-JCCO approach. Two objective functions are identified: the first aims to maximize VPP profits, while the second focuses on minimizing operational costs. These functions represent typical DM and RT energy markets, regulated by the respective market operator and ISO. Additionally, the mathematical models for DERs are included. NFs and LR machine learning methods are utilized to generate DM scenarios and approximate real electricity market clearing scenarios, respectively. JCC are modeled and approximated using PDFs. For tractability, CVaR and H-X algorithms are applied to derive optimal results.

Finally, the Mathematical Program with Equilibrium Constraints (MPEC) approach is reviewed and formulated to solve a sıngle-lvel objective function. This approach is crucial for formulating complementarity constraints, enabling the development of a feasible mathematical VPP model capable of addressing non-linearities in the execution of the DR-JCCO model.

CHAPTER 5

RESULTS AND DISCUSSION

The simulations performed using DR-JCCO-CVaR-H-X solutions present a unique way of addressing JCC problems. The formulated technique DR-JCCO framework ensures renewable energy resources' uncertainty and stable generation resources are defined within a threshold in which safety contraints will not be violated. The challenging part of DR-JCCO problems is conservatism and infeasibility. When the problem is formulated in a complex manner the solutions obtained might not be feasible and availble off-the-shelf solvers might need to be tested separately to determine the best performing solver.

Gurobi and CPLEX solvers are considered, but they also depend on the problem structure, YALMIP structure can be considered but works well using softwares such as MATLAB. CVXPY is ideal for formulating convex problems though errors such as DCP rules handling exceptions are very common directing the use of gurobi structure in solving H-X. In solving the problems above, structuring formats have been varied, both DR-JCCO and CVaR approaches are formulated in CVXPY and the H-X algorithm since it involves iterations to obtain optimal t in an independent loop that determines the upper and lower bound values , it is then structured using gurobi format in python and then solved using the same solver.

DR-JCCO was applied without approximation approaches,i.e, CVaR or H-X, then DR-JCCO wa formulated using CVaR and H-X and solved with relevant solvers: DR-JCCO, DR-JCCO with CVaR and DR-JCCO with H-X algorithm.

Gurobi solver was applied to solve the problem using the PC with an Intel(R) Core(TM) i5-6200U CPU 2.30 GHz 2.40 GHz 16.0 GB (15.9 GB usable). Then the results were obtained and compared under level of conservativeness, total costs and profits. Reliability and profit trade-off was also presented.

In this study, two types of demand profies are identified Figures 5.1 and 5.2 are used for uniformity purposes and considering underlying mathematical formulations. The demand shown by Figure 5.1 indicates that demand is low during early morning hours and rises steadly at midday, peak demand in that case is during midday hours and towards the evening hours, which is a characteristc of industrial loads with peak demand at midday hours towards the evening hours and then drops significantly at around 21-22 hours.

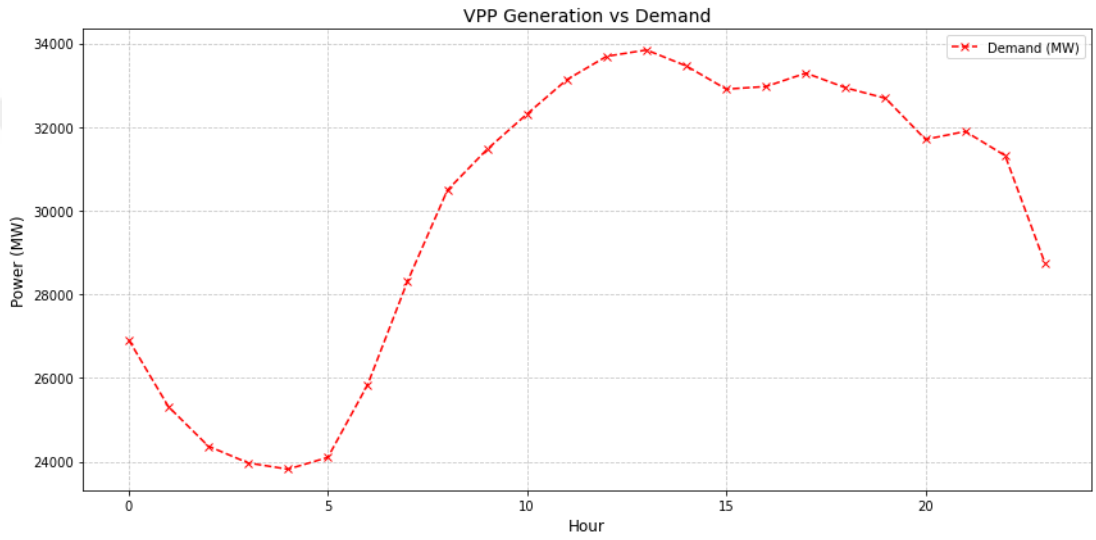

Figure 5. 1 Demand Type 1

After identification of demand profiles, the study goes ahead to explore both WP and Solar PV power (SPVP) profiles, the latter is analyzed in section 5.2.4, while WP forms the background of this study (for purposes of simplifying the optimization model). The control aspect involves mitigating uncertainties to achieve steady power flow. Although the study of power flow models is not part of this work, it is critical to show the power profiles and the stability concerns that emanate from integrating renewables into the grid network.

WP plant profile was illustrated by Figure 3.1 in chapter 3, it denotes that power output for wind is highest at about hour 05:00 and 18:00 signifying increased wind speed and suitable meterological conditions for maximum power, other factors could be air density, wind direction and level of turbulence, etc. For the case of SPVP profile,

factors such as solar irradiance, panel orientation, availability of shades and physical obstructions determine power output of a PV panel. The main factor that stands out is weather conditions, and as was shown by Figure 3.1 PV power output profile was maximum at about hour 12:00 implying availability of maximum solar irradiance and technical adjustment of the PV panels by use of Maximum Power Point Tracking (MPPT), etc.

Meanwhile, Figure 5.2 is considered in this study, the duck-curve profile is characterized by peak demand in early mornings and at the evenings, a feature that is common with residential loads, subsequent hours of the day (midday) are characterized by low demand.

The duck-curve profile is used to demonstrate how VPP can schedule its resources to meet flexible demand, also assesses and ascertains the profit margin obtained when the VPP platform is utilized.

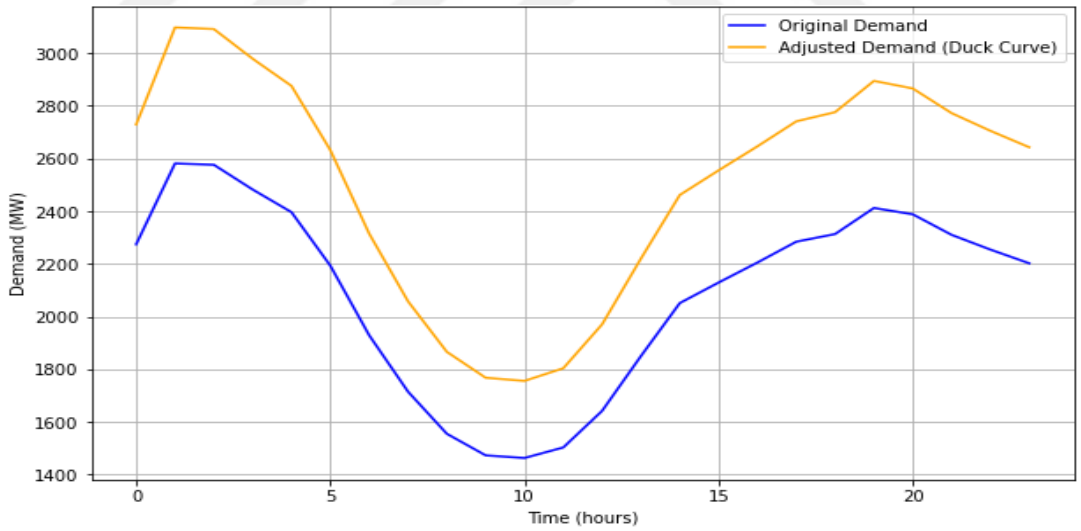

Figure 5. 2 Demand Type 2

All in all, despite the renewables having nominal efficiency settings, still the expected power output varies depending on the internal and external factors. Therefore, WP profile and demand profiles are used to carry out simulations and risk assessment studies, the unceratinties are ingested into the optimization model framed as DR-JCCO with tractable algorithms and finally application of binomial expansion (BE) for

linearization of the DRO problem, which enables optimal dispatch of the VPP resources, in this context the level of charge-discharge of the BESS is paramount. BE mathematical modeling approach will be shown in section 5.3 as an independent study showcasing the results of linearizing non-linear models.

Generally, in power systems demand and supply have to balance out to avoid blackouts and flickers or brownouts in the electrical network. Figure 5.3 shows demand and total generation being equal with negligible residual demand.

Figure 5.3 will act as the baseline to frame this PhD research problem using a bilevel approach by considering uncertainities from WP and economic dispatch of DGs.

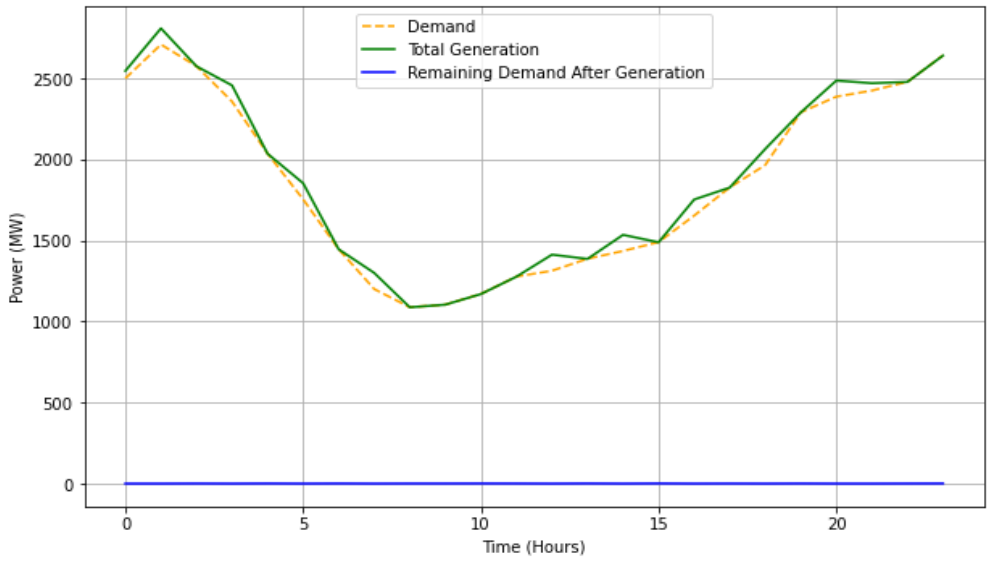

Figure 5. 3 Demand vs Generation

5.1 Forecasting Model

A significant number of wind scenarios are generated and input into the DR-JCCO model. The generated wind scenarios are shown in Figure 5.4.

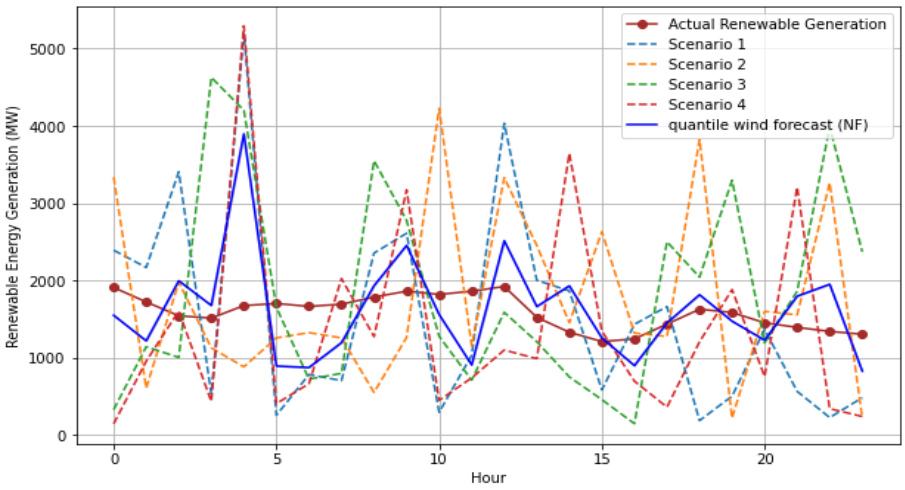

Figure 5. 4 Wind Power Scenarios

Next, uncertainities emanating from wind generation can also be estimated to enable the model to generate precise and accurate results. By applying NFs, the model can be used for decision-making, by factoring in critical power deviations that might affect the overall power generation associated with oversupply or unxpected power shortages Figure 5.5.

Further adjustments are made on the NFs model to properly quantify uncertainties, the training parameters are refined to introduce randomness into the model. The output significantly shows how reliable NFs are in generating scenarios, Figure 5.6 shows how uncertainty region changes as compared to Figure 5.5. The adjustments are attributed to the parameters and number of samples used at the initial training stage of the NFs model, also in every single execution of the program the resulting uncertainty region can be used to gauge the extent of wind power generation, and in particular the scenarios generated help determine the dispatch schedule of the VPP and coordination of its internal resources.

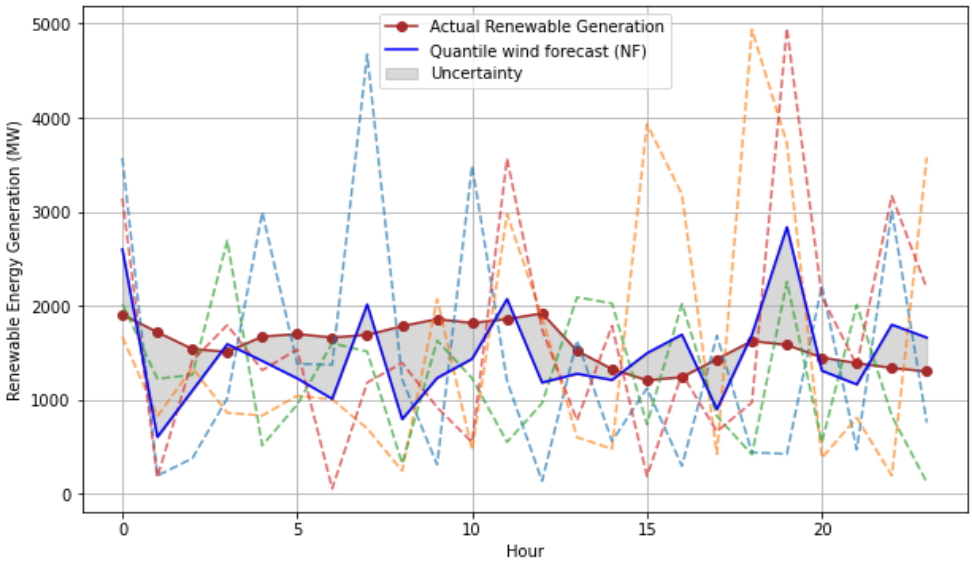

Figure 5. 5 Wind Energy Uncertainty Quantification 1

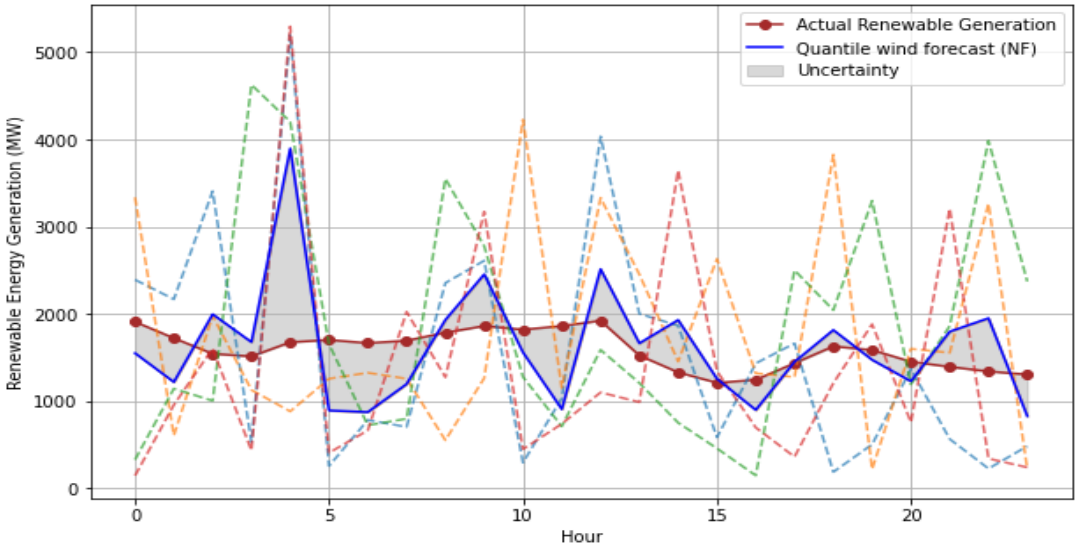

Figure 5. 6 Wind Energy Uncertainty Quantification 2

5.2 Optimization Approaches

5.2.1 DR-JCCO

Applying DR-JCCO for VPP has been solely used to dispatch DGs and BESS together Figure 5.7. The Figure clearly shows the demand is not met fully, and appropriate coordination between DGs, BESS and renewables is not optimal in generating a balanced power system.

Also, it implies that there is insufficient power supply though only DG2 is optimized within determinable time steps between hour 1 and hour 10, most of the power is generated by DG2 while DG1 is set to provide constant power. In case there is a reduction in demand such as low demand shown between hour 10 and hour 13, the BESS is slightly charged using power supplied by DG2 and WP included in the VPP generation portfolio which meets part of the changing demand. The BESS later discharges between hours 14 and 24, increasing the total VPP output.

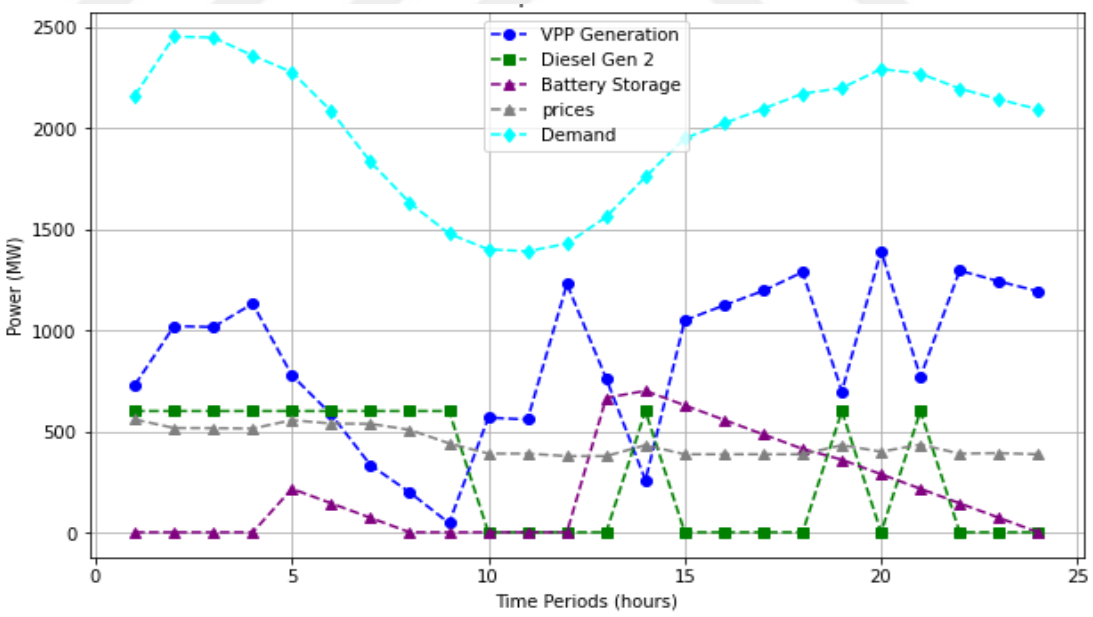

Figure 5. 7 VPP Dispatch for Scenario 1 with DG2

VPP can act as a load and end up consuming power Figure 5.8. The negative sign shows the VPP is importing power and generating a fraction of it to lower the demand, the DGs and BESS are partially dispatched to cover residual power demand.

Additionally, the method can be adjusted further to meet demand in real-time, especially during the hours when demand is minimum, i.e., between hour 10 and 15. and the VPP output decreases(-sign indicates VPP supply), likewise the BESS discharges to decrease the demand between hour 15 and 24.

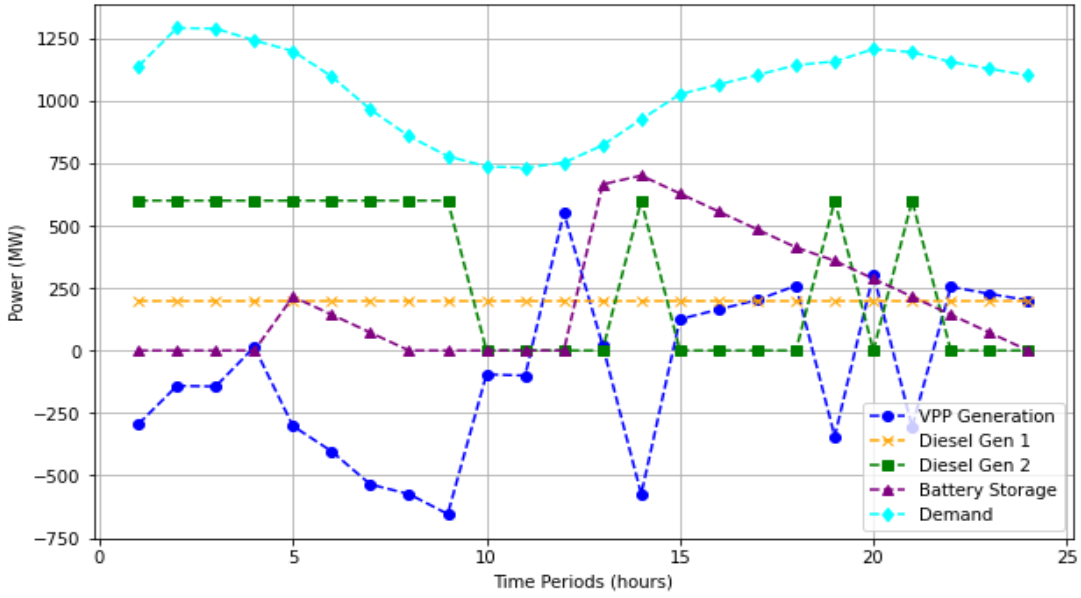

Figure 5. 8 VPP Dispatch for Scenario 2 (Internal consumption-1

Particularly, Figure 5.9 shows that DG1 is set to provide baseload power to balance the power system . The parameters of the BESS and the DGs are very critical, when the correct sizing is done the amount of power dispatched by the VPP has to at least cover 98% percent of the demand, but in case the BESS is not correctly sized, the BESS could end up supplying power for storage, which means the size of the BESS doubles the capacity of the DGs, and the aggregated power by the VPP will fail to meet the available demand, for instance Figure 5.10 shows such a scenario whereby the VPP and its internal generation units are not proportionally sized.

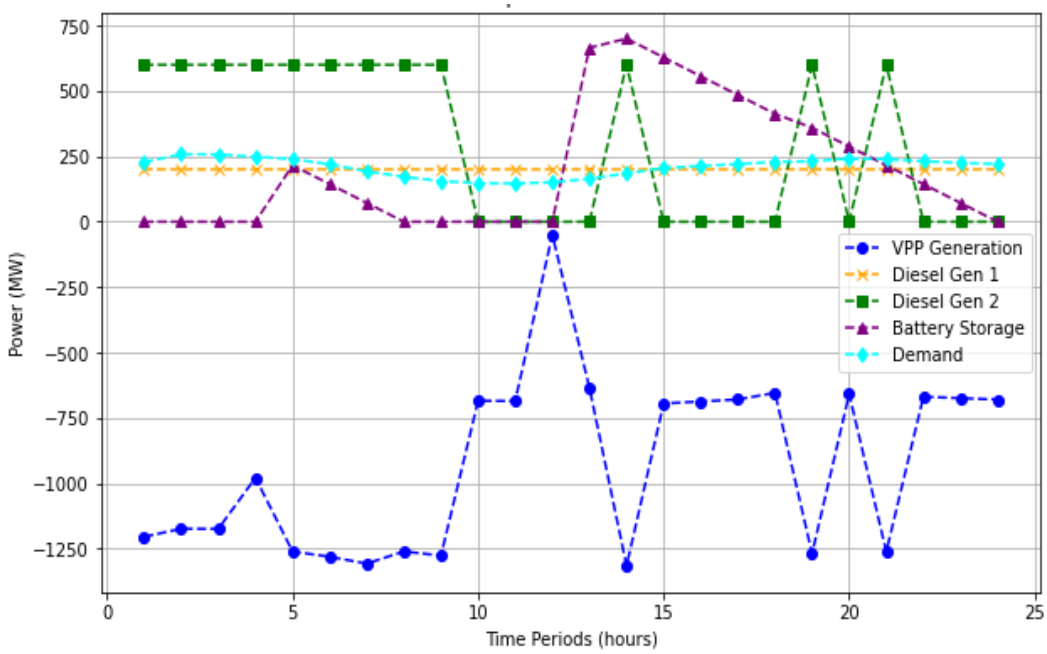

Figure 5. 9 VPP Dispatch Scenario 2 (Internal consumption-2)

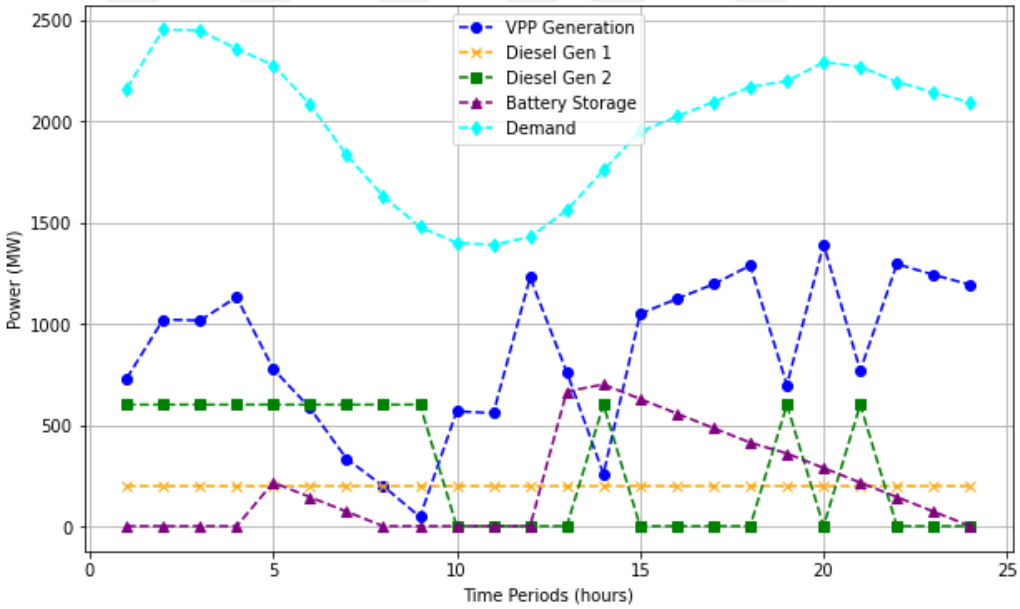

Figure 5. 10 VPP Dispatch for Scenario 2 with DG1 and DG2 (Parameter adjustment)

Meanwhile, Figure 5.11 illustrates how VPP generation meets the demand. The internal generation resources are aggregated to supply the load, while the residual demand is represented by the undispatched power of the BESS, indicated by the black

dotted lines. Since DG1 and DG2 are either exhausted or not supplying, the BESS remains the only resource capable of covering the residual demand.

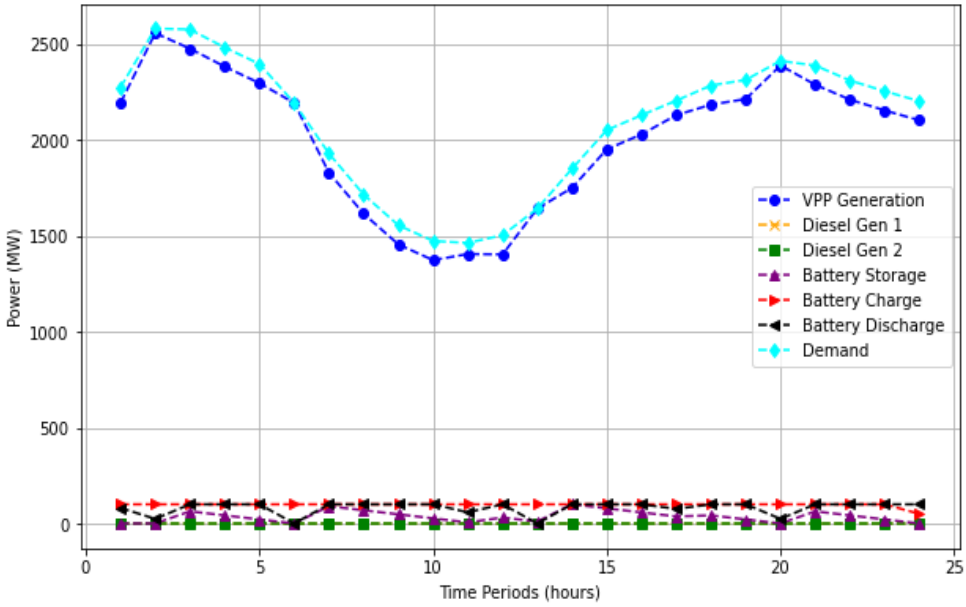

Figure 5. 11 VPP dispatch with DG1 and DG2

Next, DR-JCCO can be applied to effectively determine electricity market price, the electricity price profile is contemplated into the model as shown by Figure 5.12. For demonstration purposes, the scenarios used illustrate the appropriateness of the method for hourly electricity market clearing.

The variations reflect the robustness of DR-JCCO in price determination, the initial price spikes are due to uncertainities emanating from wind power, as the uncertainities decrease the prices tend to be more stable. Though price spikes are expected for example at about hour 13, then followed by stable prices between hour 14 up to around hour 17.

The spike can be attributed to several factors, one of them can be linked to unavailability of enough power supply to balance out demand due to high costs of power generation especially for DGs, Wind power may not be enough due to reduced wind speeds at that specific time implying that the system has to prioritize less

expensive power generation assets. Still, as the demand rises the prices steadly increase and at the last hour they start dropping due to the fall in demand.

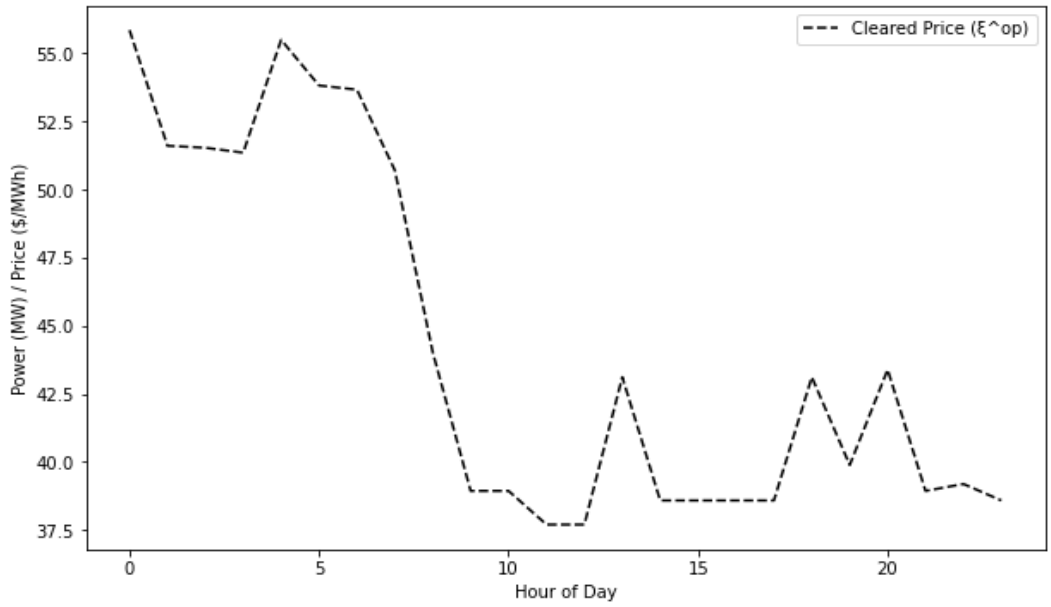

Figure 5. 12 Energy System Market Clearing Price

Figure 5.13 shows a more optimized VPP dispatch plan with VPP generation and demand being almost at an equilibrium. The prices vary throughout the 24-hour period, with the price curve decreasing with respect to the reduction in demand. However, the prices spike between hour 10 and 11. Figure 5.14 illustrates the dynamic electricity price profile over a 24-hour period. A peak in electricity demand is observed between the 3rd and 4th hour; however, electricity prices concurrently decline during this interval.

In contrast, a noticeable price spike occurs between hours 7 and 10, indicating a period of high market prices. This suggests that profitability in such intervals is highly dependent on market positioning,i.e., suppliers with committed bids during this period could realize significant profits, while consumers would incur high costs.

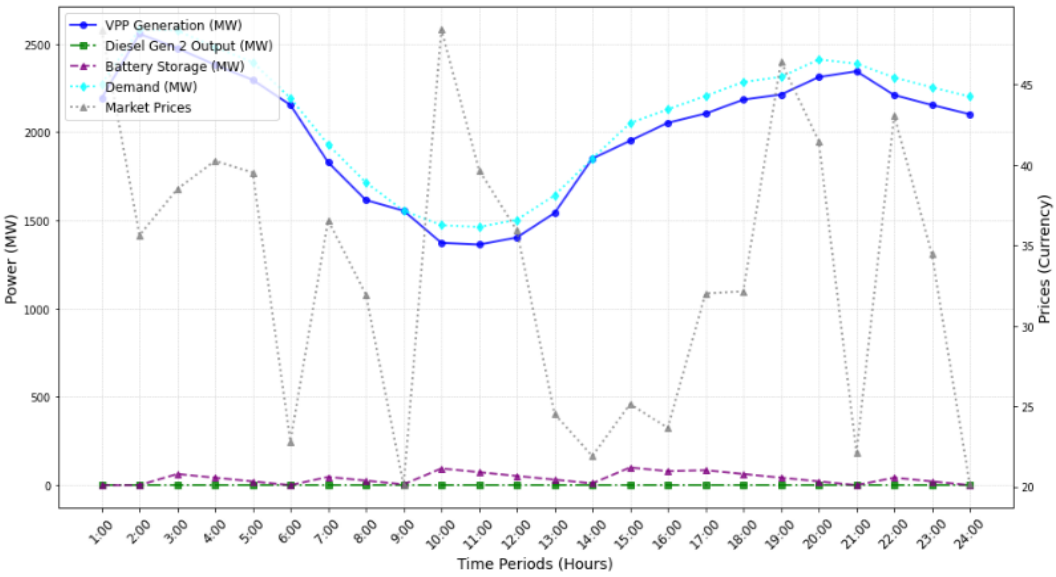

Figure 5. 13 Optimized VPP Dispatch and Dynamic Electricity Market Prices Scenario-1

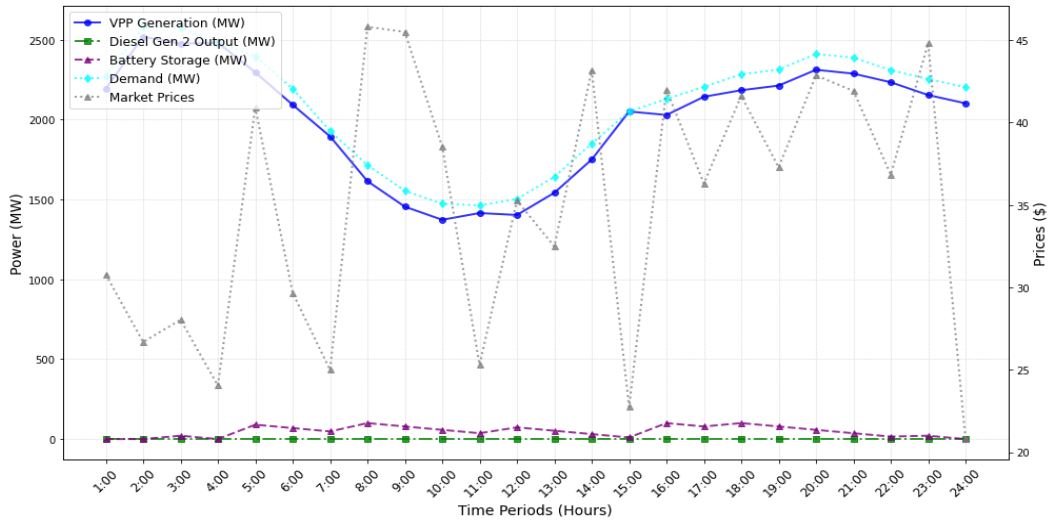

Figure 5. 14 Optimized VPP Dispatch and Dynamic Electricity Market Prices Scenario-2

Furthermore, Figure 5.14 introduces DG2 to model scenario-2, characterized as a more expensive asset compared to DG1 as outlined in the optimization parameters. Consequently, the VPP incurs substantially higher operational costs, totaling approximately USD 1,531,271.71. This increase is primarily attributed to the indiscriminate dispatch of all generation units without applying an economic dispatch strategy. The operational cost can potentially be minimized through the application of

tractable DR-JCCO techniques such as the H-X method or CVaR, as will be seen in subsequent subsections.

5.2.2 DR-JCCO-CVaR

The method used for tractability of DR-JCCO, that is CVaR provides comparable results on how bilevel VPP can achieve efficient dispatch of DGs (provide baseload), BESS and WPP. Meanwhile, the uncertainities generated are input into the model, the degree of variation enables the VPP to adjust its output together with the DERs to supply the existing demand.

Figure 5.15 shows an underutilized case for BESS which is due to DG1 and DG2 being maximally dispatched instead of BESS, maximum charge and minimum discharge rate are set to 100MW. Figure 5.15 is more detailed as the VPP and DGs power supply are shown, at the extreme ends the VPP follows the demand curve by dispatching an equal amount of power as expected and at about hour 6 there is a steady power supply until about hour 14 when VPP power decreases steadily evidenced by decreasing DG1 and DG2 power supply.

In addition, the figure represents BESS underutilized case scenario largely due power supply from the DGs.

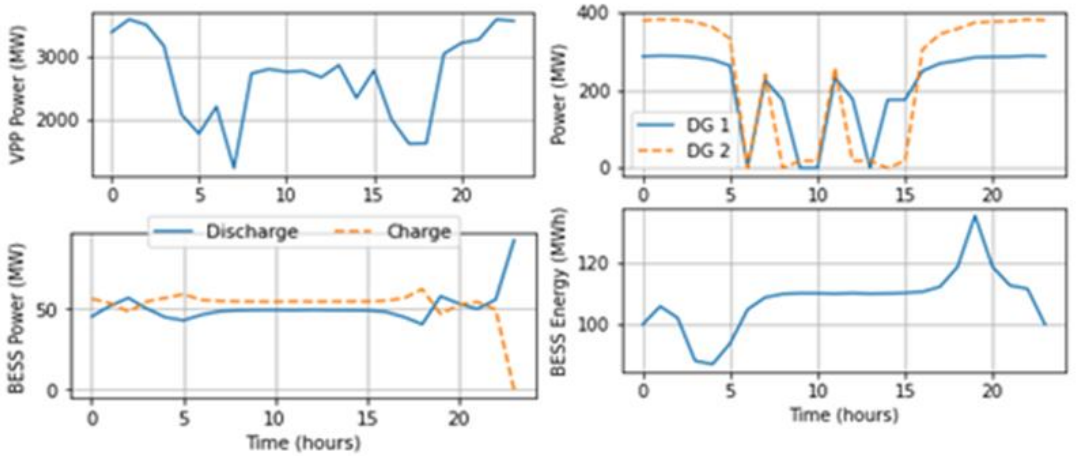

Figure 5. 15 VPP, DGs and BESS Power

Expanded form of BESS storage level over time is shown by Figure 5.16. The sizing of storage system is very important with the right specification and operational requirements, i.e., battery storage capacity, maximum and minimum SoC, C-rate and DoD, the monitoring of the BESS can be made easier and hence the optimal charge-discharge of the BESS will be guranteed. The BESS capacity determines how much power the BESS can supply to suffice the available demand. Figure 5.16 shows underutilization of BESS, less power has been extracted or supplied, the discharge period is limited to a few hours, i.e., about hour 2 and 4, then steadily the charging power increases and approximately levels out between hour 6 and hour 16 before charging to about 135MWh. The demarcated maximum and minimum SoC are not affected as the BESS is underutilized in this case, the total operational costs under CVaR is USD 490906.38570015, a reduced amount compared to when DR-JCCO is without CVaR.

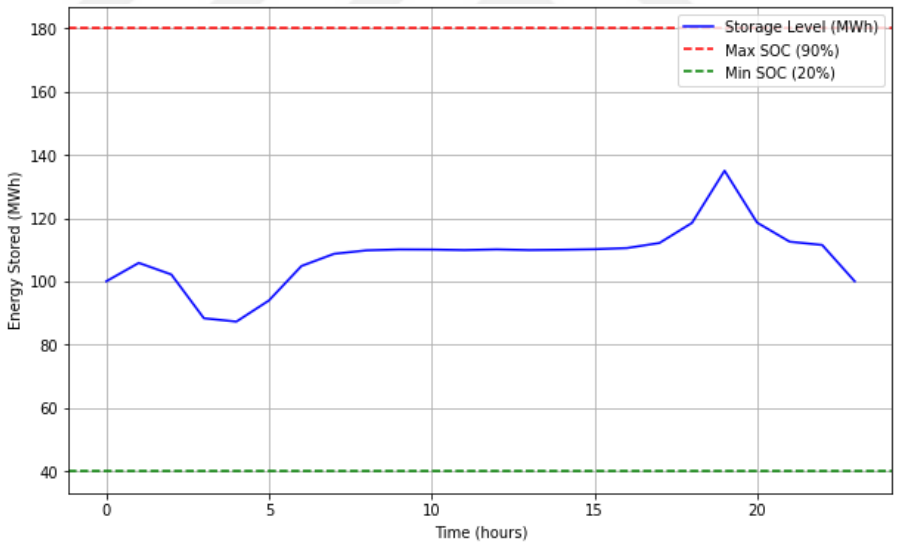

Figure 5. 16 Battery Storage Level with SoC Limits (Underutilized BESS)

The second case under CVaR is scheduling DG1 and DG2, DG1 generates constant 300MW and DG2 generates 400MW for 24 hour straight. The BESS is dispatched to cover for the remaining demand Figure 5.17 and Figure 5.18. The dispatch decision for the generators is based on the fuel consumption cost parameter , making DG1 less expensive compared to DG2.

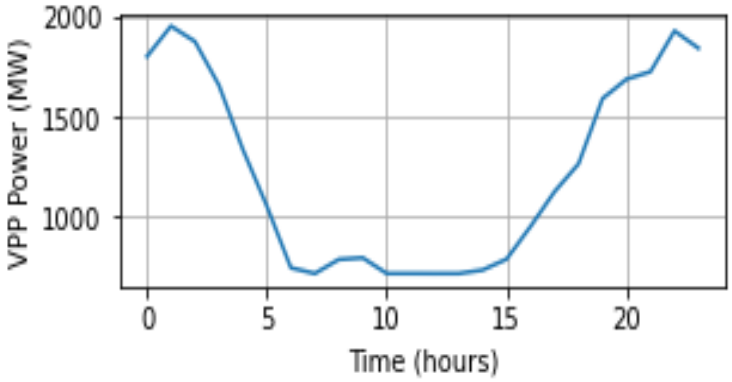

Figure 5. 17 VPP power with 200MWh BESS

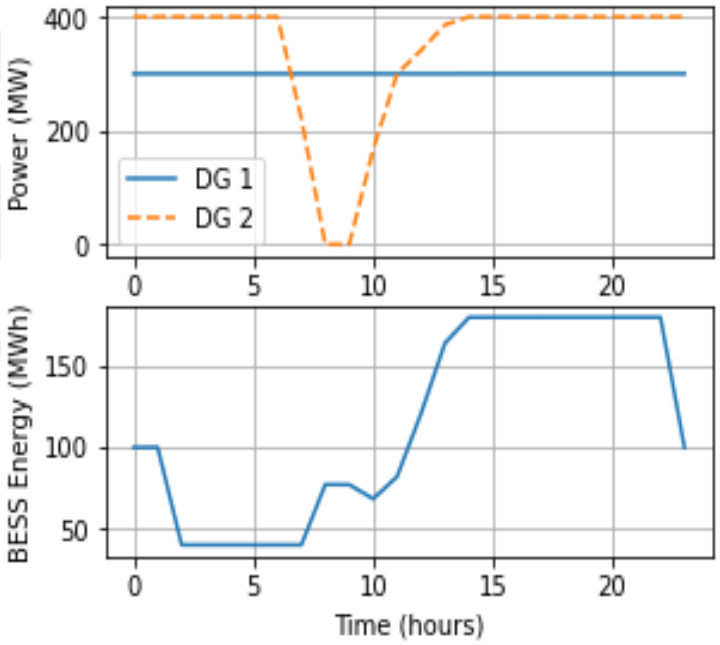

Figure 5. 18 DGs and BESS Dispatch

Expanded view of BESS storage level under SoC contrainsts is shown by Figure 5.18, the initial energy stored is 100MWh, and after charging and discharging cycles the BESS is left with initial stored energy of 100MWh, Note that the capping for the BESS is contrained by max and min SoC set at 90% and 20% as shown by Figure 5.19 and 5.21, respectively.

In particular Figure 5.21 is added to show how the smooth curve for the BESS can be obtained, which is not always the case for real physical systems, the nature of the curves might change from case to case.

In addition, the smooth curve maight not be the accurate represenation of Figure 5.19 because of the variation at about hour 8, constant BESS production is not accounted for, generally the smooth curve only serves to demonstrate minimization of operational costs using BESS as one of the solution.

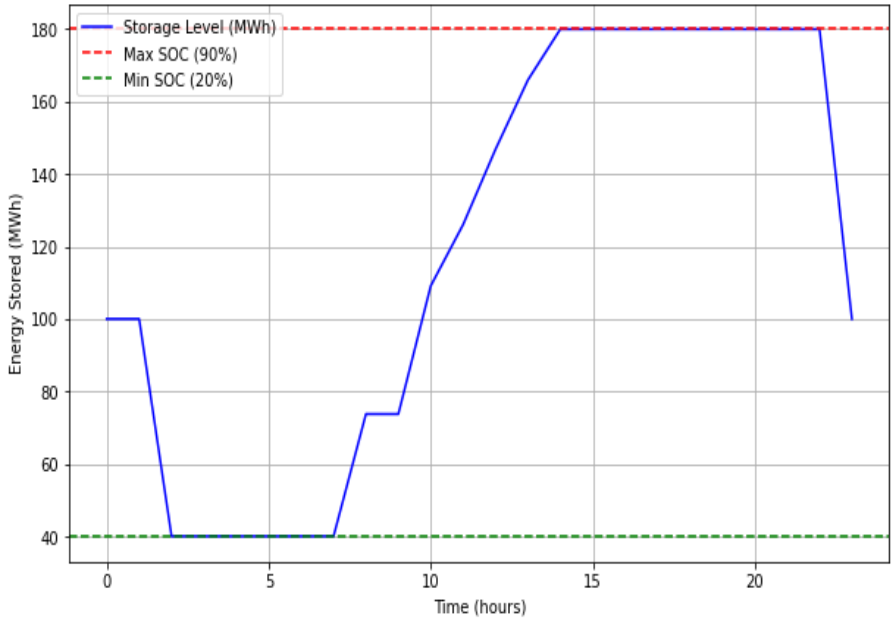

Figure 5. 19 BESS Level with SoC Limits

Figure 5.21 illustrates the power generation from DG1 which is set at maximum 300MW and has the least fuel cost, while DG2 generates 400 MW and is set to vary depending on the available demand, together with BESS they are scheduled to supply the system demand. The VPP aggregates these resources and optimally dispatches them following the demand curve shown by Figure 5.2, the peaks formed on the VPP generation profile signify the sensitivity of the method to meet the demand. The BESS discharge is on two extreme ends, see Figure 5.22 BESS charge-discharge curve.

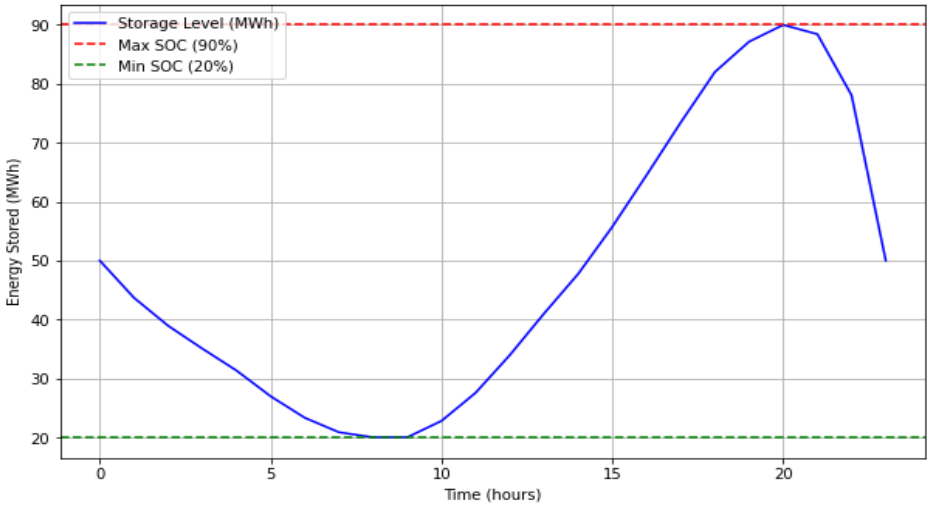

Figure 5. 20 Smoothed BESS Level with SoC Limits

Next, the CVaR algorithm ensures results are output with slight variations, for instance charge-discharge shown in Figure 5.21. The Figure indicates that the BESS varies its chargeing cycle between hour 5 and hour 10, the BESS charges with high active power and then the rate of charging decreases and abruptly spikes at around hour 13 and finally the charging power decreases to 0MW, from hour 15 the BESS is neither charging nor discharging until around hour 21 when it starts to discharge, the operation costs for this case is about USD 342800.2331366956, evidence that the BESS is properly sized and scheduled.

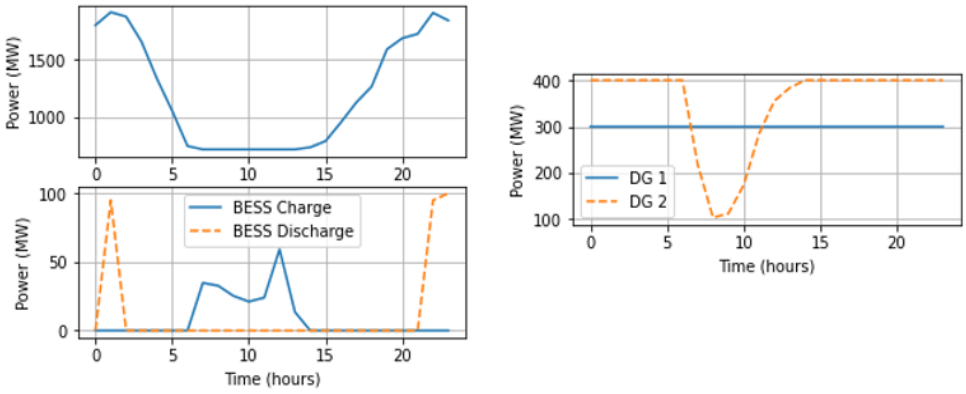

Figure 5. 21 VPP -BESS Charge-Discharge Power with DGs

The BESS charging power increases and decreases withn a very short period of time,i.e., between hour 5 and hour 10, signifying that the BESS is used more as the

area shown by DG2 in Figure 5.22 is narrow compared to the area shown in Figure 5.21.

The VPP power output also varies as a response to the changing demand, its power supply increases as the BESS quickly dispatches between hour 5 and 10 and levels up at about hour 14, while VPP in Figure 5.21 gives constant power output between hour 5 and hour 14, indicating that BESS is not maximumly used instead DG1 is deployed and DG2 is not dispatched fully between hour 6 and 7, respectively.

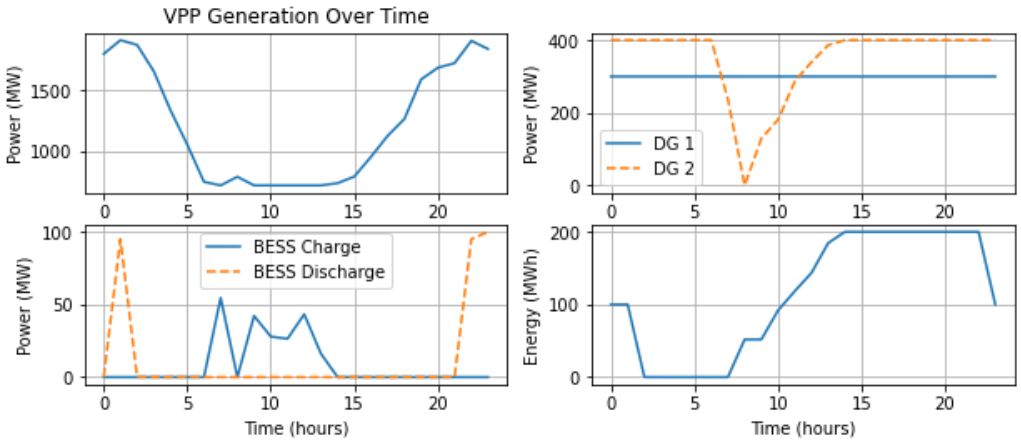

Figure 5. 22 VPP Power Generation b) DG 1 and DG 2 Production c) BESS Charge-discharge Curves d) 200MWh BESS (Scenario-1)

The attractive nature of the CVaR algorithm is the ability to self-regulate and optimally dispatch the BESS within safe levels. The strategy ensures a real-case scenario is reflected when charging, in this context the charging of the BESS variesas as the active power keeps on changing, Figure 5.21 , 5.22, 5.23 with the exception of 5.20 the safety limits of the BESS are not factored in, the results shown by Figure 5.21, i.e, between hour 3 and 6 , energy stored in the BESS is zero but charges slighly and then discharges at about hour 9.

These sharp charge-discharge cycles may over the long term, have adverse effects on the overall health of the BESS see Figure 5.23.

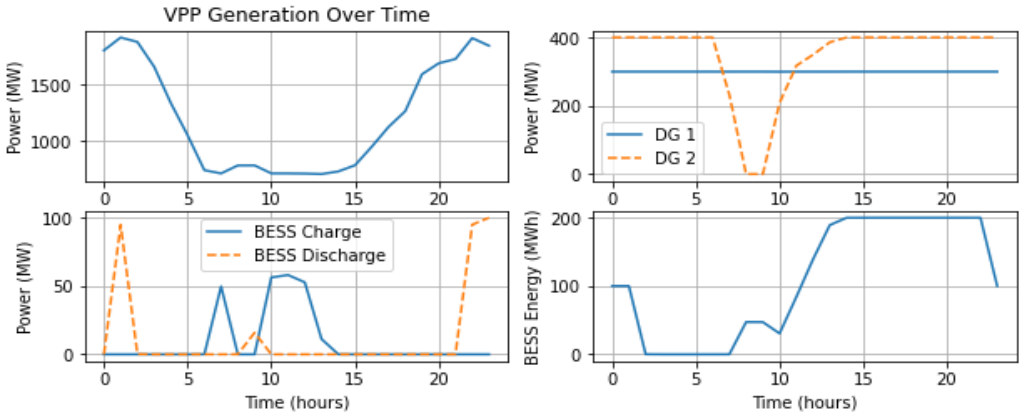

Figure 5. 23 VPP Power Generation b) DG 1 and DG 2 Production c) BESS Charge-Discharge Curves d) 200MWh BESS (Scenario-2)

Under similar conditions without considering safety limits, the BESS charge-discharge rate is 100MW as shown by Figure 5.24. Other settings include, 100MW initial storage, 200MWh BESS capacity with 0.95 charge-discharge efficiency. The BESS discharges fully and gains 0 state and at hour 5 it begins to charge though not steadily, the charging power in this case is similar to the changing demand. Between hour 2 and hour 5 the BESS neither charges nor discharges, the DG2 combined with DG1 is sufficient to cover the system demand. Up untill hour 5, the BESS charges steadily and its output is adjusted with respect to the demand.

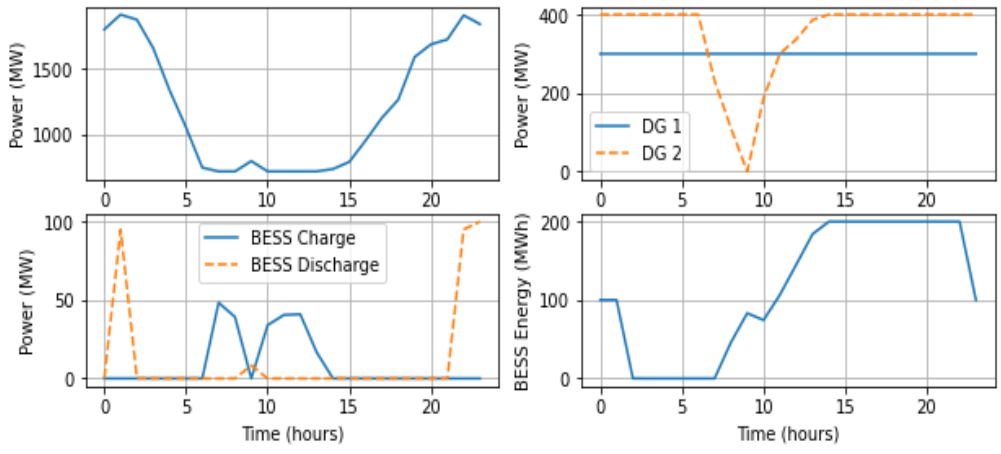

Figure 5. 24 VPP Power Generation b) DG 1 and DG 2 Production c) BESS Charge-Discharge Curves d) 200MWh BESS (Scenario-3)

This form of dispatch using DR-JCCO-CVaR is highly remarkable and positively indicates the ability of the method to factor in huge variations emanating from renewables, storing power from WPP and coordinating dispatch of DERs. The same variations are expected Figure 5.26, the figure shows VPP generates about 400MW between hour 5 and hour 10 which is committed into the electricity market and deployed, DG1 provides baseload power and the BESS gets charged after the demand is met, DG2 supplies 400MW until 6, the amount it supplies changes and finally goes offline for about 1 hour, and when the DG2 goes online the BESS starts to charge steadily, only to dicharge at peak hours.

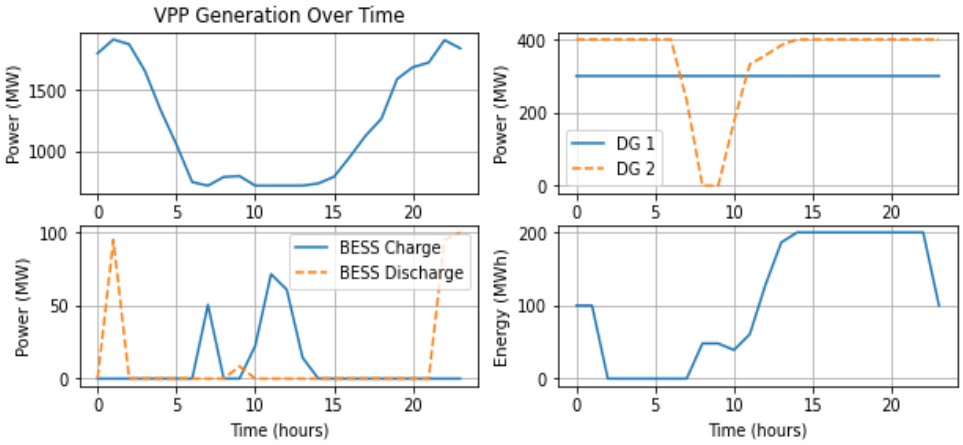

Figure 5. 25 VPP Power Generation b) DG 1 and DG 2 Production c) BESS Charge-Discharge Curves d) 200MWh BESS (Scenario-4)

The model did not factor curtailment planning as shown by Figure 5.26, the generated WP was deemed sufficient and the model focused on dispatching DGs and BESS .H-X performed curtailment of the WP to illustrate high-level modeling of DERs under continuous scheduling.

In conclusion, the total profit under the CVaR approach was approximately USD 500,000, traded across the generated scenarios. This is illustrated in Figure 5.27, based on the assumption that the traded amount closely reflects used scenarios and the observed power magnitudes.



Figure 5. 26 Zero Wind Curtailment

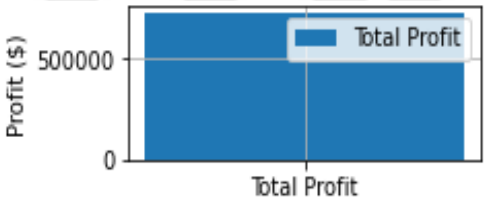

Figure 5. 27 Total VPP Profit Under CVaR

5.2.3 DR-JCCO -H-X

H-X algorithm solely uses an iterative algorithm to track the DR-JCCO and its convergence, which reduces the conservative nature of DR-JCCO attested in section 5.2.1.When optimal t is obtained, the VPP resources are all scheduled to meet the demand, Figure 5.28 below shows scenarios generated with respect to the optimal

value t.

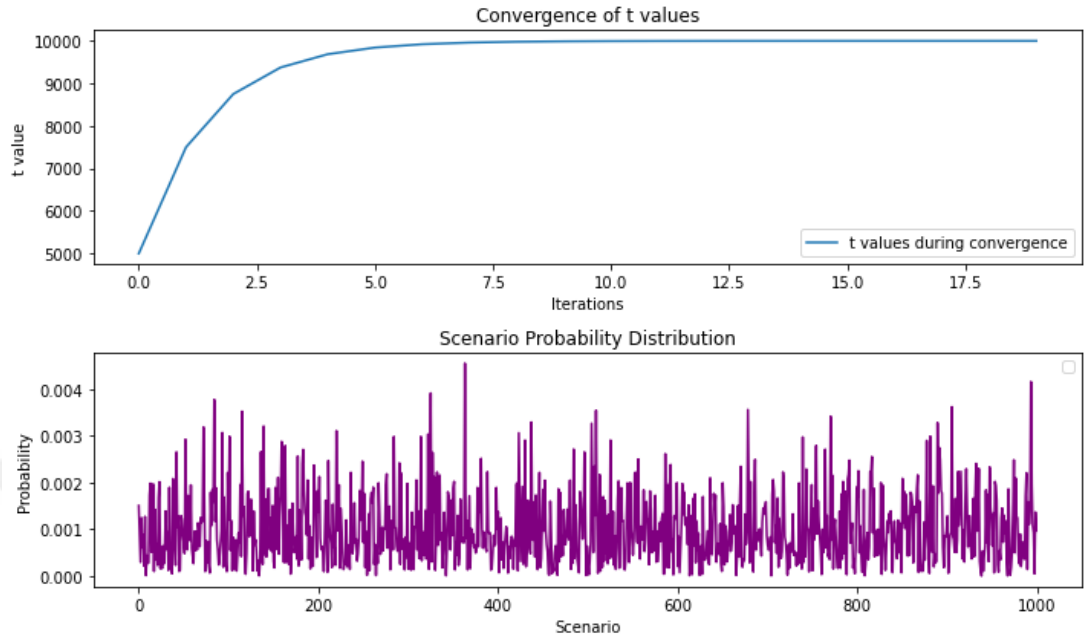

Figure 5. 28 Optimal t Value and Generated Scenarios

When H-X is applied to discharge the BESS, the SoC of charge decreases very rapidly implying the iterating loop reaches optimality very fast. Due to the high performance of H-X in relation to time, BESS is dispatched to cater for the demand, when DG1 and DG2 supply is insufficient to meet the demand. At around hour 20 the SoC reaches 0 see Figure 5.29 .

The spikes signify the discharge-charge of the BESS, which may not be a good indication for the general health and safety precautions of the BESS. As much as the method is fast and approximates the DRO problem accurately, in the long term the BESS efficiency could drop due to high charge-discharge cycles.

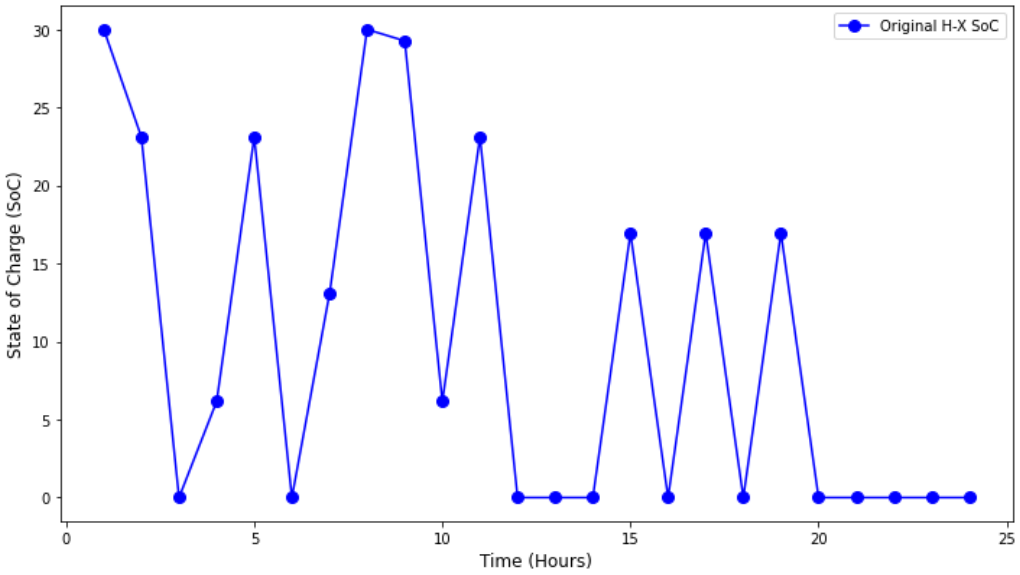

Figure 5. 29 H-X SoC for 30MWh BESS

Figure 5.30 shows wind power generation, curtailment and an adjusted demand profile, the curtailment process is actualized by using percentage of wind power required for curtailment and penalization parameters. In case of WP surplus, 80% of the total wind power generated is utilized the rest is curtailed using Wind Usage Fraction (WUF) and curtailment fraction, for demonstration purposes the model used 0.9 and 0.5 as WUF and Curtailment Fraction (CF), respectively.

The strategy is important when assessing the impact of overgeneration within the grid network system, for instance the amount of wind curtailed shown by Figure 5.31 is about 0.12MW at maximum when 0.9 WUF is applied, which is a bit low when compared to curtailing at 0.5; the resulting amount of WP curtailed is about 2.9MW at maximum as illustrated by figure 5.30. The instataneous nature of H-X in dispatch of distribued generation assets makes it suitable for continuos power supply in power networks, also the demand curve used in Figure 5.30 is adjusted to reflect the realistic demand curve which varies with time.

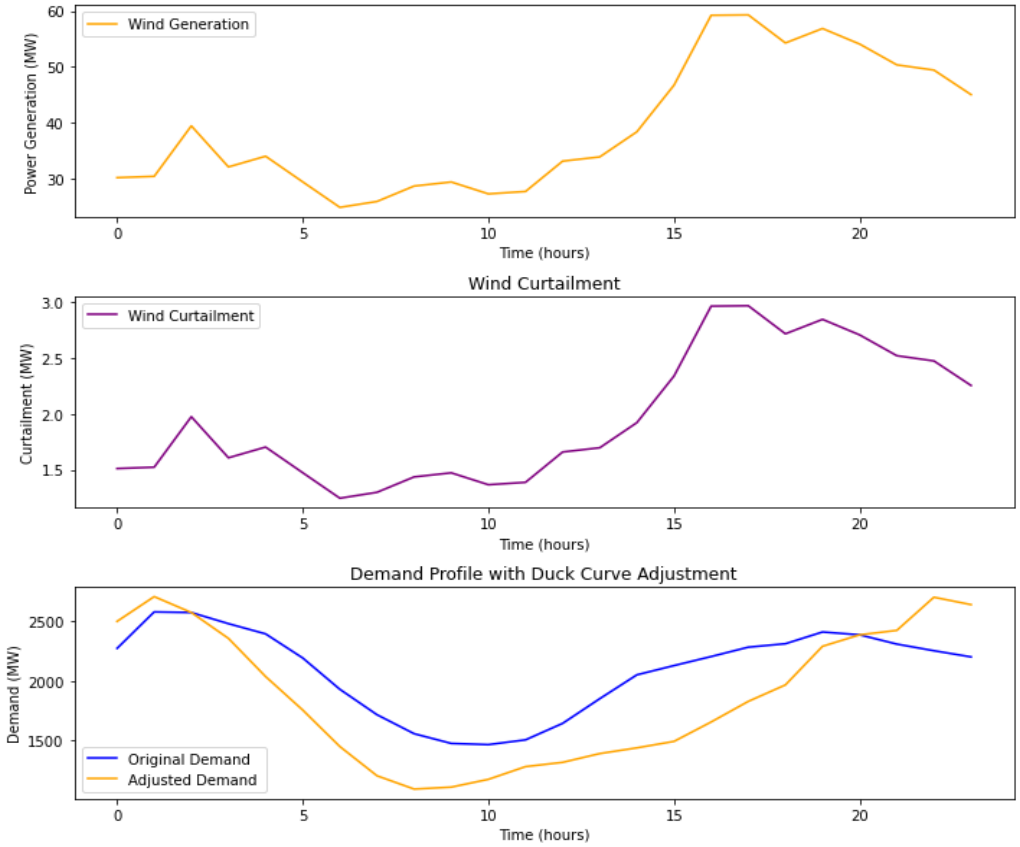

Figure 5. 30 WP Penetration Levels and Demand Adjustment

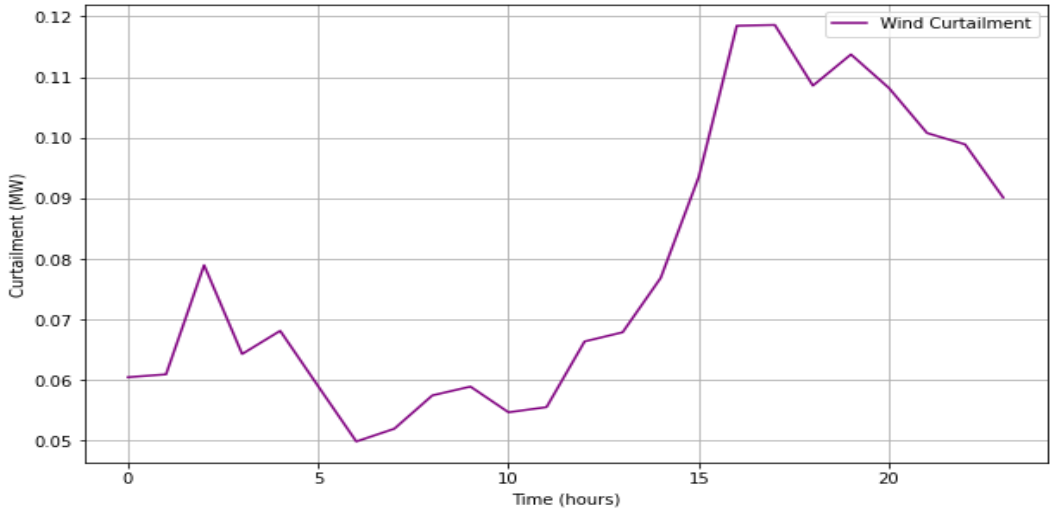

Figure 5. 31 Wind Power Curtailment

The figures can be scaled to get more clarity of the charg-discharge of the BESS and DG1 and DG2 power supply. Figure 5.32 is scaled to show cases when DGs are

deployed especially when VPP supply is less than the demand. The Figure displays under-utilization of the BESS with rapid charge-discharge instances, the reason why the BESS is not fully utilized is because the overall VPP supply is enough to cover the demand, the regular charging or discharging of the BESS only covers a small part of the demand. Additionally, the BESS constraints are activated as the BESS SoC minimum of 20% is observed while maximum SoC of 90% is demarcated by red dotted line, this case is similar to the one in Figure 5.16. As mentioned earlier, the robust nature of the H-X method instantly schedules DG2 and DG1 during peak demand at about hour 22 and 23, respectively. The dispatch is based on the ability of the H-X method to determine operational costs such as fuel consumption, start-up and shut-down costs of the DGs and minimize the operational costs to permit scheduling and coordination of these resources to meet the demand using VPP modeling approach.

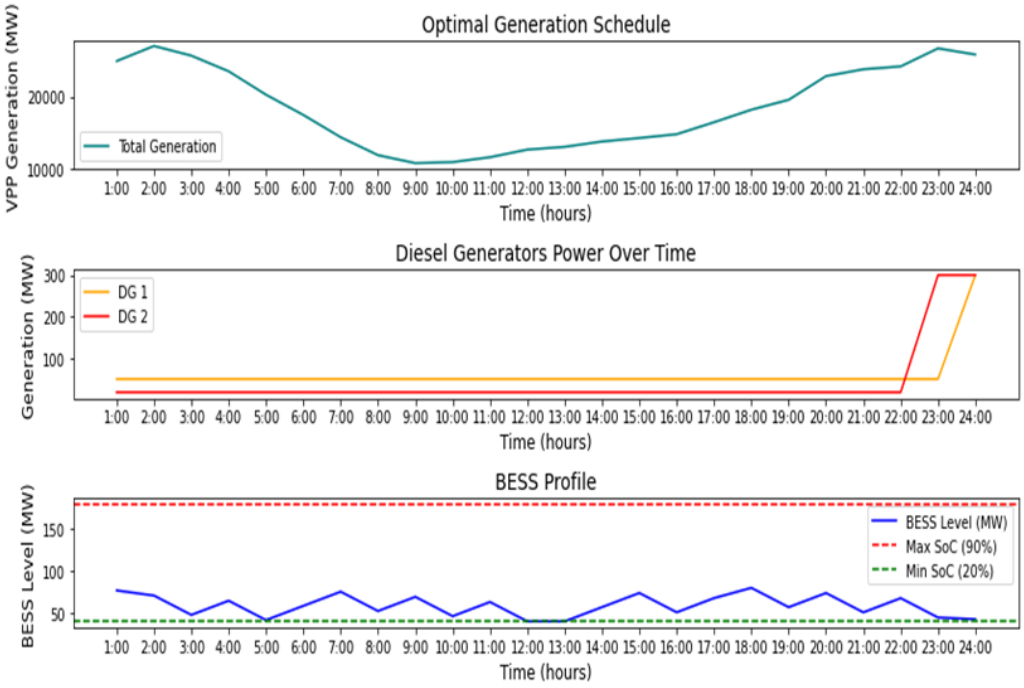

Figure 5. 32 Under-Utilization Scheme of a 200MWh BESS

Next, the VPP dispatches its generation assets by first coordinating internal resources using the DR-JCCO-H-X approach. As illustrated in Figure 5.32, this coordination enables the VPP to respond to varying demand, with the amount of power dispatched

by the BESS decreases over time.The method also ensures the safety of the BESS is adhered to by optimally charging and discharging the BESS within the specified limits.

Subsequently, the relatioship between the size of the BESS and the power supply capacity of the DGs has been established. If the size of the BESS regarding storage capacity is 400MWh and the DGs are not properly sized,i.e., 50MW and 100MW the BESS will be under-utilized, and the VPP profits will be less implying that the BESS gets charged-discharged less frequently to minimize operational costs such as the cost of dispatching the DGs to charge the BESS could be very high and to limit exponential cost of charging the BESS, the VPP schedules the rest of its resources to meet the demand and minimally charged the BESS, consequently,the size of the DG1 and DG2 in terms of power supply capacity determines the rate of charge-discharge of the BESS see Figure 5.33. Note the amount of power charged-discharged from the BESS and the 0MWh from about hour 19, the BESS is fully discharged forcing the VPP to rely on the DGs for power supply.

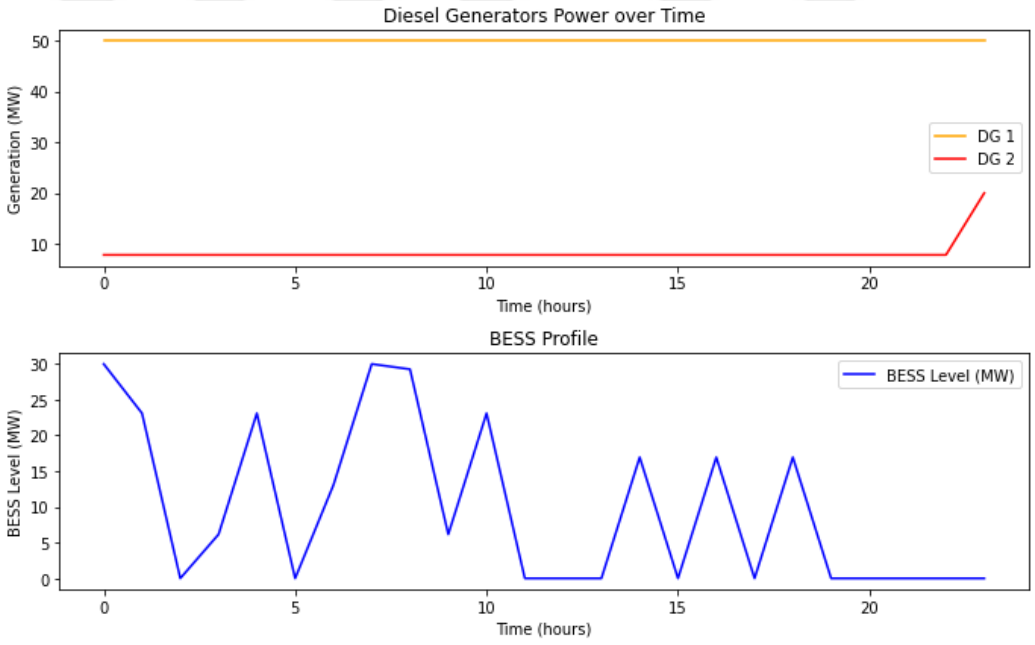

Figure 5. 33 30MWh BESS with DG1and DG2

Additionally, as identified by Figure 5.33 the small size of the BESS allowed the VPP to optimally schedule most of its power as attested by Figure 5.34, showing the rapid

charge-discharge cycles which finally settles at 0MW from about hour 19 to hour 24. The duration between these hours prompts the VPP to resort to ramping up DG2 by 20MW and dispatch constant 50MW from DG1 to meet the demand at peak hours. Though in real physical systems, rapid charge-discharge of the BESS is not recommended as it could damage the storage cells or even accelerate the degradation rate of the BESS.

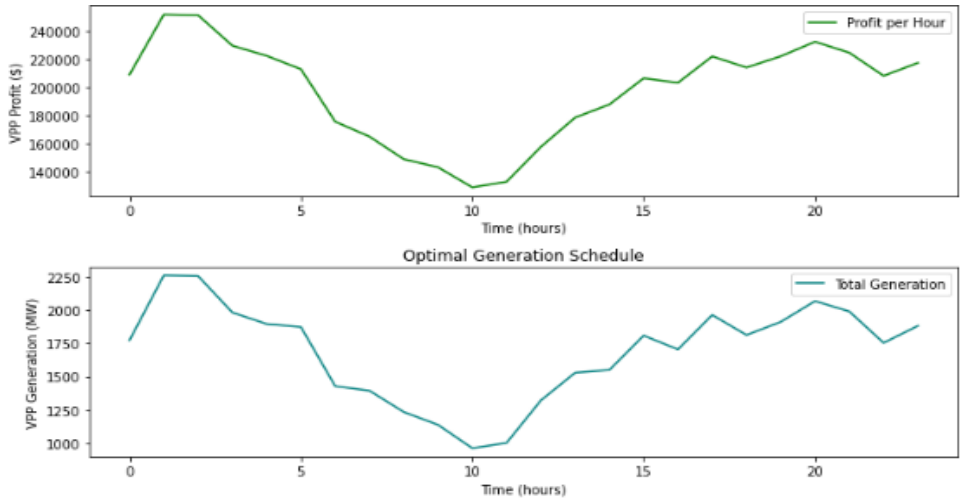

Figure 5. 34 VPP Optimal DERs Dispatch and Profit Acquisition (>30MWh <200MWh BESS)

Figure 5.35 and 5.36 show that by increasing the BESS size and keeping DG1 and DG2 at 100MW and 200MW, the profits made by the VPP increase compared to Figure 5.34 because both DG1 and DG2 supplying more power, raising operational expenses for DG1 and DG2, similarly, the fact that the size of BESS in Figure 5.35 and 5.36 is moderately large, it therefore permits spontaneous charge-discharge of the BESS at a relatively low expense when compared to discharging the DGs.

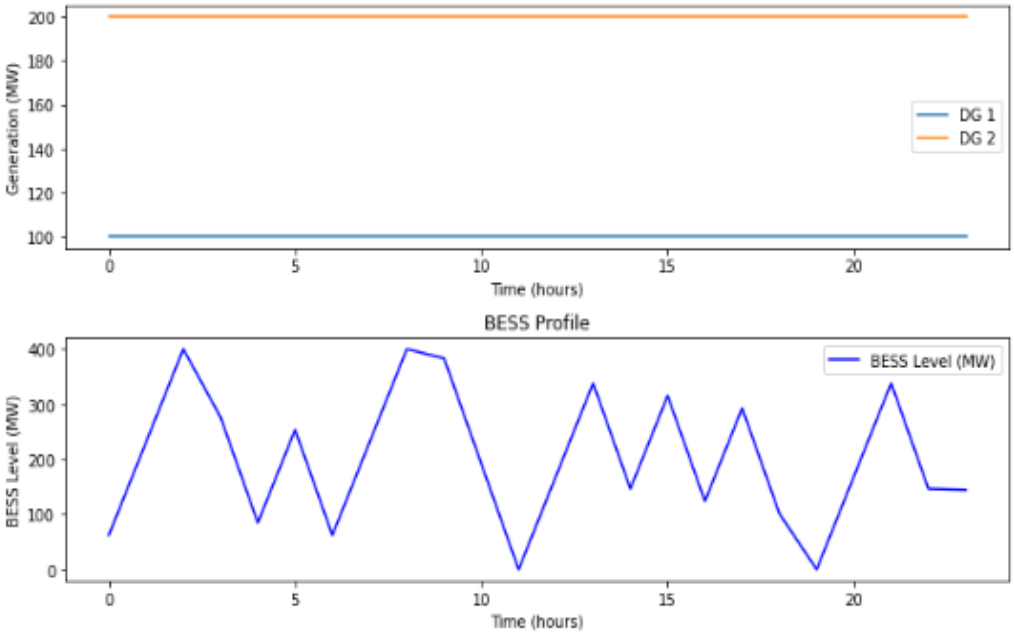

Figure 5. 35 400MWh BESS DG1 and DG2 profile

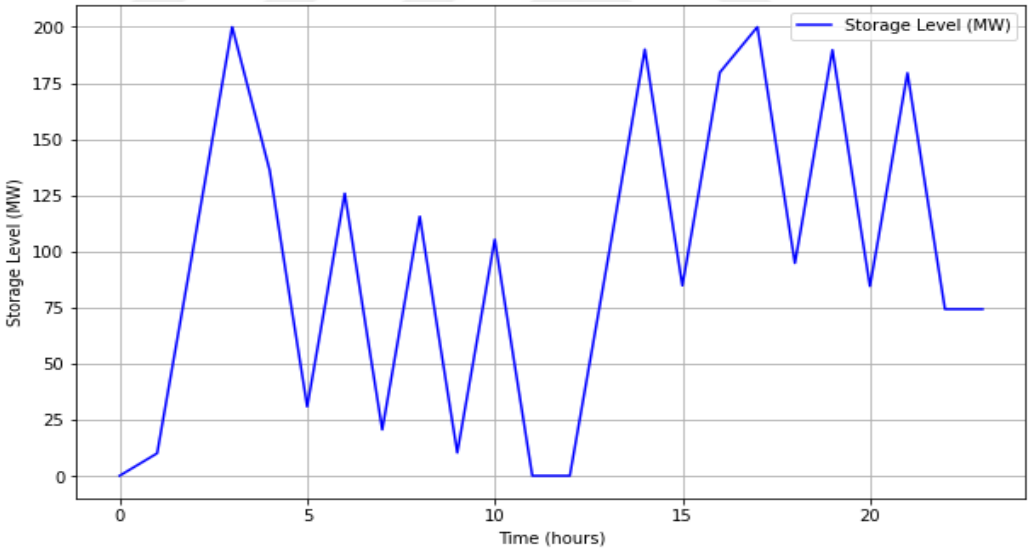

Figure 5. 36 200MWh BESS

Figure 5.37 can be compared to Figure 5.34, which dispatches the DGs less frequently by utilizing the BESS more extensively.

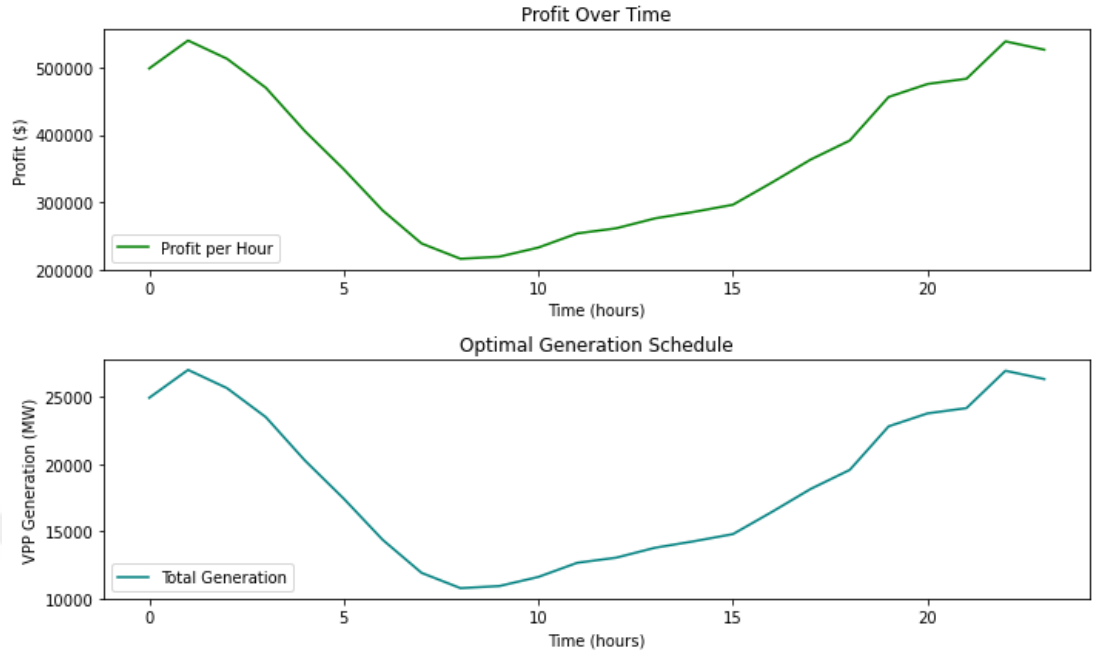

Figure 5. 37 VPP Optimal DERs Dispatch and Profit Acquisition (>200MWh <400MWh BESS)

Furthermore, Figure 5.38 and Figure 5.39 illustrate how the demand profile changes when wind generation is added into the VPP energy mix, the demand significantly decreases, WP curtailment is still essential to demonstrate how to effectively handle WP or overall renewable energy generation to balance both supply and demand, in this scenario the curtailed WP is then used to charge the BESS.

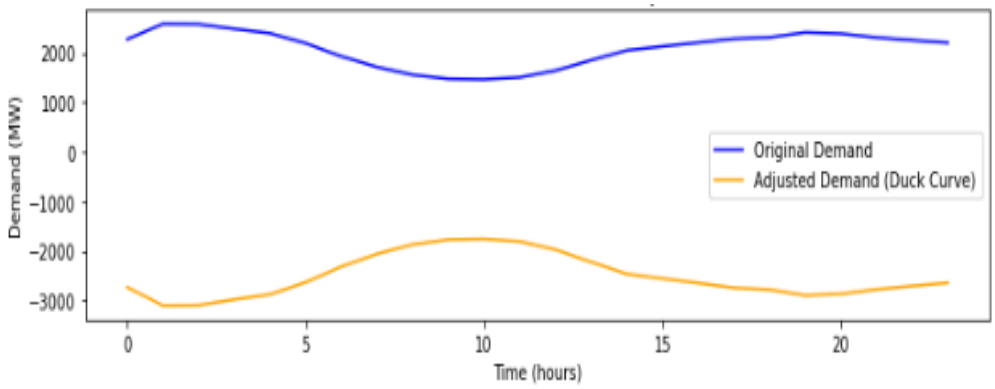

Figure 5. 38 Demand Profile Adjustment

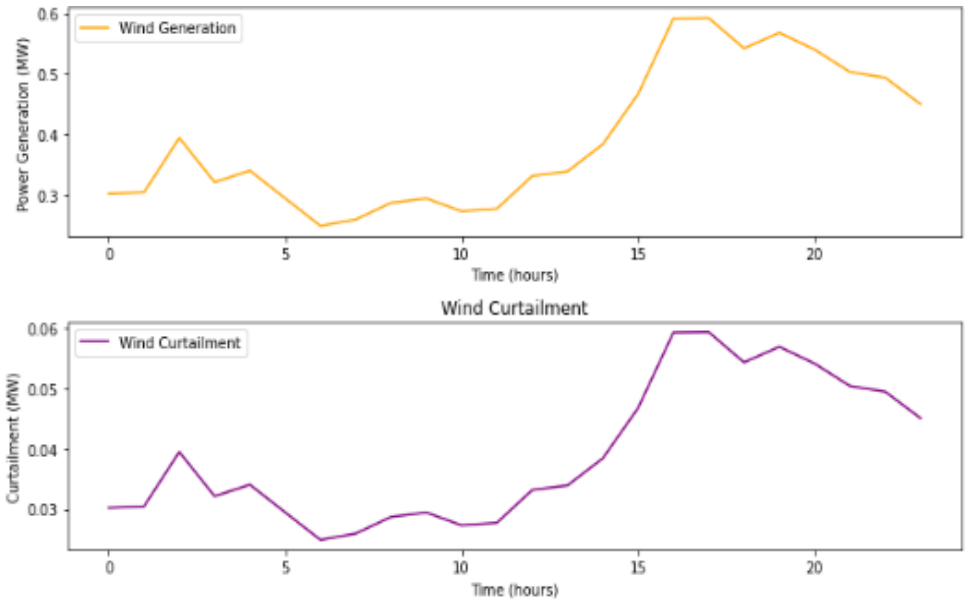

Figure 5. 39 WP Generation and Curtailment

On the other hand, Figure 5.40 shows DGs power supply limited to a minimum of 10MW for DG2 and about 58MW for DG1. The 100MWh BESS is optimally charged-discharged within maximum and minimum SoC. From Figure 5.40 it can be established that the BESS is charged-discharged repetitively implying that the BESS only covers the residual load after the VPP has cordinated the dispatch of the DGs and in that case the VPP is able to cover the rest of the demand while keeping the BESS on standby mode.

Additionally, in an optimal approach, the DGs are set to supply 50MW and a minimum of 10MW from DG1 and DG2, repectively see Table 5.1 case 6 depicting the ramping up of DG2 at about hour 22 with 15MW of power. The DG2 undergoes scheduling for the next hour to supply a constant of 20MW. The overall sizing of the BESS and scheduling of the DGs is highlighted in Table 5.1.

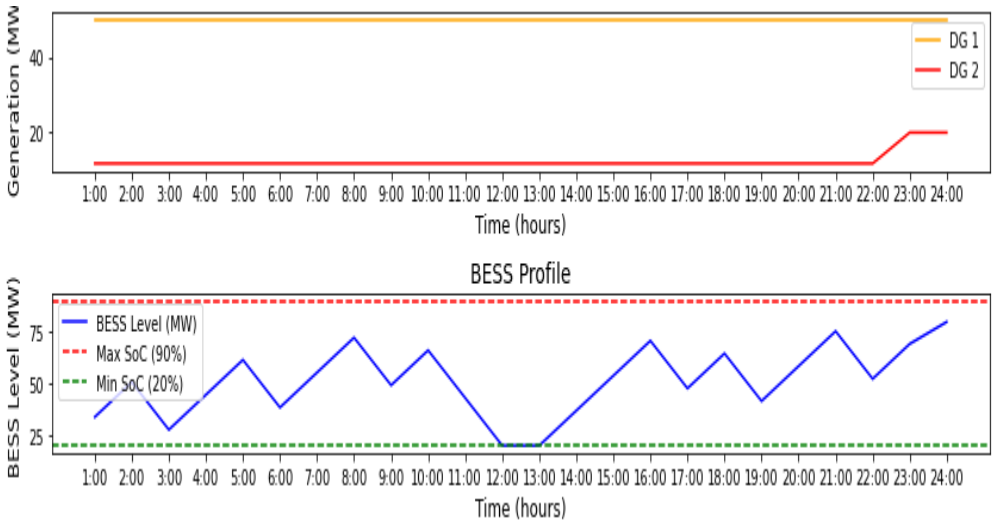

Figure 5. 40 DGs Dispatch with 100MWh BESS

Table 5. 1 DG2 Scheduling During Peak Hours

Case No	BESS storage Capacity(MWh)	DG1(MW)	DG2	Ramp up(evening peak hours)
1	200	50	20	
2	200	250	295	300
3	400	100	200	
4	40	58	10	20
5	50	50	20	
6	100	50	10	15
7	30	50	20	10

Table 5.1 provides evidence that the VPP only schedules the less costly DG in this case DG1, in order to meet peak hour demand the expensive DG2 is scheduled to cover the residual demand, while Figure 5.40 and 5.41 when compared to Figure 5.33, 5.35 and 5.36, they apply storage constraints to enable the BESS to commit its power in a more optimal way, highlighting the remarkable differences observed in DGs and BESS sizing.

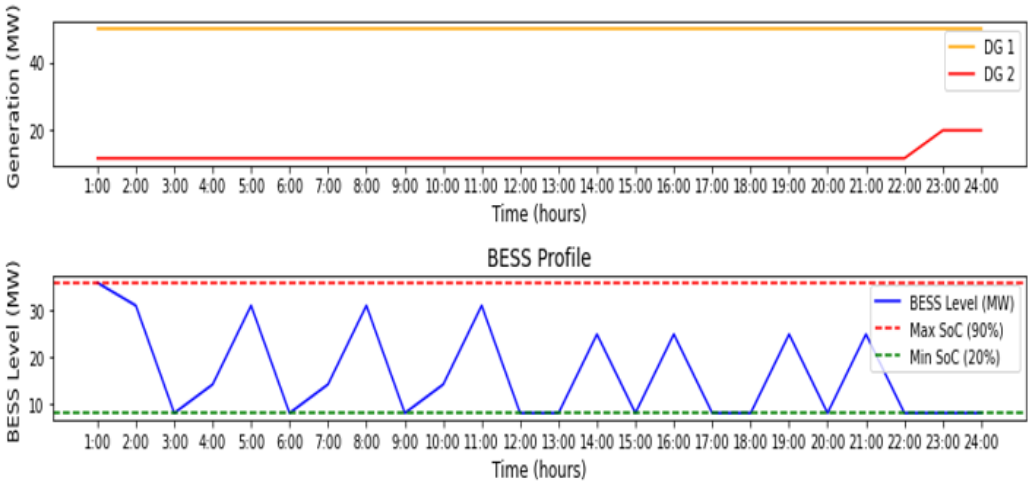

Figure 5. 41 DGs Dispatch with 40MWh BESS

Meanwhile, Figure 5.42 presents the quantified profits obtained from the operation of the VPP under H-X algorithm, the profits are generated according to the demand and the capability of the VPP together with its internal resources to supply enough power to meet the system demand.

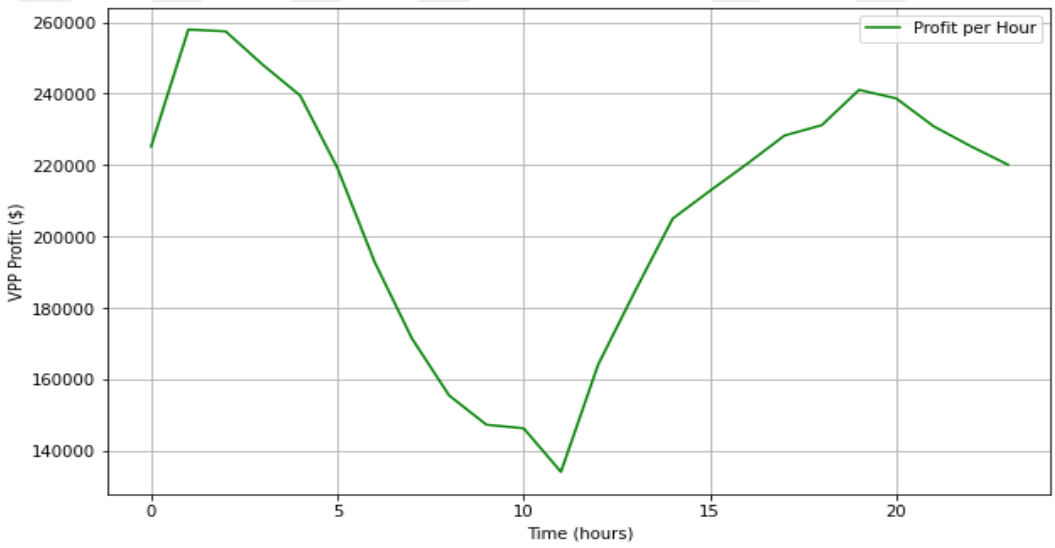

Figure 5. 42 VPP Profit Under H-X Algorithm

As previously demonstrated, the BESS sizing is very crucial in the sense that when the BESS capacity is increased to 400MWh both DG1 and DG2 have to supply power that

can be stored before the peak hours which are generally demarcated from about hour 22 to hour 23 see Figure 5.35.

Conversely, when the size of the BESS is suitably selected such as 4MW, the charge-discharge cycles are well coordinated, implying the DGs and part of the wind power generation charge the BESS and then discharge when the VPP cannot meet most of the demand .Overall, the optimization model suggests that reducing the size of the BESS without considering the size of the DGs could result in high operational costs with low hourly profits.

5.2.4 Benchmarking with REopt Optimization Model

This study looks into the results gotten with a more advanced REopt platform [212] The results gotten are analyzed and found that the REopt uses a deterministic optimization model unlike the model used in this study which is DR-JCCO with CVaR and H-X algorithms. The results obtained from the dispatch of the BESS are presented in Figure 5.43.

The load is supplied by the BESS and the grid, the grid charges the BESS and supplies the load. This is an example of grid-connected BESS, and can serve as an example of arbitrage trading whereby the battery can be used to supply the load and export power to the grid at an agreed upon price.

The SoC increases as the grid power decreases and after it reaches about 99%, then the grid charging power decreases steadily but at the same time demand is served by the grid at an average of 900kW. At hour 17, the BESS starts to discharge slowly to meet the demand, the grid power that serves the load decreases and reaches 0 between 19 hour and 21 hour, while the BESS discharges and attains SoC of about 0.5% as minimum and the process of charging the BESS begins again using grid power.

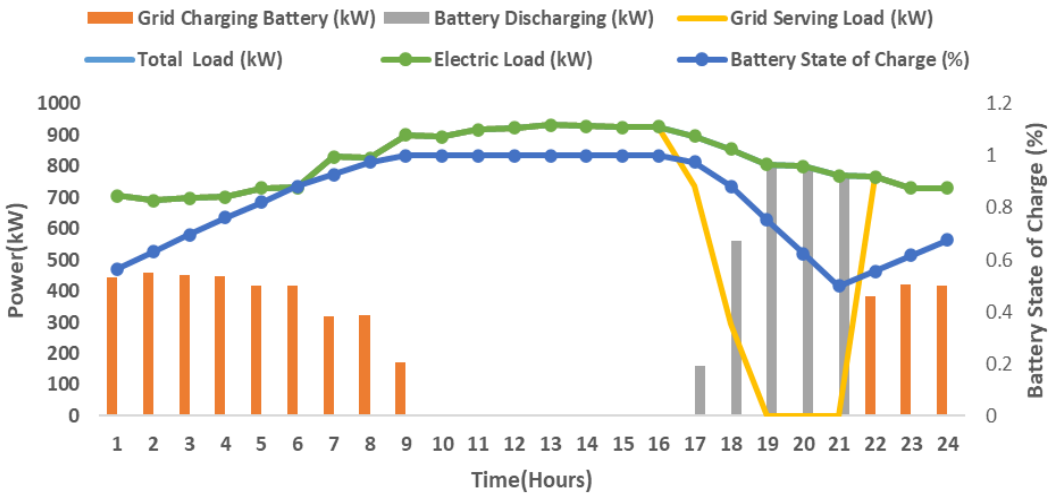

Figure 5. 43 BESS Operation Cycle-1

Whilst, Figure 5.44 the PV charges the BESS and serves the available demand at the same time, it can be inferred that PV and the BESS are connected together and the load can be served by both the grid, the PV and the battery.

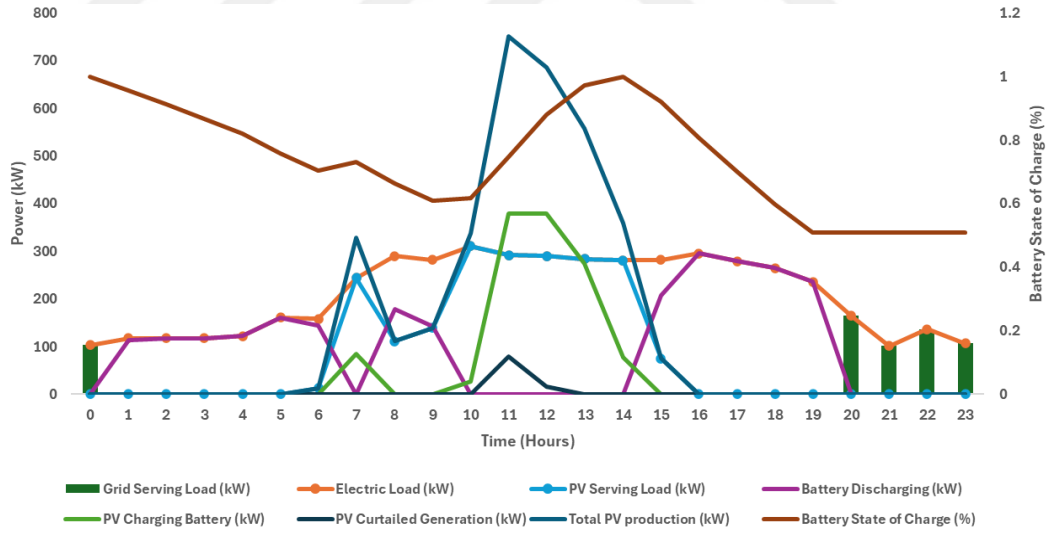

Figure 5. 44 DERs Scheduling

The PV power is only used to charge the BESS, the grid power serves only the demand. When there is PV production the BESS is charged, and when PV is unavailable the BESS discharges steadily to obtain SoC of about 0.5% as minimum, by following the load/demand profile between hour 16 and 19, respectively. Subsequently, the residual

demand is supplied by the grid until the next day, at which point the cycle starts all over again.

5.3 Exploring the Role of BE in Model Linearization

BE given in section 4.6.1, remodels the VPP platform using the Big-M method, the formulation linearizes the multiplication of continuous variables to simplify mathematical solutions for non-linear functions which are complex to solve using the available solvers. The objective function indicated by equation (4.58) represents profit maximization, it is therefore simulated using respective system constraints, i.e., equation (4.45), (4.46), (4.56) and equation (4.57).

First the method ensures economical dispatch of generators, i.e., DG1 and DG2, whereby the fuel consumption of DG1 is 2.58$/MMBtu, the algorithm tries to minimize the operational costs by selecting the DG with minimla costs. Figure 5.45 shows the dispatch when the VPP is limited to supply 2000MW which is actually based on the directive of the TSO, the VPP can then dispatch its resources to ensure the demand is met instantenously.

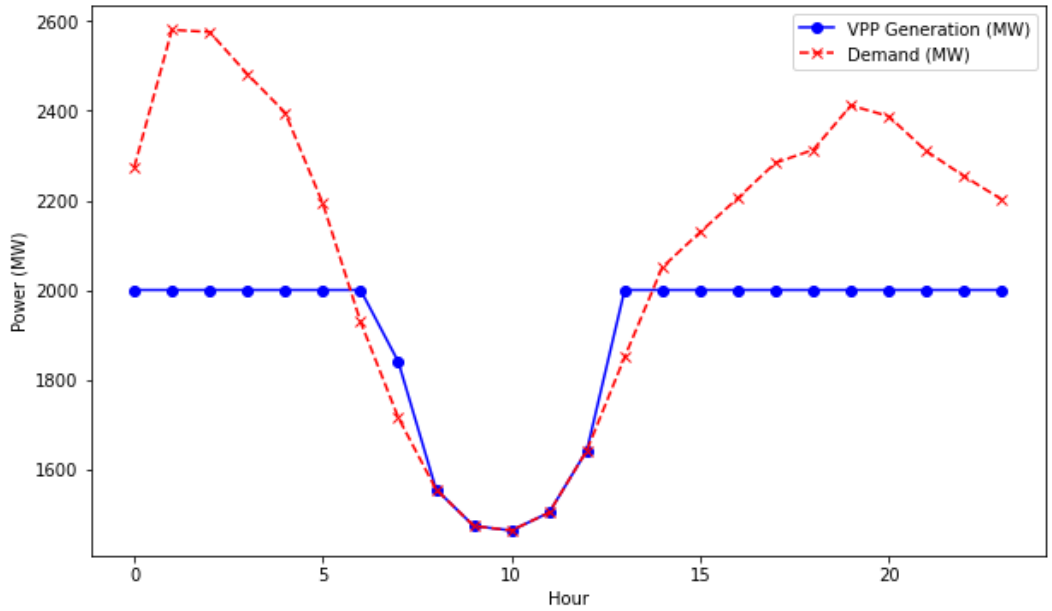

Figure 5. 45 VPP Single Profile Dispatch (With Throttle)

When the overall amount of VPP is increased, BESS is dispatched in most of the hours to cater for the demand. However, the VPP cannot supply more power than what its internal assets can generate. For example, when the combined output requirement reaches 3000 MW, the VPP's maximum supply may be limited to 2800 MW. Consequently, complete dispach of all the gensets to meet the required demand is a priority to the TSO. Figure 5.46 illustrates the 24-hour dispatch profile of the VPP, where instances of oversupply are observed around hour 2, hour 18 and hour 23.

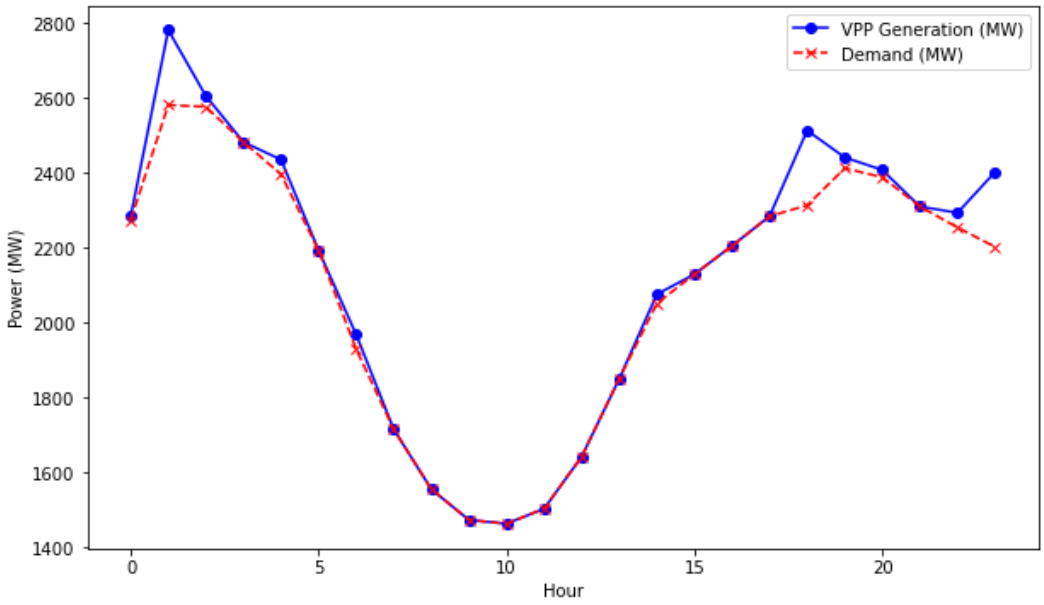

Figure 5. 46 VPP Power Generation (Without Throttle)

In the meantime, DG1 and DG2 will be dispatched as shown in Figure 5.47 depending on the fuel consumption costs indicated earlier on. BESS also will be dispatched to cater for the demand between hour 5 and hour 13 making it possible for the VPP to meet midday demand.

Figure 5.48 shows 200MWh BESS which is charged-discharged at a rate of 100MW, using BE as a pure approach, the storage level adopts linearity as it keeps on increasing and slightly decreases when discharge takes place. This should not be the case in ideal and practical situations as it could damage the BESS. In comparison to CVaR and H-X this particular scenario cannot be preferred on the long-term BESS application use cases.

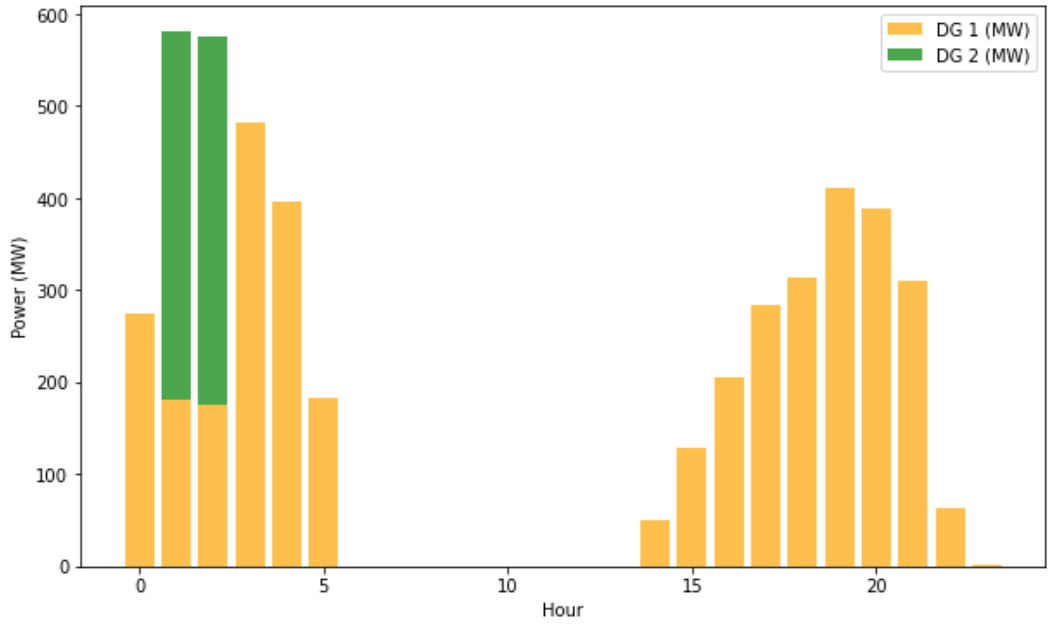

Figure 5. 47 Diesel Generator Output

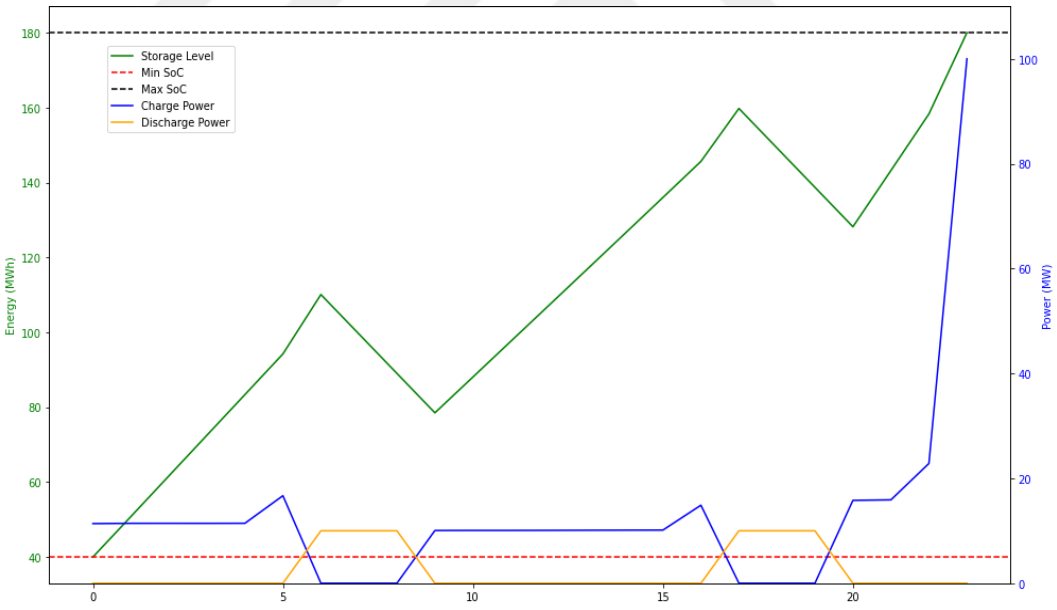

Figure 5. 48 BESS Operational Cycle -2

Other than that, CVaR and H-X utilize complementarity constraints which deal with non-linearities existing in the model. However, BE has to be researched further and how to enhance linearity of non-linear models could enhance development of even faster and efficient solvers.

5.4 Reliability, Profit and Performance Assessment

In assessing the risks involved using VPP in electricity markets, Figures 5.49 and 5.50 show how the profits could vary depending on the contemplated risk, the variation is largely based on the power generated using renewables and the electricity price changes.

For instance, Figure 5.49 the risk is quantified between 0.12 and 0.14 which results in high profits though as the risk increases the reliability of the grid network decreases, note the profits could be high but the stability of the network could be jeorpadized.

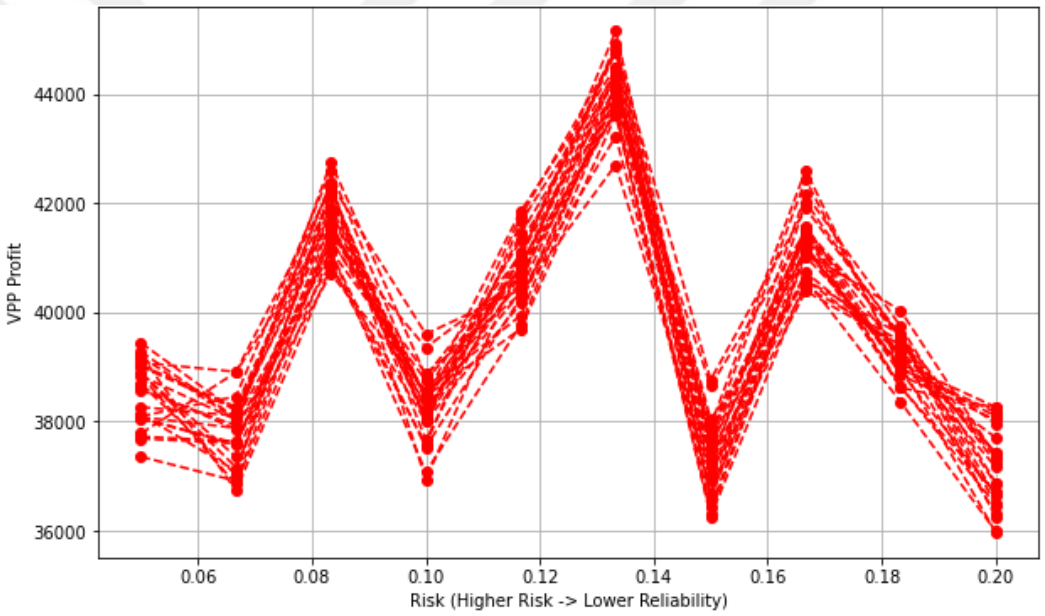

Figure 5. 49 Comparison of Profit and Network Reliability Scenario-1

Figure 5.50 shows higher profits at the beginning, which steadily dropped and remained close to USD 45000 as the highest. The multiple red-coloured lines show the potential profits the VPP owner could earn in the electricity market, although it is not guaranteed but it is a good starting point for the VPP asset owner in strategic bidding especially when gauging power uncertainities.

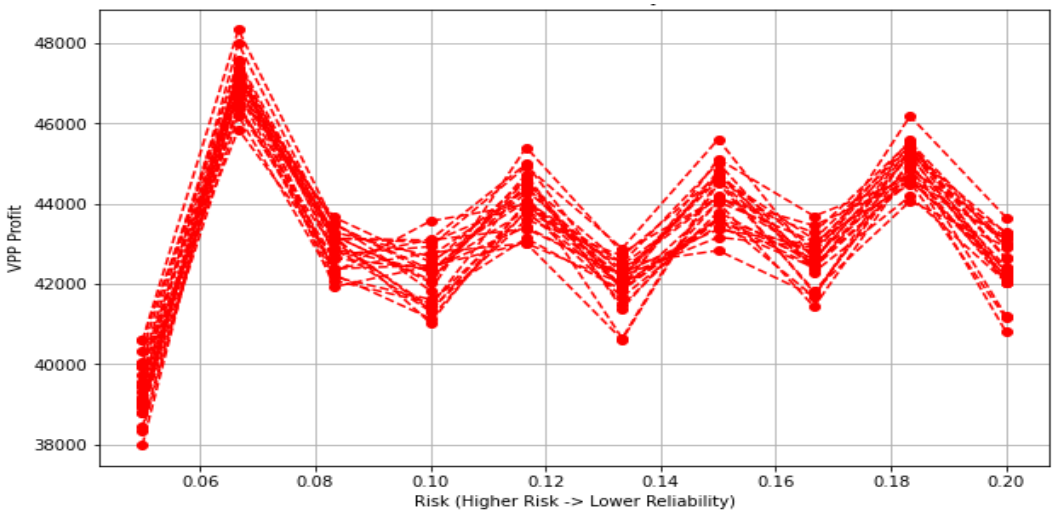

Figure 5. 50 Comparison of Profit and Network Reliability Scenario-2

This work has investigated performance of the three key methods, apart from minimization of the operational costs and profits obtained under risk assessment the three approaches have been evaluated by the following metrics, i.e, Nodes explored, Simplex iterations, Time (s), Objective value, number of solutions counted and finally Gap metric which is applied to show the best solution with the best bound.

The metrics support model evaluation in terms of quality of solutions, computational burden and algorithm performance. Figure 5.51 compares and evaluates the optimization approaches applied. The figure shows DR-JCCO-CVaR has the highest sum of simplex iterations followed by DR-JCCO-H-X technique, argumenting the fact that as the number of iterations increase the number of explored nodes also increases and the quality of solutions is higher in the CVaR method.

Also, Figure 5.52 compares the objective values of each method which depend on the number of the solutions count, which on average is lower in DR-JCCO compared to when H-X and CVaR algorithms are applied, the algorithms' objective values are high signifying the number of feasible solutions or convergence rate of the two methods is high hence the best performance.

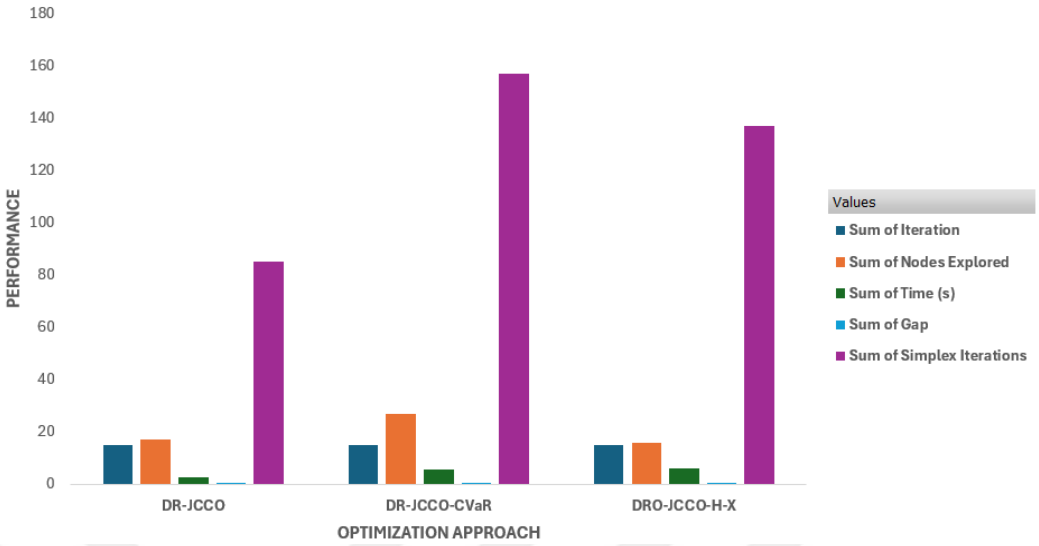

Figure 5. 51 Sum of Simplex Iterations and Key Metrics

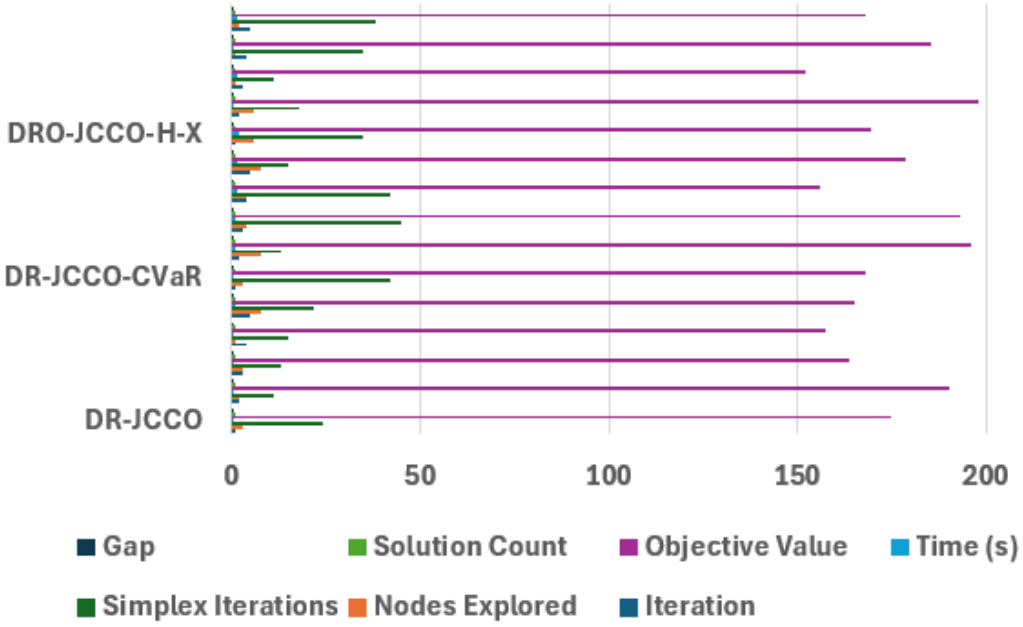

Figure 5. 52 Objective Value Comparison

Furthermore, the results shown in Table 5.2 indicate that using H-X has a better solution gap compared to CVaR but low solution quality although the time used to obtain feasible solution is higher.

On the other hand, DR-JCCO has less time when compared to other two methods, the iterations are also low corroborating that the conservativeness of solutions is higher in DR-JCCO.

Table 5.2 compares the methods under conservativeness of solutions and tractability level. CVaR and H-X algorithms reduce the regularity of solutions and increase the tractability of general DR problems, while DR-JCCO has high regularity of solutions and very low tractability even though it takes less time to converge as can be seen from Figure 5.52.

Table 5. 2 Performance Assessment of Optimization Techniques

Optimizatio-n Approach	Performance Metrics						
	Sum of Iteration	Summing Nodes Explored	Sum of Time(s)	Sum of Gap	Summi-ng Simplex Iterations	Conservativeness of solutions	Tractability level
DR-JCCO	15	17	2.738482 23	0.0229700 04	85	High	Low
DR-JCCO-CVaR	15	27	5.549756 79	0.0285982 26	157	Moderate	High
DR-JCCO-H-X	15	16	5.901545 95	0.0215661 76	137	Low	Best

Figure 5.53 suggests that a lower number of iterations or explored nodes does not necessarily guarantee high-quality solutions; rather, it may indicate a reduction in computational burden, potentially at the expense of solution quality.

So, a trade-off has to be made when choosing a better performing method, although the choice of a particular technique depends on the nature of the problem at hand. The outlined methods give better results when involving BESS and renewables in the grid network. Despite CVaR showing high quality results, H-X also gives the best alternative when sizing BESS due to its convergence rate being high, reduced computational burden and improved tractability. The method results in rapid charge-discharge of the BESS, it also proves to be efficient enhancing the overall tractability of the DR problem.

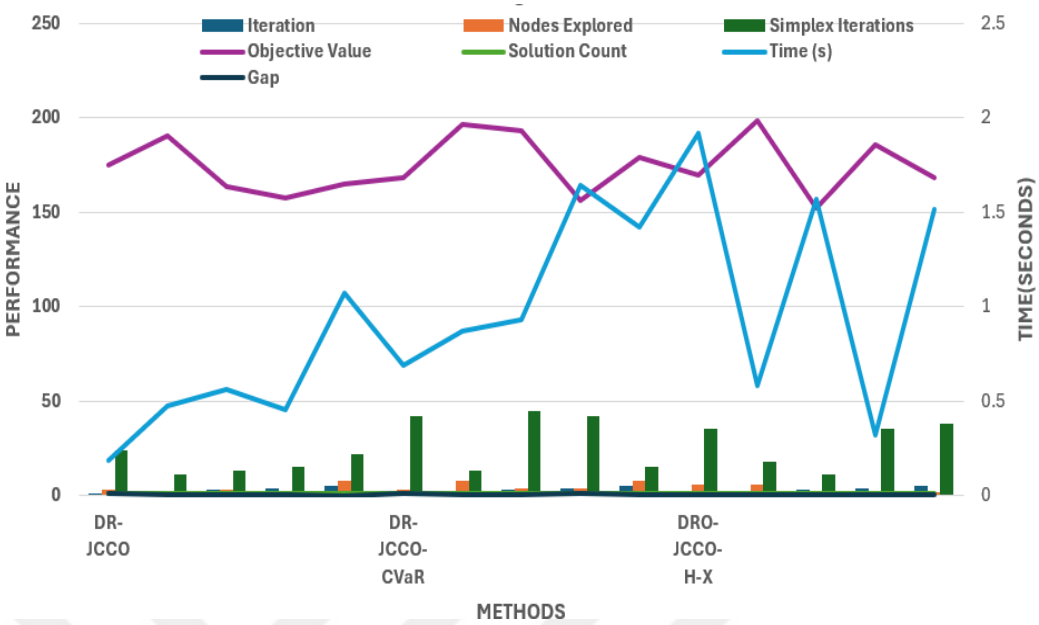

Figure 5. 53 Computational Time and Objective Value Display

Additionally, H-X benefits from calculating optimal t value, which is obtained when almost all the scenarios have been utilized and the probability threshold is kept within feasible bounds as indicated by Figure 5.28. Application of DR-JCCO has some shortcomings and as mentioned before, the intractable nature of DR-JCCO makes it challenging to solve when applied in different problems, and at times solutions end up being conservative limiting research in this field. As observed, the demand in most cases is not equally met especially for DR-JCCO, prompting an assumption of insufficient supply, but still the approach remains one of the best approaches that combines distribution and robust optimization to schedule and operate DERs. Some figures show the ability of the VPP to cover most of the demand, i.e., Figure 5.11, whereby the residual power is catered for by the generating resources. On the other hand, electricity market prices also decrease as demand reduces as depicted by Figure 5.13, and then generally hikes between hours 9 and 11 inferring that at these hours there is less supply and DGs are not fully operational, which is the opposite of what Figure 5.14 eletricity price profile represents. So, the prices could vary, and part of the variation is because of uncertainties are included in the optimization model with the aim of simulating close-to-real-life scenarios. Similarly, concerning the BESS, the constraints need to be carefully selected to optimally utilize the BESS within the

required safety conditions, by having a minimum number of charge-discharge cycles the lifespan of the BESS can be extended, though the general factors affecting the durability of the BESS such as cycling aging, DoD, C-rate and thermal conditions play a role in determining the durability of storage systems. Figure 5.15 shows how battery stress is managed by minimizing charge-discharge cycles and increasing power supply from the DGs. However, even if the BESS does not supply, it does not imply that the BESS is likely to last long, this view is supported by calendric aging [213] which plays a huge role in determining the lifespan of the BESS. Intuitively, idling the BESS makes it worse than putting it in operation, the cells could degrade over time due to internal chemical reactions, the remedy put forward is minimizing idle time to have slow self-degradating process.

Generally, VPP-DRO-CVaR robustness supports smooth charge-discharge of BESS and equally schedules DGs to supply the demand more effectively. Given that the startup and heat rate costs of DG1 is 10.5 USD/MMBtu and that of DG2 11USD/MMBtu, and the startup cost for DG1 and DG2 is USD 100 and USD 120 per start, respectively. The optimization method ensures DG1 one is given priority by generating constant power, for example 300MW over a 24-hour period, and whenever the demand exceeds the available supply from DGs then the BESS and VPP coordination mechanism steps in to balance supply and demand. In particular, during BESS underutilization, the VPP dispatches DGs to meet most of the demand, the total cost was found to be USD 490906.38570015, when compared to DR-JCCO the operating cost was USD 1531271.7056 which was very high due to intractability nature of the DR problem and the frequent dispatch of the DGs, adjusting the parameters and expecting consistent variations in the results proved to be challenging, thereby highlighting the computational and economic complexity associated with the DR-JCCO approach. In regard to H-X algorithm application, the profits made could easily be tracked, reasonably reduced operational costs as the DGs were not heavily utilized, in fact the more expensive DG is deployed during peak hours to cover the residual load. It is realized that the results showing the VPP scheduling of its internal resources depend on the sizing of both the BESS and the DGs, and it is not suitable to have a large BESS with low wind power and DGs production. The power generated

by the DGs could be stored for peak hour consumption, and by examining wind power generation the curtailed power could be stored to form part of the energy mix that could be dispatched when needed. Also, the sizing process has to consider the available demand and amount of power produced from the DGs, in most cases the DGs are utilized in a 24 hour period to avoid cold start expenses and while in production the VPP regulates the generated amount during low demand to charge the BESS and then schedule them during peak hours. Therefore, applying H-X algorithm has a lot of performance benefits, the BESS can be discharged with reference to the optimal t value and the defined scenarios. To enable alteration of the BESS storage size, then robust changes have to be investigated further by adjusting the parameters and system level variables. Additionally, the results obtained from CVaR are almost identical when the rate of charge-discharge of the BESS is monitored. In regard to the VPP costs and profits, the three methods generate varying costs which in part are due to the model settings involving parameters and system constraints used in the optimization techniques.

Finally, it is imperative to note that the simulations for the optimization models are based on Figure 5.2. and when further comparison is done using REopt model results, for instance the results shown by Figure 5.44, the PV generation peaks between 10 and 14 hours and the BESS is neither prioritized nor discharged to its minimum SoC, also the load/demand profile is not closely followed by the generation assets. For the case of the CVaR and H-X strategies, power supply from generation units is scheduled and coordinated to accurately track the demand profile making the BESS the central focus for the optimization models.

5.5 Conclusions

The findings obtained demonstrate the application of advanced optimization techniques, which are used to integrate renewables into the grid network. Furthermore, in Chapter 1, the objectives of this work were established around the development of a VPP platform aimed at facilitating RES integration in support of the SDGs. This objective was further supported by the adoption of optimization models selected for

their low computational burden and minimal information loss. Next, by finding the right balance when integrating the BESS and DGs and by extension renewable energy, the reliability of the grid network can be assessed and the impact of the uncertainties on the general safety of the power transmission network can be quantified. It was observed that traditional methods such as RO and SO suffer from drawbacks including excessive solution conservatism and high computational burden. These limitations motivated the adoption of a DRO framework for modeling the VPP within a bilevel structure. The literature review revealed that a DRO model can be computationally challenging to solve as it is an NP-hard problem, which led to the reformulation of the problem as DR-JCCO problem. Meanwhile, tractability remained a concern, and prior approaches such as CVaR, though widely used, were deemed insufficient for the objectives of this work. Notably, NFs come in handy when investigating the level of uncertainties that could cripple the grid network, whereby quantile estimation of uncertainities provide a mechanism that could efficient decision making. The methods define and address the DR-JCCO problem, a well-established challenge in operations research, and advances the discussion by proposing a bilevel model grounded in data-driven principles applicable to energy systems. Distinct from purely stochastic or robust frameworks, the proposed DR-JCCO formulation benefits from a hybrid structure that limits information loss while retaining both distributional and resilience perspectives. The algorithms that can easily track the problem have been implemented with emphasis placed on the H-X algorithm a novel contribution to integrated energy system modeling. The demonstrated efficacy of the H-X algorithm in minimizing operational costs and promoting optimal BESS utilization affirms its applicability and potential superiority within the DR-JCCO paradigm.

5.5.1 Future Work

The VPP model incorporating WP and DGs presents a novel approach to integrating RESs into the grid network. The results have demonstrated effective sizing of BESS and DGs, along with significant reductions in operational costs. The DERs have been considered in power system modeling to ensure system constraints are appropriately accounted for using a power flow analysis a case study that will be developed further.

The role and value of BESS in large-scale grid applications was emphasized, and mathematical models for WP and SP have been presented, therefore both WP and SP will have to be systematically modeled into the optimization model to orchestrate the diverse generational sources into the grid network The overall mathematical modeling of the VPP in a bilevel framework was explored, with BE being employed to linearize nonlinear models, laying the groundwork for further investigation into alternative mathematical tools that could enhance the linearization process.

Additionally, the following sub-topics will need to be considered in subsequent studies:

- **Improvement of the H-X Algorithm**: Further research is needed to enhance the computation of the optimal t values within the H-X algorithm. This would improve its ability to regulate the charge-discharge cycles of the BESS, thereby facilitating more efficient long-term usage of the storage system and reducing degradation rates during operation.
- **Dispatch of Multiple VPPs**: A potential area for future exploration involves the inclusion of multiple Virtual Power Plants (VPPs). This would enable advanced analysis of coordinated scheduling and dispatch mechanisms across interconnected VPPs, a critical consideration for accurate and equitable settlement procedures in electricity markets.
- **Advancement of EPEC Models**: While MPECs have received considerable attention, EPECs remain underexplored specifically in the context of distribution networks. Future work should aim to bridge this gap and extend the modeling capabilities to better capture the complexities of distributed energy systems.
- **Inclusion of Complex Grid and Power Flow Models**: The integration of detailed power flow models and more intricate grid topologies presents an opportunity to further test and validate the proposed algorithms. Such enhancements would allow researchers to identify robust methods that simultaneously safeguard grid reliability and ensure economic viability for energy stakeholders.

- **Start-up Possibility:** The work presented herein has strong commercialization potential, particularly through the incorporation of real-world data from energy consumers and producers. The optimization algorithms can be refined to enable the VPP to actively participate in electricity markets through advanced bidding strategies. Moreover, proper sizing and integration of WP and SP can minimize curtailment and associated economic losses. Finally, the mathematical models developed in this study can be adapted for feasibility assessments in BESS, WP, and SP grid integration processes. Subsequently, the outcome of this study could support the formation of a start-up energy service company, provisionally named Texosmart, aimed at enabling both researchers and customers to experiment with various optimization methods for more accurate trading decisions in the spot electricity market. Figure A.1 and A.2 presents a schematic representation of the TexoSmart platform, which will be further developed to accommodate a diverse suppliers and consumers.

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APPENDICES

Appendix A: Prototype Interface for a VPP Platform

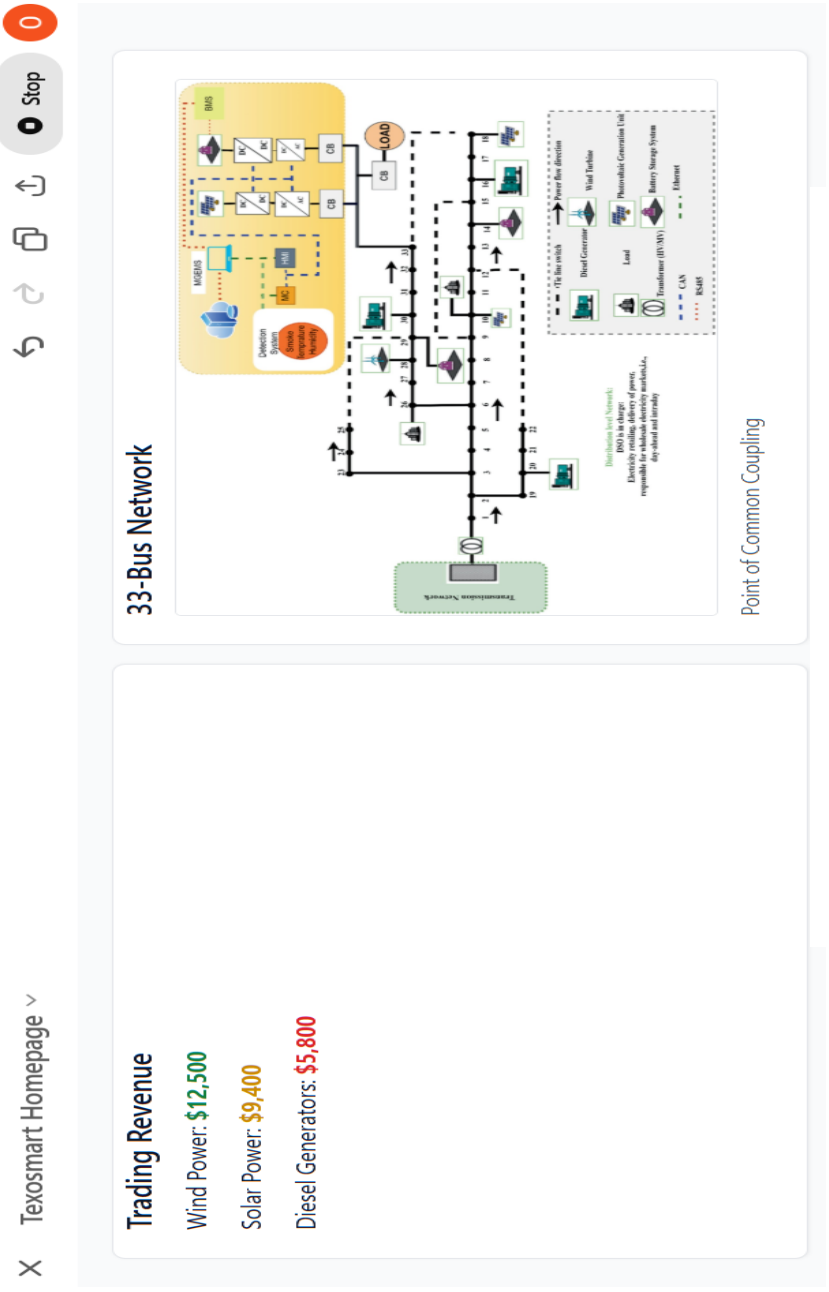

Figure A. 1 VPP Research Platform

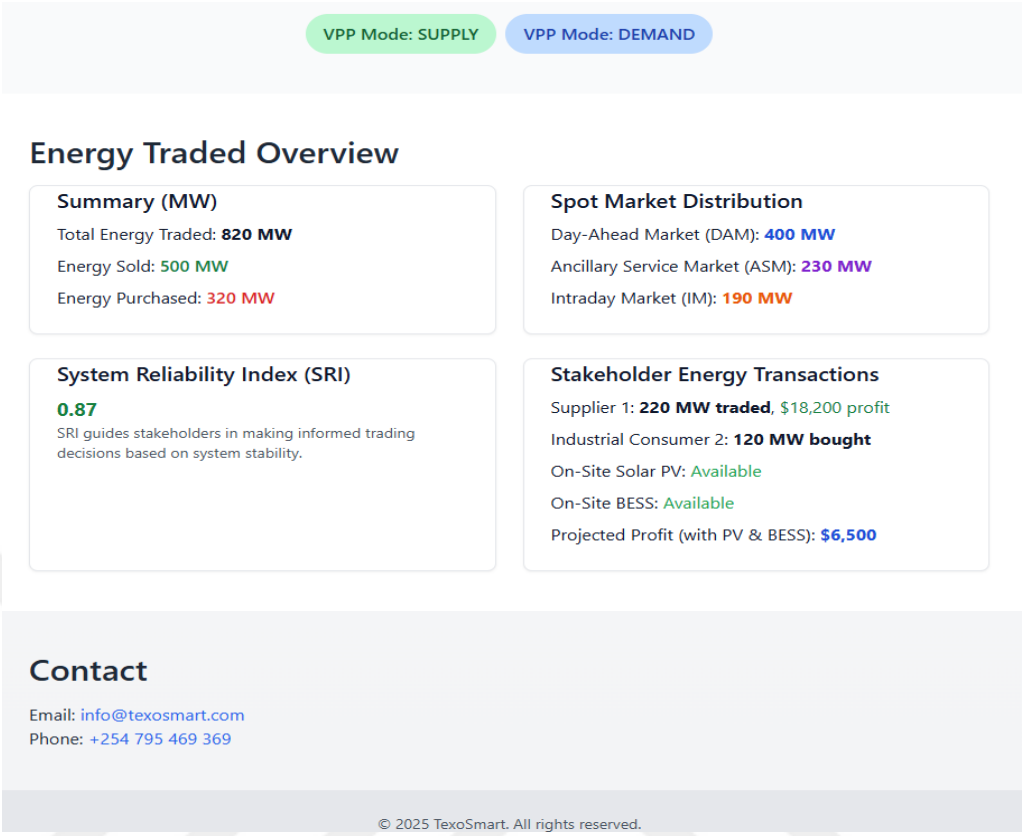

Figure A. 2 Spot Electricity Market Energy Trading

Appendix B: List of Publications

B.1 Journal Papers

1. O. N. Onsomu and B. Yeşilata, “VIRTUAL POWER PLANT SOLUTION FOR KENYA RURAL ENERGY NEEDS”, IJESG, vol. 7, no. 1-2, pp. 14–26, 2022, doi: 10.55088/ijesg.1103920.

2. O. N. Onsomu, A. Çetin, E. Terciyanlı, and B. Yeşilata, “INTEGRATION OF GRID SCALE BATTERY ENERGY STORAGE SYSTEMS AND APPLICATION SCENARIOS”, (EJSET), vol. 5, no. 1, pp. 76–86, 2024, doi: 10.55696/ejset.1409774.

3. Onsomu, O. N., Terciyanlı, E., & Yeşilata, B. (2024). Comprehensive review of energy management strategies: Considering battery energy storage system and renewable energy sources. Engineering Reports, 6(11), e12995.

4. Onsomu ON, Terciyanlı E, Yeşilata B. Optimal Dispatch of a Virtual Power Plant Considering Distributed Energy Resources Under Uncertainty. *Energies*. 2025; 18(15):4012. https://doi.org/10.3390/en18154012

5. Şen, O., Onsomu, O. N., & Yeşilata, B. (2025). Sustainable and Efficient Energy Use in Data Center Cooling: Techniques and Innovations. *New Energy Exploitation and Application*, *4*(2), 263–282. https://doi.org/10.54963/neea.v4i2.1682

B.2 Conference Papers

1. O. N. Onsomu and B. Yeşilata, "Virtual Power Plant Application for Rooftop Photovoltaic Systems," *2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, Ankara, Turkey, 2019, pp. 1-5, doi: 10.1109/ISMSIT.2019.8932895.

2. Onsomu, O. N., & Yeşilata, B. (2023). Review of Microgrid Energy Management Techniques on Virtual Power Plant System. Journal of Optimization and Decision Making, 2(2), 381-388.

3. Onsomu, O. N., Terciyanlı, E., Bayındır, K. Ç., & Yeşilata, B. (2023, November). Potential Use of Technical Virtual Power Plant Approach in Distribution Network for Mitigation of Contingencies. In *2023 7th International Symposium on Innovative Approaches in Smart Technologies (ISAS)* (pp. 1-6). IEEE.

4. O. N. Onsomu, K. Ç. Bayındır, E. Terciyanlı, C. Ş. Korkmaz, and B. Yeşilata, "Optimal Placement of Renewables and Storage for Distribution Level Network Stability," no. 11.