Mathematical Modelling of Financial Motivated Cyber Attack by FDI and Security Constrained Optimal Scheduling of Virtual Power Plants in Electricity Market

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Submitted by:

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2K19/PSY/08

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CANDIDATE'S DECLARATION

I, MEEGADA INDEEVAR REDDY, Roll No. 2K19/PSY/08 student of M.Tech. (Power System), hereby declare that the project Dissertation titled "Mathematical Modelling of Financial Motivated Cyber Attack by FDI and Security Constrained Optimal Scheduling of Virtual Power Plants in Electricity Market" which is submitted by me to the Department of Electrical Engineering Department, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associate ship, Fellowship or other similar title or recognition.

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CERTIFICATE

I, MEEGADA INDEEVAR REDDY, Roll No. 2K19/PSY/08 student of M. Tech. (Power System), hereby declare that the dissertation/project titled "Mathematical Modelling of Financial Motivated Cyber Attack by FDI and Security Constrained Optimal Scheduling of Virtual Power Plants in Electricity Market" under the supervision of Prof. Radheshyam Saha and Prof. Sudarshan K Valluru of Electrical Engineering Department Delhi Technological University in partial fulfillment of the requirement for the award of the degree of Master of Technology has not been submitted elsewhere for the award of any Degree.

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ABSTRACT

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Power system is a wide interconnected network of electricity generation, transmission, and distribution systems. With the technical advancement, increase in day-to-day demand from industrial, agricultural and residential consumers, and the disadvantages of monopoly system demanded the power sector for disintegration and deregulation. Power system deregulation and integrating communication devices are advantageous for better monitoring and decision making by the system operator. At the same time, it increases the risk of cyber intrusion. In 2003, the eastern United States and Canada had major power system blackout due to the failure of grid. Despite of the fact that the blackout was caused by factors that are other than cyber-attack, many academics believed that similar catastrophe may occur with targeted cyber intrusion. In 2007, Idaho National Lab researchers attempted to attack a synchronous generator. The attempt was successful, and the generator got self-destructed within minutes. This incident alarmed cyber-security decision-makers, prompting them to establish a critical infrastructure that is vulnerable to prevent cyber-attack. The existing bad data detection procedure in state estimation is incapable of detecting a certain sort of cyber-intrusion known as a stealth attack. Stealth attacks can be used to influence state estimate results for financial gain or to cause technical problems for the power system.

Unbundling of transmission lines, ensuring social welfare among the power system utilities, promote investment in the electricity sector. The deregulated power system has brought up power market as an efficient tool and has created an enabling environment to accelerate the all-around development of power generation, transmission and distribution systems. The effective monitoring and decision making is achieved with the integration of communication lines and internet network. Cyber-Physical System technology is utilized for more safer and secure grid operations.

In this dissertation, financially motivated false data attacks are investigated, by injecting manipulated data into day-ahead and real-time electricity markets operation. For determining the optimal attack vector, it is assumed that the attacker runs a bi-level optimization problem that comprises the attacker's profit maximisation objective and the market clearing problem. While manipulating measurement devices such as RTUs, the attacker needs to take care of being identified by the ISO’s bad data detection (BDD) mechanism. The proposed attacking model is implemented on the PJM-5 bus test system to demonstrates the potential impact of financially motivated cyber intrusions in the

power markets. During the attack, the relationship between market clearing power and LMPs is established. The simulation results are deduced to demonstrate the effect on locational Marginal pricing in achieving the attacker's goal of profit maximization.

Secondly, Renewable energy generation has become more prominent in the power sector around the world. Large integration of RE sources into the electricity markets has brought further complexities in the markets. Distributed energy sources (DE) have limited participation in these markets. Considering uncertainties related to RE intermittence nature, and market prices small-scale REs such as wind power, solar PV power, ESSs, and utilities comprising CHPs, DG sets, flexible demands, etc., are aggregated in to single entity in the name of (VPP) and participate in the electricity markets. Hence, it is important to find out an optimal scheduling solution to these VPPs.

In this dissertation two-stage stochastic programming approach for optimal scheduling of VPP in the electricity market is presented. The uncertainties are modelled using scenario bounds and are formulated using stochastic programming approach. Simulation results are carried out on 4-hour planning horizon.

Since, electricity markets are competitive in nature, each and every market participant tries to maximize their profits through strategic bidding. Keeping in the view, the uncertainties related to RE generation, market prices and reserve deployment requests, VPP also tries to maximize its profit. It is necessary to take strategic decision to counter the other market participants.

Therefore, a bi-level model is proposed for finding out optimal scheduling solution in the electricity markets. Uncertainties are modelled using scenario realization technique. VPP maximize its profit by making strategic decision on trading power in the DA and reserve markets. To exercise the power of VPP in altering market decision, the upper-level problem in the bi-level model address the VPP objective to maximize the profits, while lower level addresses the market clearing problem of both DA and reserve markets. The proposed model is then reformulated in to single level MILP problem using KKT optimality conditions and strong duality theorem.

Finally, the proposed model is implemented on IEEE-24 reliability test bus system. The results are analysed based on the profit acquired by the VPP with and without flexible demands. The importance of the reserve market in balancing the system is demonstrated through appropriate scenarios, additionally, demand-side flexibility

smoothens the load curve and connects the generating and demand side curves, allowing the VPPs to achieve the best profit. At the end, impact of strategic and non-strategic decision making on VPP's profit is also analysed.

CHAPTER 1
INTRODUCTION

CHAPTER 1

INTRODUCTION

1.1. Background

Power system is a widely interconnected electrical network. It consists of generators, transmission & distribution network and loads. Due to continuous increase in load demand and the limited energy production, power producers in that area used to have control over the economics of power sector. In most of the twentieth century, if a consumer wanted to purchase energy, they have to buy from the utility that held the monopoly in that area in supplying electricity. Some of these utilities are vertically integrated, which means they generate electricity, transmit from the power plants to load centers and then distribute to end-users. This form of vertically integrated system, removed the incentive to the operational efficiency and encouraged unnecessary investments. This system is called regulated power system.

The disadvantageous of regulated power system raised concern on the growth of the power sector. Due to this, strengthening electricity sector became a primary objective of every country. The changes were brought with the new tools to work the system efficiently. Deregulation is introduced to restructure the power system and to promote investment in the electricity sector. Electricity markets, and open access of transmission network are part of deregulation. Thus, monopoly system is on the verge of extinct. This deregulation introduces competition among the producers and buyers of the power. Economists argued that the introduction of competition lowers electricity prices, but most of the successful electricity markets now experience higher prices than expected.

Chile was the first country to reform the power sector. It was implemented through legal and institutional changes. Following Chile, many other countries in the world have adopted the system of electricity market, some of them were PJM (Pennsylvania, New Jersey, and Maryland), New England and New York. Texas and California are moving towards the development of the market. Australia and New Zealand along with these many European countries have the markets at different stages of development, Scandinavia has the world's most mature market [1].

In India restructuring of power sector started with the enforcement of Electricity Act-2003. This act introduced *open access* and *unbundling of transmission network*.

This has led to the establishment of power exchanges. By the end 2008, India's first power exchanges "*Indian Energy Exchange*" started to trade the power. *POSOCO* acts as system operator and where, "*Central Electricity Regulatory Commission (CERC)"* is regulating authority of power markets. *PXIL* and *BPXL* are few other power exchanges in established in India. The power is traded through DA, real time and term ahead markets. Renewable energy is traded through "*Renewable Energy certificate (REC)"* mechanism as a weekly market.

1.2. Electricity Markets

The electricity market in economic terms, may be referred to as a place where electricity is a commodity that is capable of being, sold, and traded. In simple, an electricity market is a place where buyers and sellers meet on a special platform, but unlike the physical markets, here, electricity is sold as a commodity [2]. Electricity as a commodity is different from other commodities. The amount of power generated should be equal to the power consumed. Hence, it is important for real time balance of the system to ensure stability of the grid. The buyer and seller present the bids before the actual schedule, and are allowed to trade the electricity.

Independent System Operator (referred as ISO or system operator) will look after the dispatch. Types of electricity markets, and market clearing process is clearly explained in the following chapters. They use bi-directional flow of the information in more efficient way for responding to wide range market clearing process. There should be no asymmetries in sharing the information to any class of market partisans. Thus, ensuring transparency in policy making and in the market clearing process.

These electricity markets are no longer a monopoly, on the same lines it is far from a perfect market. Globally, the objectives of the electricity market are cost-minimization and reliability. In spite of this electricity has several key issues such as risk management, lack of information, uncertainty in prices, RE integration, balancing the system, security, transmission congestion, and non-existence of power. The main advantage of deregulation, is to create a competitive market environment and to assure social welfare, in which consumers were able to purchase their energy from the cheap generating units. Fig.1.1 shows the structure of electricity markets.

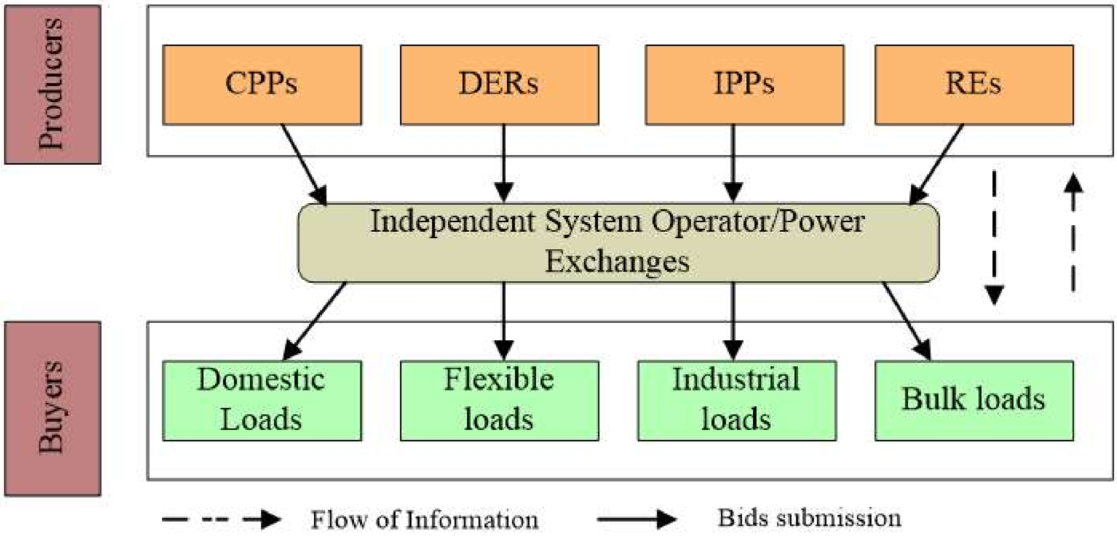


Fig.1. 1 Structure of Electricity Markets

1.2.1. Basic principles of Energy market:

The following principles form the foundation of any Energy market. These principles can also be termed as design principles of the energy market. The principles should encourage open and fair competition between all power producers and demands. Following are the six major principles adopted by most of the successful energy markets in the world.

1) Competition and market access:

All the participants in the energy market should have open access without any discrimination and there should be competition between each market participant. End Consumers benefit more from the market participants responding to the market in a competitive environment than from a regulated system.

2) Access to the transmission network:

Transmission and distribution systems should be fully unbundled for the market. Unbundling helps in ensuring the objectives, transparency and non-discriminatory access to the network.

3) Competitive neutrality:

Markets should be non-discriminatory, i.e., they should not favor one technology or business model over another, and they should encourage consumers to have their requirements met at the lowest possible cost while still encouraging innovation.

4) Risk allocation:

The market should be ready to take the risk. Markets take the risk, allocate costs, and provide accountability for decisions that are to be best placed to manage and promote efficient outcomes.

5) Information Asymmetries:

Market players require accurate and timely information to make decisions regarding competitive markets to operate well. If the information asymmetries exist, they won't feel like they're competing on unbiased platform.

6) Integrating new technologies

Today's power industry has integrated with different new types of technologies which include medium and small scale RE sources, Distributed Energy sources etc., as a result complexity of the system has increased manifold. The trend of these changes stimulated the evolution of smart grid. Similar to changes in the grid system, Electricity markets are also required to meet the challenges in integrating these new technologies for scheduling and determining market prices.

1.3. Members in Electricity Markets

In the electricity markets, various stake holders play their role in maintaining reliability and transparency for the successful operation of the grid. The various market stake holders are as follows:

1.3.1. Producers/Sellers/Generators

Electricity is generated through various technologies which includes public conventional power plants, hydro power plants and other RE sources. There may be a group of small-scale power producers that aggregate their production, form a single entity to participate in the market, this concept is termed as Virtual Power Plants. The other producers, who have independent generation, are called as independent power producers. Private generating units come under this category.

All the above power producers having license to trade, satisfying market principles are allowed to sell their production in terms of both quantity (MW) and price($/MW) in each time period in the market-based power systems.

1.3.2. Consumers/Buyers/Loads/demands

Loads belong to consumers or end-users. Each demand entity submits their need to buy power in terms of both quantity[1] (MW) and price ($/MW). The loads in the market are large-scale industrial loads, commercial loads, and households. Depending upon the nature of the loads, these are classified as constant demands, flexible demands and interruptible demands. Entities having flexible demands shift their demand from one hour to other hour based upon the market prices in each time period, thus obtain profits. But in the case of constant demands, they bid for constant amount of power in each time period. Interruptible loads can switch off their demands from one time period to other time period. Thus, allowing them to participate whenever, the market price is low.

1.3.3. Power Exchanges

Power Exchange is a third-party entity, independent of market participants. They are considered as the trading centers for electricity markets. Power Exchanges allows market players to submit their bids for each time period depending upon the type of market operation[2]. Each and every market participant must have trading license to buy/sell power in the market. Power Exchange should ensure fair and non-discriminatory market clearing process.

Based upon the submitted bids power exchanges solves market clearing process. The results of market clearing process are in terms of amount of power cleared in each time period of a particular participant and its respective market price. This information is then shared with ISO/TSO for congestion management and system security.

1.3.4. Independent System Operator/ Transmission system operator

ISO/TSO, is considered as system operator and regulating entity of the market operations. It is independent of other market participants. ISO/TSO owns transmission rights in the power transmission system. It has all the information about the system topology, transmission capacity of each line, and reactive power requirements etc.,

ISO/TSO should be non-discriminatory, providing open-access to transmission system and unbundling all the services under its control. It runs market clearing problem based upon the cleared bids obtained from the power exchanges, to determine congestion in the transmission lines. Thus, final market clearing prices are obtained based upon the congestion. This pricing system is said to be locational marginal price.

ISO/TSO is primarily responsible for ensuring reliability of the grid. In some of the markets, ISO acts as administrator and regulates the market operation such as competitiveness, market clearing prices, transmission rights and also governs the system consistency.

1.4. RE Integration and Virtual Power Plants

At present, integration of new technologies including RE sources is quite challenging. Due to the dynamic real time load demand and power generation, intermittency and variability of RE sources, and imperfect forecasting, there is some randomness in RE scheduling (viz. wind farms, solar PV plants, etc). Hence, it can be treated as a double edge sword. Although, RE sources are promising solution to reduce carbon footprints but they impose generation-demand imbalances and increases regulating burden in the power system. These challenges are also faced by the electricity markets.

1.4.1. RE integration Complexities

RE power being largely non-dispatchable, the generation scheduling of CPPs in combination with RE generators is a tough challenge being encountered by system operators in electricity markets. The other group of challenges faced by the electricity markets is uncertainty related to market prices and balancing the system. Competition among the market participants, increases price fluctuations which leads to uncertainty in the market clearing prices.

Market participants predict their generation and demand for a particular time period and bid accordingly. But, the actual value of power traded may differ from the scheduled value. As a result, balancing markets such as reserve markets and ancillary markets are necessary.

1.4.2. Concept of Virtual Power Plants

In order to address the above issues, related to RE uncertainties, it is endeavored to integrate RE generating utilities with other DERs such as small scale CPPs, storage units, Combined heat and power plants, DG sets, and flexible demands. This concept of integrating the small-scale utilities is called as virtual power plant. This provides a centralized solution to above uncertainties. These energy sources aggregate their production, optimize their internal demands as a single entity through a control center, and there by participates in the electricity markets.

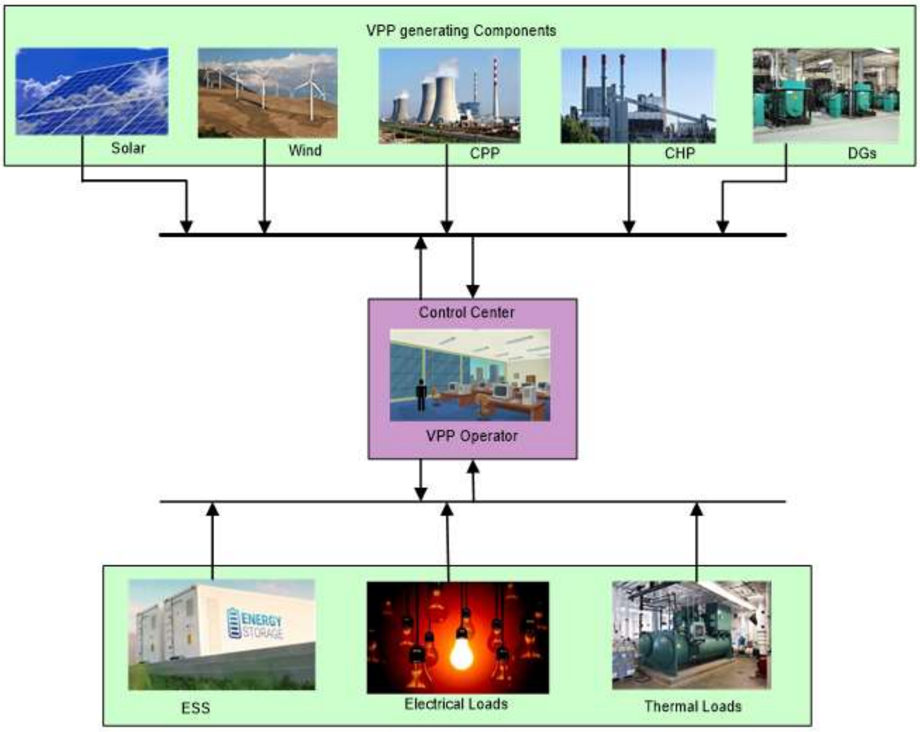


Fig.1. 2. Structure of VPP showing all the components

1.5. Cyber-Attacks on Power system

At present the power sector is operating in Day Ahead, and Real Time markets. Reserve markets are operated to address the balancing needs of the system. Power system is coupled with strong communication network for transmitting and distributing electricity from generating station to the load centres. This data is utilised by the electricity market to run the market clearing problem without violating security constraints. This huge network is consistently operated and monitored in real time mode by the Energy management system which inter-alia consist of master terminal units (MTUs), remote terminal units (RTUs), and sensing devices. This increases the risk of cyber-attacks. Measurements from the RTU's and sensing devices are collected by the Master terminal unit and transmitted to the control center using radio frequency signals. The information collected by the RTUs range from power flow values, status of circuit breakers, energy delivered and consumed etc., Although the SCADA System has firewall as the first stage of security to the communication network, still cyber-threat is a challenging issue for ISO/TSO to defend its integrity. Fig.1.3, shows the block diagram flow of market operation utilizing the information from the control center and state estimation process. It also represents the attacker's target place for injecting false data and the flow of shared information among the market participants

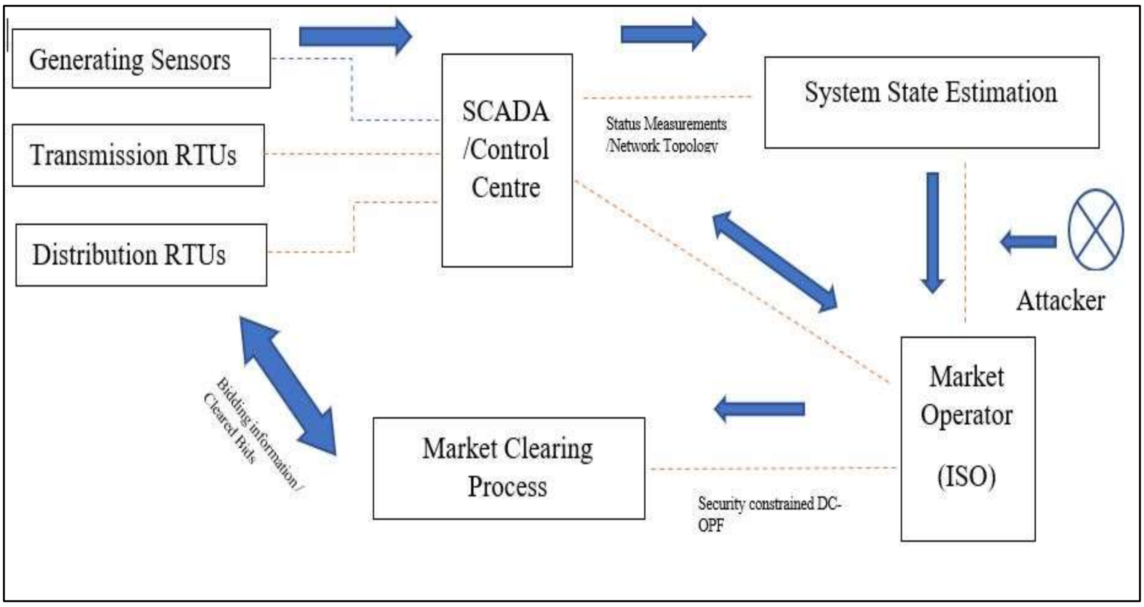


Fig.1.3. Electricity Market operation under FDI attacks and attacker as virtual participant.

For reliability and proper scheduling system operator uses the data obtained from the state estimation. State estimation (SE) is an important function in real-time decision-making. State estimation identifies the current operating states of the systems by providing precise and efficient observations on operational limitations. The input quantities are power flow, generation and demand parameters. The estimated outputs are bus voltages and angles. Cyber attackers can attack the system by injecting false data in to the system which affects the output of the state estimation. Using this technique, bad data injected in the network can be detected. But the attackers use advanced cyber technologies to launch a stealthy attack which can pass through the bad data detection process in the state estimation.

This type of stealthy attacks may cause damage to grid resulting in blackouts and financial loss to the nation. On other hand adversary concentrates on the market clearing process, and acts as a virtual participant so that the adversary enter in to the market. By designing stealthy attack, the attackers aim to manipulate the market prices in specific time periods and trade the power strategically, therefore obtains financial profits without causing damage to the grid operations. These types of attacks are called as financially motivated false data injection attacks.

Hence, it is important to investigate these financially motivated attacks in the electricity markets. This assessment provides information about the vulnerable devices, and about the key nodes located in the power system network.

Nomenclature:

BDD	Bad data detection procedure
CPP	Conventional Power Plant
DAM	Day-Ahead Market
FDIA	False Data Injection Attack
ISO	Independent System Operator
TSO	Transmission System Operator
Res	Renewable Energy Sources
RTM	Real Time Market
RRM	Reserve Regulation Market
RTU	Remote Terminals Unit
SCADA	Supervisory control and Data Acquisition system
SE	State Estimation

CHAPTER-2

Literature Review

CHAPTER-2

Literature Review

2.1. Literature Survey on False Data Injection attacks on the Electricity Markets

Deregulation regime of power system has taken pace at a slow rate; many of the power systems around the world adopted deregulation, but failed to implement in real time. Researchers and economist have suggested various form of the electricity markets from operational and participants view point. Among them the few prominent works are studied to acquire the knowledge on market-based power system. Deregulation of power system, and power planning for regulated and deregulated markets is studied in [1]. Different market trading strategies and the changes brought by the deregulation in the power system is explained in [2]. In this reference author discussed the clear view of market design and various strategic roles played by the different market participants.

With the technical advancement and integration of power system with the communication system to ensure efficient and reliable operation, cyber security against cyber intrusion is also necessary. These, Cyber-attacks on power systems are classified into two types. The first type of attacks aims in creating damage to the grid and the latter type of the attacks focus on financial gains through electricity markets. False data injection attacks were first studied by the Linu et al. [3].

Attackers with the aim to damage grid, estimates attack vulnerability areas to inject false data into the measuring devices, which leads to grid failure or shutdown of some major grid components. Mathematical programming with equilibrium constraints for modelling cyber-attacks on electricity markets is formulated in the reference [4].

Attacks on state estimation in electric power systems via false data intrusion are investigated by the authors in the references [5-9]. R. J. Piechocki et al. in [5] formulated sparse false data used for malicious data attacks. The author mitigates the proposed attack by implementing pro-active defense mechanism. M. M. Pour et al. reviewed various types of cyber intrusions and their respective mitigation methods in the smart grid system [6]. R. Tan et al. predict and minimize the impact of misleading data attacks on automatic creation in the reference [7]. The authors predicted residual value of automatic generation control (AGC) signal for the future time periods. Financially motivated FDI on security constrained economical dispatch in Real-Time Electricity Markets and its defending mechanism are examined in [8]. In the references [9, 10], load frequency control is used to identify the FDI attacks on AGC. In this work the author used automatic control error signal act as major detection signal. Many other attacks including over/ under Compensation FDI attacks are formulated in the references [9-11]. On the other hand, different detection techniques are used to detect such cyber intrusions are proposed by the authors, such as principal component analysis (PCA), SVM algorithms [11], statistic decent realize learning algorithm [12], and minimizing residual value of power state estimator [13] are presented. Cyber-attacks against state estimator are discussed in [14]. A Survey on FDIs on state estimation is conducted by R. Deng et al. [15]. An unobservable FDI attack is deployed to attack power flow measurements is presented in [16]. J. Zhao et al. in [17], proposed forecasting aided imparted FDI against Non-Linear State estimation is discussed.

The second type of attack is based on gaining financial benefits from the fake data intrusion. These are special type of attacks where attacker does not cause any blackout, instead the attacker as a virtual participant in the power market injects FDIs in to the system to misguide market operations. As a result, financial loss occurs to the other market participants. Reference [18] elucidates special class of FDI attacks using load distribution. Attacks by overloading the transmission lines [23] by introducing corrupt generators and load forecasting error in the security constrained economic dispatch is presented in the references [19- 22]. In those works, the proposed attacking strategy results in LMP shift. These attacks are said to be financially motivated attacks. Modelling dummy data attack vector which is used to change congestion pattern in the system is proposed by X. Liu et al. [24]. A new framework in designing FDI attack using stochastic robustness by limited adversary is presented in [26]. Deep learning techniques for FDI attack detection on power grid is examined in [28], A non-linear auto regressive exogenous configuration of ANN is used to identify FDI attack on state estimation is formulated in [27]. Dynamic data attacks using bi-level optimization is presented in [29].

Mathematical models representing electricity market process for various application are formulated in the references [30-32]. Models related to Decision making, and non-linear optimization problems in electricity markets [30], along with Bi-level optimization in power system is presented in [31]. Mathematical formulation of electricity markets under complementary constraints is discussed by Steven A. Gabriel et al.

2.2.Literature survey on Virtual power plants in electricity markets

The market clearing process in the electricity markets under various uncertainties is designed in [33]. I. Aravena et al. presents zonal market model with renewable integration is presented in [34]. Renewable energy sources are uncertain in nature, the effect of these energy sources on the power system is elucidated in [35]. Electricity market mechanism and bidding strategy is analysed by the B. Jie et al. [36], based on power balancing market. This work considers energy mix where conventional power plants and RE sources are the market participants.

Virtual Power Plant bidding strategy for participating in energy and reserve markets is studied in the paper [37]. Introduction to the mathematical stochastic programming applied to electrical engineering is presented in [38]. S. R Dabbagh et.al proposed risk assessment in finding optimal scheduling strategy for the VPP in its decision-making process, and the VPP is allowed to trade in both energy and spinning reserve market [39]. Two stage network constrained robust unit commitment model is explained in [40]. L. Tianqi et.al [41] analysed optimal scheduling of VPPs considering cost of battery loss. The statistical scenario of RE is illustrated in [42-45]. Impacts on power markets due to adequacy in RE generation are presented in [46]. The challenges being faced by the whole sale generation scale in the electricity markets with the intermittence RE sources is explained in [47,48]. Optimal bidding strategy using the Nash SFE equilibrium with interruptible loads for VPP participation in the energy markets is proposed in [49]. Mathematical Models of VPP under uncertainties with various offering strategies is provided in [50].

Using WTs, PVs, and ESSs as aggregators, Liwei Ju et al [51] suggested a bi-level stochastic scheduling model for VPPs. The price-based demand response (PBDR) and the incentive-based demand response (IBDR) are both taken into account. The interval approach and the Kantorovich distance are used to model uncertainty.

In [52], the author formulates the credibility theory to assess the feasibility of risk tolerance for VPPs utilising fuzzy chance constraints. In [53], the author proposes a bilevel optimization problem with a unique demand response scheme and CVaR risk management technique. In the power markets, various offering strategies such as MILP have been proposed for VPP optimal scheduling. For optimal bidding of VPP in DA and frequency regulation markets, a deep learning-based technique known as the Bi-directional Long Short-Term Memory (B-LSTM) network is used in reference [55]. In [56], thermal loads and non-renewable sources are considered VPP aggregators.

In [57], the author considers and schedules thermostatically regulating loads in VPP, as well as other DERS, using a Bi-level problem. Various research, like CVar risk analysis in [58,59,60], have attempted to model various uncertainties in various ways. Monte Carlo Simulation is employed in [61], while scenario-based approaches are explained in [62-64], and fuzzy based modelling uncertainties are discussed in [65]. In references [66] and [43-45] an interval approach and a 2 m point estimate method are considered, respectively. Interval approaches are limited to deterministic applications, whereas fuzzy methods are considered to be time expensive. Each method of uncertain modelling has its own set of positives and negatives. According to the poll, scenario-based techniques have better outcomes than other methods. The method's accuracy is calculated by the size of situations chosen.

The majority of the literatures provide optimization models in scheduling VPP in DA markets. Nevertheless, only a few studies have demonstrated scheduling in real-time and balancing markets. It is found that the optimal scheduling problem demonstrated is proposed with few shortcomings. Primarily, only uncertainties connected to RE sources are modelled. Secondly, the proposed models are focused on DA, real-time markets, and spinning reserve markets but rarely demonstrated using Up and Down reserve markets. Thirdly, most of the previous researchers proposed models do not take into account for market pricing uncertainty. Any market operator must model the uncertainties associated with market prices because they affect market participants strategic behaviour. Finally, cleared bids and offers obtained in the market clearing problems are transmitted to ISO for congestion management, where final locational marginal prices are produced alongside congestion pricing. These prices are calculated by taking into account network constraints.

Modelling the VPP's behaviour in the electrical markets based on the other players' biddings is crucial. Furthermore, there is a knowledge gap in incorporating uncertainty parameters and modelling the scheduling problem of market participants' strategic bidding. As a result of the foregoing study, we offer a bi-level stochastic model for VPP strategic scheduling that takes into account market prices, renewable energy generation (Solar PV and Wind power generation), and reserve deployment requests.

2.3. Dissertation Contribution

Although Electricity markets use cyber technologies that improves the quality of decision making and scheduling of market participants, the threat from the cyber intrusion through the network is accessible to such malicious attacks. This dissertation describes one such possible cyber-attack on the power system. The main distinction between false data injection attacks and financial motivated data attacks is that the former aims to gain financial profit through false data injection, whereas the latter aims to cause both economic and physical damage to the system.

Distributed energy sources, on the other hand, are required to participate in electricity markets as a single entity, despite of their uncertainties. By using optimal scheduling solution, and uncertainty modelling these DERs along with the conventional power plants aggregate their production. They collaborate to form a virtual power plant and participate in electricity markets. This dissertation proposes optimal scheduling of these virtual power plants in the electricity markets while taking into account market price uncertainties, the intermittent and variable nature of RE generation, and reserve deployment requirements.

2.3.1. Detailed contribution

Following are the detailed contributions of this dissertation:

2.3.1.1 Illustration of electricity market clearing process. We first review the need of the electricity markets in the present trends, market principles and the clearing process. More specifically we describe the structure of electricity market and their formulation. We concentrate on Day-Ahead, Real-Time and reserve markets. This market clearing process is formulated using DC optimal power flow models.

2.3.1.2 Illustration of false data injection attack formulation. Here, the attack vector is designed, considering network topology and meter measurements are known to the cyber-attacker. A bi-level attacking model is formulated to construct a new attack vector, which passes through the bad detection procedure run by the Independent System Operator (ISO). The attacker's objective of profit maximization is taken as the upper-level problem. In order to gain the profit, the attacker tries to buy the power from the DA market and sell it in the real time market where, locational marginal prices at specific bus are high in that specific time period. In the lower-level problem, market clearing problem of both DA and real time market is formulated with the ISO objective of profit maximization. And, the bi-level model is reformulated in to single-level problem by using KKT conditions and strong duality theorem.

2.3.1.3 Demonstrating the effect of attack vector on the network flow and LMPs. After designing the attack vector, the same are injected into the measuring devices. By manipulating these data, the attacker changes the pattern of network flow in each transmission line such that the congestion pattern in each time period is changed. The measuring devices which are more vulnerable are attacked easily. Due to the change in the congestion pattern, LMPs are changed, so that the attacker buys the power at lower prices and participates in the real time where, power is sold at higher LMPs.

2.3.1.4 Illustration of RE integration in to the electricity markets. Renewable energy sources are integrated in to the power system either in to a centralized or decentralized way. Small scale renewable energy sources along with some other distributed energy sources are aggregated into virtual power plants (VPP). This concept of virtual power plant is evolved as a centralized solution for these small-scale generating units thus, allows them as single entity in the electricity market. The uncertainties in the RE generation are taken as stochastic process. Each uncertain parameter is realized into a set of scenarios using scenario realization technique.

2.3.1.5 Modelling of VPP in the electricity markets. VPP as a single entity consisting of RE sources and energy storage system as its aggregators participates in the electricity markets. Specifically, VPP is allowed to participate in the DA market and reserve market. The uncertainties related to market prices and reserve deployment are model using scenario realization technique. A two-stage stochastic optimization model is formulated for finding optimal scheduling of these Virtual Power Plants in the DA and reserve electricity markets.

2.3.1.6 Demonstrating the VPP as price maker by making strategic decision in the electricity markets. VPP as a strategic player can make the decision according to market environment. In this case, VPP always tries to obtain profits by trading the power in both DA and reserve markets while optimizing its own resources. Thus, VPP acts as price maker and able to control the prices in the electricity markets. This can be described using bi-level stochastic model, using scenario realization technique for modelling uncertainties. VPP's objective of profit maximization is formulated as upper-level problem, while in the lower-level problem market clearing process of both DA and reserve market is formulated. And, the modeled bi-level problem is reformulated in to single-level problem by using KKT conditions and strong duality theorem.

2.4.Dissertation Organization

The remainder of this dissertation is organized as follows: In Chapter-3, the market clearing process of Day Ahead, Real time and balancing reserve markets is explained. Mathematical formulation of these markets using power flow optimization models is discussed. The knowledge of these mathematical models is used in Chapter-4 and Chapter-5 in formulating lower-level problem of bi-level model. At the end, KKT conditions are deduced for the discussed model, which is utilized while formulating single level MILP problem. In Chapter-4, financially motivated false data injection attacks on electricity market are analyzed. This study gives a clear picture about the state estimation, bad data detection procedures. The attacking vector is obtained by designing bi-level attacking model; at the end of this Chapter, simulation results are presented showing the impact of cyber intrusion. In Chapter-5, the concept of VPP and its various components are discussed. For optimal scheduling of this VPP, a two-stage stochastic model is formulated. In this chapter, uncertainty modelling, decision making sequence of the VPP is explained. VPP as a price maker, making strategic decision along with the market participants, is modelled as a bi-level model in Chapter-6. At the end of this chapter simulation studies are carried out considering different cases. Finally in Chapter-7, the future scope of research is presented and conclusion on the dissertation work is drawn. For the sake of clarity nomenclature for every chapter is presented at the end of each chapter respectively.

CHAPTER 3
Mathematical Formulation of Market-based Power System using Optimal Power flow Models

CHAPTER 3

Mathematical Formulation of Market-based Power System using Optimal Power flow Models

3.1. Introduction

Electricity markets are modelled using DC and AC optimal power flow studies. One of the most significant roles of control centre is to ensure the reliability, security, and efficiency of the system operations, which may be accomplished through effective monitoring and decision-making. A market is a web-based platform where generation companies (GENCOs) and load serving entities (LSEs) bid and offer energy. The control centre attempts to maximise social welfare for all players by using reported prices and network limits. A well-known programme for accomplishing this optimization is the Optimal Power Flow studies. The DCOPF is a linear form of the optimal power flow, whereas the ACOPF is a nonlinear formulation that includes reactive power parameters. These optimal studies are used to define electricity prices (Locational Marginal Price or LMP) in both day–ahead and real–time markets. Mathematical formulation of DCOPF, as well as the general structure of day–ahead, real–time markets, and reserve markets are detailed in the following sections. These models are processed by the ISO/TSO. ISO is a system operator which is independent of both buyers and sellers in the market. In some markets it is considered as regulating entity.

3.2. Day-Ahead Electricity Market

Day-Ahead electricity market can be termed as DAM. In this type of power market, buyers and sellers submit their bids to ISO/TSO one day-ahead to the dispatch period. ISO runs DCOPF program as market clearing process, based on the bidding information submitted by the buyers (loads) and sellers (generators), Market clearing price (LMPs/Nodal Pries/ Area clearing Price) at each bus of the power network are calculated, and quantities of the energy cleared is determined and then the information is processed to concerned participants.

Most of electricity markets in the world are operated as Day-head markets. The optimization problem must take into account the network's topology and physical constraints. The objective function of the ISO/TSO is to maximize the social welfare of each market participant. Based on the objective function and constraints the DCOPF model for DA market is formulated as security constrained economic load dispatch.

3.2.1. Mathematical Formulation of DAM

The problem of DA market optimization is presented in the references [4,11,15] and is formulated as follows:

$$\min_{\lambda, P_{it}, D_{jt}} R_{EP} = \sum_{i=1}^{\Omega_g} \sum_{t=1}^{T} C_{it} P_{it} - \sum_{j=1}^{\Omega_d} \sum_{t=1}^{T} B_{jt} D_{jt} \tag{3.1}$$

$$S.t \quad \sum_{i \in \Omega_n} P_{it} = \sum_{j \in \Omega_n} D_{jt} \qquad \forall \Omega_n \in N_{bus};\ (\lambda_t) \tag{3.2}$$

$$P_{it}^{min} \leq P_{it} \leq P_{it}^{max} \qquad (\mu_{it}^{max}, \mu_{it}^{min}) \tag{3.3}$$

$$D_{jt}^{min} \leq D_{jt} \leq D_{jt}^{max} \qquad (\gamma_{it}^{max}, \gamma_{it}^{min}) \tag{3.1}$$

$$F_{l}^{min} \leq F_{lt} \leq F_{l}^{max} \qquad \forall l \in \Omega_l;\ (\vartheta_{it}^{max}, \vartheta_{it}^{min}) \tag{3.2}$$

Where C_{it}, B_{jt} are the price in \$/MWh respectively and P_{it}, D_{jt} is the quantity in MWh offered by generators (suppliers) and demands (consumers) respectively. Constraint in the Eq. (3.1) shows ISO's objective of maximizing social welfare and minimizing cost of generation R_{EP}, Where $F_{lt} = \sum_{i=1}^{\Omega_n} S_{lj} \left(\sum_{i=1}^{\Omega_g} P_{it} - \sum_{j=1}^{\Omega_d} D_{jt} \right)$; $\forall n \in N_{bus}$ represents power flow in the transmission lines. Constraint in the Eq. (3.2) represents balancing constraints where, the amount of power generated should be balanced by the demand consumption in each time period. Eq. (3.3), imposes limits on the generating capacity offered by the seller. Where, Eq. (3.4) puts upper and lower bounds on the load demand bidded by the buyer, and Eq. (3.5) keeps limits on transmission line capacity respectively. Variables λ, μ_{it}^{max}, μ_{it}^{min}, γ_{it}^{max}, γ_{it}^{min}, ϑ_{it}^{max}, ϑ_{it}^{min} are corresponding dual variables of Eq. (3.2), Eq. (1.3), Eq. (1.4) and Eq. (1.5) respectively. Locational Marginal Price at each bus in the DA market is interpreted as LMP_{bus}.

3.2.2. Locational Marginal Pricing for DAM

LMP's are market clearing prices defined for each time period. In general, the marginal energy price, congestion price, and loss price are the three components of LMP at each bus. The LMP technique is used to trade electricity in most of the energy markets, including the PJM Interconnection, New York, and New England markets.

$$LMP_{bus} = Energy\ Cost + Congestion\ cost + losses\ cost$$

$$LMP_{it}^{EA} = \lambda_t + \sum_{l\in\Omega_l} \vartheta_{lt}^{min} * S_{li} - \sum_{l\in\Omega_l} \vartheta_{lt}^{max} * S_{li} \tag{3.6}$$

Where, $Energy\ Cost = \lambda_t$ (3.7)

$$Congestion\ cost = \sum_{l\in\Omega_l} \vartheta_{lt}^{min} * S_{li} - \sum_{l\in\Omega_l} \vartheta_{lt}^{max} * S_{li} \tag{3.8}$$

$$losses\ cost = \lambda_t \times (\mathrm{DF_i} - 1) \tag{3.9}$$

Where λ_t is the Lagrangian multiplier for each time period in a day corresponding to the equality constraint in the Eq. (3.2). $\vartheta_{lt}^{max}, \vartheta_{lt}^{min}$ are the dual variable for each transmission line in each time period corresponding to the constraint in the Eq. (3.5). DF_i, is the delivery factor at the i^{th} bus. Here, we ignore the loss component, and will have $DF_i = 1$ in Eq. (3.9). As a result, the LMP consist of two components, Energy and Generation costs. Whenever, there is congestion in the transmission network LMPs at each bus are different.

3.3. Real Time Electricity Markets

Real time electricity markets are meant to adjust the deviations in the quantity traded by the market participants. This type of market operates for every 5 to 15 minutes ahead to the real time dispatch. The deviations in the loads and system constraints are allowed to adjust and ISO/TSO runs the market clearing process [11,15]. The ISO/TSO (system operator) plays a pivotal role in system operation from its control centres, and performs the following tasks:

i. Collecting information from measuring devices installed in the physical layer of the power network.

ii. Online monitoring of the network, and estimating the network's status using state estimation.

iii. Based on the results obtained from the state estimation a generation dispatch model is processed.

The acquired LMPs will be used to calculate the real-time electricity price. Market clearing price (LMPs/Nodal Pries/ Area clearing Price) and the cleared amount of energy with respective to a particular bid is obtained as result from the market clearing problem, and then, the same information is processed to concerned participants.

3.3.1. Mathematical Formulation of RTM

Similar to the DA market clearing process, RT market solves SCED optimization problem and is formulated as follows:

$$\min_{\lambda,\Delta P_{it},\Delta D_{jt}} R_{RT} = \sum_{i=1}^{\Omega_g}\sum_{t=1}^{T} C_{it}\Delta P_{it} - \sum_{j=1}^{\Omega_d}\sum_{t=1}^{T} B_{jt}\Delta D_{jt} \tag{3.10}$$

$$S.t \quad \sum_{i\in\Omega_n} \Delta P_{it} = \sum_{j\in\Omega_n} \Delta D_{jt} \qquad \forall\Omega_n \in N_{bus};\ (\tilde{\lambda}_t) \tag{3.11}$$

$$\Delta P_{it}^{min} \le \Delta P_{it} \le \Delta P_{it}^{max} \qquad (\tilde{\mu}_{it}^{max}, \tilde{\mu}_{it}^{min}) \tag{3.12}$$

$$\tau D_{jt}^{min} \le \Delta D_{jt} \le \tau D_{jt}^{max} \qquad (\tilde{\gamma}_{it}^{max}, \tilde{\gamma}_{it}^{min}) \tag{3.13}$$

$$\Delta F_{lt} \le 0 \qquad \forall l \in Cl_+;\ (\tilde{\vartheta}_{it}^{max}) \tag{3.14}$$

$$\Delta F_{lt} \ge 0 \qquad \forall l \in Cl_-;\ (\tilde{\vartheta}_{it}^{min}) \tag{3.15}$$

Where ΔP_{it},ΔD_{jt} represent the incremental change in power generation and load demand values. The term R_{RT} in Eq. (3.10) represents the ISO objective function of minimizing incremental cost of generation. Constraints in the Eq. (3.11) represents balancing constraint. The incremental change in the generation value should be equal to amount of incremental change in the demand value. Constraints in the Eq. (3.12) and Eq. (3.12)) are limiting constraints on the incremental power generation and demand values respectively, where, $\Delta F_{lt} = \sum_{i=1,l\in\Omega_l}^{\Omega_n} S_{lj}\left(\sum_{i=1}^{\Omega_g}\Delta P_{it} - \sum_{j=1}^{\Omega_d}\Delta D_{jt}\right)$ represents change in power flow. $\tilde{\lambda}_t$, $\tilde{\mu}_{it}^{max}$, $\tilde{\mu}_{it}^{min}$, $\tilde{\gamma}_{it}^{max}$, $\tilde{\gamma}_{it}^{min}$, $\tilde{\vartheta}_{it}^{max}$, $\tilde{\vartheta}_{it}^{min}$ are dual variables of Eq. (3.11), Eq. (3.12), Eq. (3.13), (3.14) and Eq. (3.15) respectively. Furthermore, ISO (system operator) computes line flow changes through each transmission line l and tries to keep line flow measurements within the limits, (for both positively ($l \in Cl_+ : F_l \geq F_l^{max}$) [20,21] and negatively congested lines($l \in Cl_- : F_l \leq F_l^{min}$) respectively.

3.3.2. Locational Marginal Price for RTM

4. Similar to the day-ahead market, LMPs at each bus in the RT market are governed by following equation

$$LMP_{it}^{EP} = \tilde{\lambda}_t + \sum_{l \epsilon Cl_-} \tilde{\vartheta}_{lt}^{min} * S_{li} - \sum_{l \epsilon Cl_+} \tilde{\vartheta}_{lt}^{max} * S_{li} \tag{3.16}$$

Where $\tilde{\lambda}_t$ is the Lagrangian multiplier for each time period, corresponding to the equality constraint Eq. (1.8). $\tilde{\vartheta}_{lt}^{max}, \tilde{\vartheta}_{lt}^{min}$ are the dual variables for each transmission line in each time period corresponding to the Eqs. (3.14) and (3.15).

Note that the LMPs at each bus in the real-time market are determined depending on transmission line congestion patterns. i.e., $\hat{C} = \{l \in (Cl_-, Cl_+)\}$. As a result, if one of the transmission lines is manipulated to overload by introducing malicious data into the network, the congestion pattern shifts, affecting LMP measurements. Knowing this, the attacker is always looking for ways to modify the network's congestion pattern for financial gain. An attacker could create a power system blackout in addition to gaining financial gain. Different types of protective relays can be found on a transmission line. For example, special type of overloading relays will disconnect the line if it is overloaded in order to prevent over-heating and physical damage. This sudden loss creates blackout in the system. Here, we mainly concentrate on FDI attacks with financial motivation.

3.4. Reserve Electricity Market

Power systems should be designed with sufficient reserve capacity to loss of stability during normal operation, sudden load disconnections, and or in the event of unforeseen conditions. Reserve capacity is referred to in the reserve market as an ancillary service that is required for the system and the power market to function properly. This service can be obtained in a regulated and, mandatory way, or it can be provided by an ancillary services reserves market. These reserve markets are important in balancing power grid from the uncertain events in the power supply and demand.

In the Reserve Market, generators and sometimes loads offer bids to sell their power to meet demand i.e., raising in the production at a faster rate whenever required. The generators and demands in the reserve market are called market agents. Similar to that of DA and real time energy markets that deals with active power, the reserve market also deals with active power reserves. The capacity of the power offered by the reserve market agent is defined in terms of MW/h.

3.4.1. Types of Reserve Markets

Generators and demands can provide the following types of reserve:

- ***Regulation Reserve (RR):*** This type of reserve capacity is provided by fast acting units connected to grid, which are usually connected to the Automatic Generation Control unit and are capable of regulating small up and down imbalances produced by the unpredictable nature of loads.
- ***Spinning Reserve (SR):*** This type of reserve capacity is provided by the online ready units. These reserve capacity units are used to accommodate larger variations in load, losses, and unanticipated events.
- ***Supplemental Reserve (XR):*** This type of reserve capacity is provided by fast-start units, which can be online or offline. This type of reserve is used to correct large imbalances caused by unforeseen events.

Regulation reserve provides bidirectional control for balancing the system, i.e, either they can increase the generation or decrease the generation, whereas spinning and supplemental reserve provides unidirectional control.

Regulation Reserve (RR) could be modelled in two ways: regulation reserve up (RR+) and regulation reserve down (RR-) (RR-). In order to provide reserve capacity, these controls can have independent different values. While the unit provides the same amount of regulating reserve in both directions as a single control.

Contingency Reserve (CR) is the combination of spinning and supplemental reserves. Operating Reserve is the sum of the contingency reserve and the regulating reserve (OR). This can be summarized as follows:

- SR + XR = CR
- RR+ + SR + XR = OR
- RR+ +CR = OR

Similar, to the Day-Ahead and real time markets, market agents in the reserve markets put their offers to balance the system during the uncertain events. Here, in this study we consider *Regulation Reserve (RR) market.* Virtual Power Plants (VPP) discussed in the earlier chapter, having fast response in increasing and decreasing power generation can also participate in the RR market. This RR market is modelled in the same way as the DA markets. The objective of the ISO/TSO (system operator) is to minimize the cost of reserve capacity requirements. In reserve markets, the system operator reacts to market participants for reserve capacity deployments. This can be accessed by assigning up and down reserves as necessary.

3.4.2. Mathematical model for regulation reserve markets

The mathematical formulation of Regulation Reserve (RR) market is detailed as follows:

Obj: $$min_{\Gamma_{RM}} \sum_{i\epsilon\Omega_{RU}} C_{it}^{G,RU} P_{it}^{G,RU} - \sum_{i\epsilon\Omega_{RD}} C_{it}^{G,RD} P_{it}^{G,RD} \quad (3.17)$$

S.t $$P_t^{RU} + \sum_{i\epsilon\Omega_{RU}} P_{it}^{G,RU} = \overline{P}_t^{RU} \qquad \forall t;\ \lambda_t^{RU} \quad (3.18)$$

$$P_t^{RD} + \sum_{i\epsilon\Omega_{RD}} P_{it}^{G,RD} = \overline{P}_t^{RD} \qquad \forall t;\ \lambda_t^{RD} \quad (3.19)$$

$$\underline{P}_{it}^{G,RU} \leq P_{it}^{G,RU} \leq \overline{P}_{it}^{G,RU} \qquad \forall t, i\epsilon\Omega_{RU};\ \overline{\mu}_{it}^{G,RU}, \underline{\mu}_{it}^{G,RU} \quad (3.20)$$

$$\underline{P}_{it}^{G,RD} \leq P_{it}^{G,RD} \leq \overline{P}_{it}^{G,RD} \qquad \forall t, i\epsilon\Omega_{RD};\ \overline{\mu}_{it}^{G,RD}, \underline{\mu}_{it}^{G,RD} \quad (3.21)$$

The reserve regulating electricity market clearing problem can be also formulated as linear programming problem. The objective function in the Eq. (3.17) is to minimize the cost required for the reserve deployment whenever the system operator called to do so. It includes two terms, defined as below:

i. The term $C_{it}^{G,RU} P_{it}^{G,RU}$ is the cost incurred for up reserve capacity offered by the generating units with faster starting response
ii. The term $C_{it}^{G,RD} P_{it}^{G,RD}$ is the cost related to down reserve capacity by the generating unit with faster shutdown capacity.

Where, set Γ_{RM} includes optimization variables $\{P_{it}^{G,RU}, P_{it}^{G,RD}, P_t^{RU}, P_t^{RD}\}$ and dual variables are provided following a colon corresponding to each constraint. Variables

$\left\{\overline{P}_t^{RU}, \overline{P}_t^{RD}\right\}$ represents, the total amount of required reserve capacity in (MW). Eqs. (3.18) and (3.19) represents the balancing constraint on up and down reserves respectively. The reserve capacity requested by the system operator should be equal to reserve capacity cleared in each time period. Where, constraints (3.20) and (3.21) impose bounds on the generation of reserve utilities for up and down capacities respectively offered by the market agents.

3.5. Bi-Level Programs

A mathematical program consist of two optimization problems in their constraints are formulated as a bi-level program. The main problem is said to be upper-level problem, which acts as leader or maker of the objective function. The nested problem is said to be lower-level problem, which acts as follower. It is a simple optimization problem that optimizes upper-level objective function over the constraints including both upper-level and lower-level problems.

These types of mathematical models are used in power system for optimizing REs, energy storage system, optimal scheduling and to some smart grid applications. In this work, we model the false data injection attacks in the electricity markets as well as optimal scheduling of VPPs using the bi-level optimization programming. Because in both the cases, the objective function to be optimized is based on the constraints present in more than one optimization problem and are followers of the upper-level objective function.

3.5.1. Mathematical Formulation:

The above-mentioned bi-level problem is reformulated as a single-level problem using Karush-Kuhn-Tucker (KKT) optimality conditions and the strong duality theorem.

The objective function and constraints for a convex optimization problem are linear and continuous, resulting in a viable convex set. The local optimum solution to these linear convex optimization problems is also the global optimal solution. As a result, KKT conditions are both necessary and sufficient to obtain the global optimal solution in a convex optimization problem. In the re-formulation of problem using KKT conditions, the Lagranges function is first derived by using derivative with respect to each variable. Using the generalized bi-level model, the lower-level optimization problem is replaced using KKT optimality conditions. Thus, the resulting problem is a mixed integer equilibrium constrained programming model

$$Min_{x\in X,y,\lambda} \quad f(x,y) \tag{3.28}$$

$$s.t \quad h(x,y) \leq 0 \tag{3.29}$$

$$k(x,y) \leq 0 \tag{3.30}$$

$$\lambda_i \leq 0 \qquad \forall i \in l \tag{3.31}$$

$$\lambda_i k_i(x,y) = 0 \qquad \forall i \in l \tag{3.32}$$

$$\nabla_y \mathcal{L}(x,y,\lambda) = 0 \tag{3.33}$$

$$0 \leq \lambda_i \perp (k(x,y)) \leq 0 \qquad \forall i \in l \tag{3.34}$$

Where,

$\mathcal{L}(x,y,\lambda) = g(x,y) + \sum_{i=1}^{l} \lambda_i k_i(x,y)$ is the lagrangian function of the lower-level problem. $\lambda_i$is duality constraint. Eq. (3.28), is the objective function which is to be minimized. Eqs (3.29) and (3.30) are the constraints related to upper and lower-level problem. Eq. (3.32) represents the lower- level equality constraint obtained by taking the derivative of the lagrangian function with respect to the variables x, y. Eq. (3.34) is the complementary constraint corresponding to the inequality constraint. This equation is termed as complementary slackness and possess non-linearity.

$$Min_{x\in X,y,\lambda} \quad f(x,y) \tag{3.28}$$

$$s.t \quad h(x,y) \leq 0 \tag{3.29}$$

$$k(x,y) \leq 0 \tag{3.30}$$

$$\lambda_i \leq 0 \qquad \forall i \in l \tag{3.31}$$

$$\lambda_i k_i(x,y) = 0 \qquad \forall i \in l \tag{3.32}$$

$$\nabla_y \mathcal{L}(x,y,\lambda) = 0 \tag{3.33}$$

$$0 \leq \lambda_i \perp (k(x,y)) \leq 0 \qquad \forall i \in l \tag{3.34}$$

Where,

$\mathcal{L}(x,y,\lambda) = g(x,y) + \sum_{i=1}^{l} \lambda_i k_i(x,y)$ is the lagrangian function associated with the lower-level problem. $\lambda_i$is duality constraint. Eq. (3.28), is the objective function which is to be minimized. Eqs (3.29) and (3.30) are the constraints related to upper and lower-level problem. Eq. (3.32) represents the lower- level equality constraint obtained by taking the derivative of the Lagrangian function with respect to the variables x, y. Eq. (3.34) is the complementary constraint corresponding to the inequality constraint. This equation is termed as complementary slackness and possesses non-linearity.

3.5.2. Complimentary Constraints:

The nonlinear complimentary constraints having the form $X.Y = 0$ with $x, y \geq 0$ corresponding to the inequality constraints in the lower-level problem can be

$$0 \leq X \leq M^X u \qquad (3.35)$$
$$0 \leq Y \leq M^Y(1 - u) \qquad (3.36)$$
$$u \in \{0,1\} \qquad (3.37)$$

linearized using big-M method presented in the following equations

Where M^X and M^Y are large enough positive constraints.

The sections 3.6 and 3.6.1 describes the general mathematical formulation of the KKT optimality conditions, and complimentary constraints. The concept is utilised for formulating bi-level optimization in to single level mixed integer equilibrium constrained program and then into mixed integer linear program problem, depending upon the application for which the optimization is meant for.

Nomenclature:

sets	
Ω_g, Ω_d	Set of generators and demands respectively in the network
T	Operating time periods
Ω_n	Set of generators and demand connected to bus n
Ω_l	Number of branches (lines) in the network
Ω_{RU}	Set of market agents in the Up-reserve markets other than the VPP
Ω_{RD}	Set of market agents in the Down-reserve markets other than the VPP
S_{lj}	Generalized shift factor matrix
DF_i	Delivery factor of the i^{th} bus
N_{bus}	Number of buses in the network
Parameters	
B_{it}, B'_{it}	Electricity Price ($\$/MWh$) offered by the i^{th} demand in DA and RT markets during the t^{th} time period.
C_{it}, C'_{it}	Electricity Price ($\$/MWh$) offered by the i^{th} generating in DA and RT markets during the t^{th} time period.
C_{att}	Minimum threshold Value
D_{jt}^{max}	Maximum demand (MW)offered by the j^{th} demand in DA market during the t^{th} time period
D_{jt}^{min}	Minimum demand (MW)offered by the j^{th} demand in DA market during the t^{th} time period
F_{lt}^{max}	Maximum capacity of l^{th} transmission line in (MW)
F_{lt}^{max}	Minimum capacity of l^{th} transmission line in (MW)

P_{it}^{max}	Maximum generation capacity (MW)offered by the i^{th} demand in DA market during the t^{th} time period
P_{it}^{min}	Minimum generating capacity (MW)offered by the i^{th} demand in DA market during the t^{th} time period
$\underline{P}_{it}^{G,RU}, \overline{P}_{it}^{G,RU}$	Lower and upper limits of Up reserve capacity offered by the i^{th} market agent in the time period *t* in Reserve market [MW/h]
$\underline{P}_{it}^{G,RD}, \overline{P}_{it}^{G,RD}$	Lower and upper limits of down reserve capacity offered by the i^{th} market agent in the time period *t* in Reserve market [MW/h]
$\overline{P}_{t}^{RU}, \overline{P}_{t}^{RD}$	Up and Down reserve capacity offered in the reserve market in the time period *t* in [MW/h]
X_{DA}	Set of DA market variables
X_{RT}	Set of RT market variables
$\chi_{it}^{G,RU}$	Up-reserve capacity offer price by the i^{th} market agent in the reserve market in the time period *t* [$/MWh]
$\chi_{it}^{G,RD}$	Down-reserve capacity offer price by the i^{th} market agent in the reserve market in the time period *t* [$/MWh]
ΔD_{jt}^{min}	Minimum incremental change in demand (MW)offered by the j^{th} demand in RT market during the t^{th} time period
ΔP_{it}^{max}	Maximum incremental change in generation capacity (MW)offered by the i^{th} demand in RT market during the t^{th} time period
ΔP_{it}^{min}	Minimum incremental change in generation capacity (MW)offered by the i^{th} demand in RT market during the t^{th} time period
τ	Time period in hours
Variables	
D_{jt}	Demand (MW) cleared (scheduled) in the DA market during the t^{th} time period
F_{lt}	Transmission capacity scheduled for the l^{th} line during the t^{th} time period
P_{it}	Generating capacity (MW) cleared (scheduled) in the DA market during the t^{th} time period
$P_{it}^{G,RU}$	Up- reserve capacity sold to the reserve market by the i^{th} market agent in the time period *t* [MW]
$P_{it}^{G,RD}$	Down- reserve capacity sold to the reserve market by the i^{th} market agent in the time period *t* [MW]
P_{t}^{RU}	Up- reserve capacity requested by the system operator in the time period *t* [MW]
P_{t}^{RD}	Down- reserve capacity requested by the system operator in the time period *t* [MW]
ΔD_{jt}	Incremental Demand (MW) value cleared (scheduled) in the RT market during the t^{th} time period
ΔF_{lt}	Incremental change in scheduled capacity of l^{th} transmission line in (MW)
ΔP_{it}	Incremental generation (MW) value cleared (scheduled) in the RT market during the t^{th} time period
$\lambda_t, \tilde{\lambda}_t$	Locational Marginal Price in ($) at the i^{th} bus during the t^{th} time period in DA, and RT markets
ΔZ_{mt}	False data injected in the m^{th} transmission line (MW) during the t^{th} time period

CHAPTER 4

Mathematical Modelling of Financially Motivated FDI attacks on Electricity Markets

CHAPTER 4

Mathematical Modelling of Financially Motivated FDI attacks on Electricity Markets

4.1. Introduction

At present the power sector is operating as DA and RT markets. These markets provide a competitive environment resulting in diminishing of monopoly existence in the power sector. These types of markets operate on double sided auction-based systems and are being operated by the ISO/TSO. In these types of markets, sellers and buyers participate through an online platform and submit their bids in quantity and price. The DC-OPF model is used to determine LMPs, considering the topology and physical constraints of the power system and power demand as per the load forecasting values. The demand forecasting values are different from the actual demand values during the real time market operation. Hence there is accuracy problem in the power system state estimation. Adversary takes this as a chance and manipulates the meter readings by injecting false data. Meanwhile the attacker takes care of not being detected in the BDD procedure.

This chapter mainly focuses on financially motivated FDI attacks considering attacker as one of the virtual players in electricity market. A novel attacking model is designed using bi-level optimization problem where attacker aims to gain financial benefits by misleading market clearing problem. Attacker injects false data into the RTUs wherever necessary and the rest of the RTUs are not manipulated. Taking these into consideration, the vulnerability aspects of the grid system are investigated, to enable ISO/TSO to provide adequate security to nullify the impacts of the attack.

4.2. DC State Estimation

For a DC linearized lossless transmission system with $n + 1^2$buses and a set $M = \{1,2,3, \dots m\}$ of meters. The states are typically bus voltages and phase angle. The meter data (RTU's) is typically including real power injection, branch power flow in each transmission line. 'J' is the Jacobin matrix. The relationship between the meter data 'Z' and the system states X is given by

$$Z = JX + e \tag{4.1}$$

Where, e is the measurement error matrix and is considered to follow gaussian distribution with zero mean and co-variance matrix R, $J \in R^{m \times n}$. 'e' matrix represents the deviation of run time states from the scheduled optimal states. The state estimation problem is to find an estimate $\hat{X}$ of state variable X to the best suit of the meter measurements [26-28], and that minimize weighted least square error is formulated below:

$$\hat{X} = argmin\{(Z - JX)^T R(Z - JX)\} \tag{4.2}$$

$$\hat{X} = (J^T R^{-1} H)^{-1} J^T R^{-1} Z \triangleq EZ \tag{4.3}$$

$$E = (J^T R^{-1} J)^{-1} J^T R^{-1} \tag{4.4}$$

Estimated Z is given by $\hat{Z} = J\hat{X}$

The residual value r of the state estimator is the difference between observed measurement z and the estimated measurement $\hat{Z}$and is given by $r = Z - \hat{Z} = (I - JE)Z$. Adding ΔZ to Z results in change in residual value. The *L-2 norm* of residual value

$$\begin{aligned} \|r^{new}\|_2 &= \|Z + \Delta Z - JE(Z + \Delta Z)\|_2 \\ &\triangleq \|r\|_2 + \|(I - JE)\Delta Z\|_2 \end{aligned} \tag{4.5}$$

In order to avoid of being detected in the BDD procedure by the ISO/TSO, the change in residual value(r^{new}) by adding compromised measurement ΔZ should be within the *threshold limit* $\|(I - JE)\Delta Z\|_2 \leq \epsilon$. This threshold limit is introduced as a constraint in the attacker's optimization problem.

4.3. Bi-Level Optimal Attack Vector Formulation

Considering the market clearing problem discussed in the previous chapter, if the attacker buys certain amount of power ($D_{it}\ MW$) at LMP_i^{EA}in DA market and after compromising the meter data, sells ($\Delta P_{it}\ MW$) in real time market at LMP_i^{EP}, its profit would be $[LMP_{it}^{EP} \times (\Delta P_{it}) - LMP_{it}^{EA} \times (D_{it})]$\$/h and the same follows, if the attacker sells expensive electricity in DA market and buy cheap price electricity in real time market [4,11,20]. The profit that the attacker obtains by the above virtual electricity trading is given by

$$\text{Profit} = \sum_{i=1}^{\Omega_n}\sum_{t=1}^{T}[LMP_{it}^{RT}\Delta P_{it} - LMP_{it}^{DA}D_{it}] + [LMP_{it}^{DA}P_{it} - LMP_{it}^{RT}\Delta D_{it}]$$
$$= \sum_{i=1}^{\Omega_n}\sum_{t=1}^{T}[LMP_{it}^{RT}(\Delta P_{it} - \Delta D_{it}) + LMP_{it}^{DA}(P_{it} - D_{it})]\ \$/h \tag{4.6}$$

Based on the state estimation and market clearing process, in order to achieve the attacker's objective of profit maximization, the false data injected into the network should create congestion in the desired transmission line, and for this the attacker has to find out optimal generation and load values such that the attack is stealthy and passes through BDD procedure. In order to obtain optimal attack values, the attacker needs to relate DA and RT markets with the RTU's measurement data. For this the attacker considers network topology and physical constraints of both power markets in the attack problem. The attacker needs to choose some desirable meters that are to be compromised. Consequently, the attacker needs to embed the relation between the traded power $[P_{it}, D_{it}]$, DA and RT market LMPs i.e., $[LMP_{it}^{DA}, LMP_{it}^{RT}]$ and false data injected (through the RTU's). considering all above issues, a bi-level false data injection attack strategy is proposed [30,31, and 50]. Let us define the $Z_{DA} = [P_{it}, D_{it}]$ are the DA market state variables and $Z_{RT} = [\Delta P_{it}, \Delta D_{it}]$ as the RT market state variables [4,8,29]. The attacker's bi-level problem is interpreted as

$$\max_{\Delta P_{it}, \Delta D_{jt}} Profit_{Att} = \sum_{i=1}^{\Omega_n}\sum_{t=1}^{T}[LMP_{it}^{RT}(\Delta P_{it} - \Delta D_{it}) + LMP_{it}^{DA}(P_{it} - D_{it})] \tag{4.7}$$

S.t

$$\sum_{m=1}^{M} U_{mt} \leq C_{att} \qquad \forall m \in \Omega_l \tag{4.8}$$

$$\|(I - JE)\Delta Z_{mt}\|_0 \leq \Delta\in \qquad \forall m \in \Omega_l \tag{4.9}$$

$$\Delta Z_{mt} + \Delta F_{lt} + F_{lt} - F_{lt}^{max} \leq 0 \qquad \forall ml \in \Omega_l; (\vartheta_{mt}^{a}) \tag{4.10}$$

$$\sum_{j=1}^{\Omega_d} \Delta D_{jt} = 0 \tag{4.11}$$

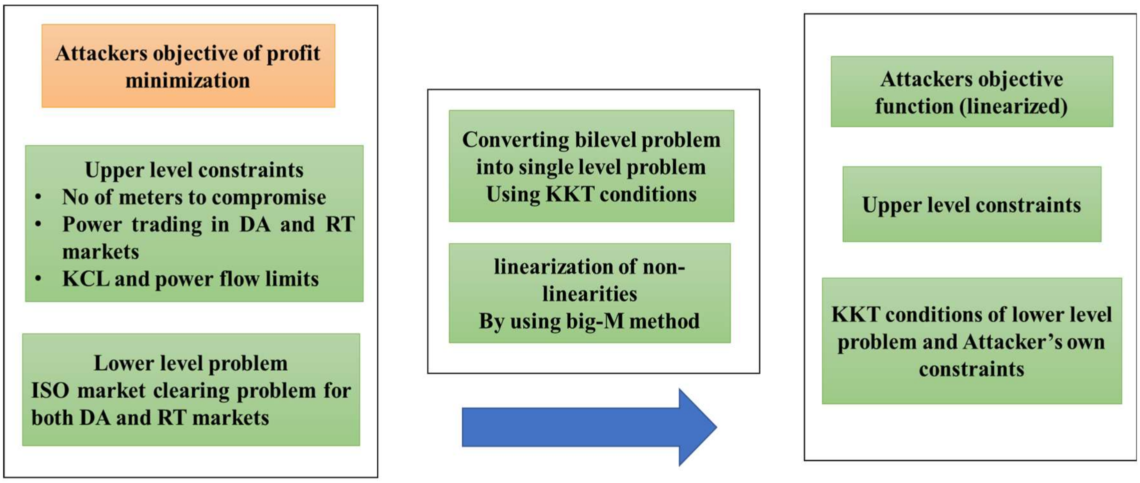
$$\frac{\Delta Z_{mt}}{F_l^{max}} \geq \sigma \qquad \forall m, l \in \Omega_l \tag{4.12}$$

$$\sum_{i=1}^{\Omega_g}(P_{it} - \Delta P_{it}) = \sum_{j=1}^{\Omega_d}(D_{jt} - \Delta D_{jt}) \tag{4.13}$$

$$[X_{DA}, \lambda_t, X_{RT}, \tilde{\lambda}_t] \in arg\ min\ (R_{DA} + R_{RT}) \tag{4.14}$$

$$S.t \begin{cases} (3.2) - (3.5) \\ (3.11) - (3.15) \end{cases} \tag{4.15}$$

In the above bi-level optimization problem, Eq. (4.7) governs the attacker's objective of profit maximization by participating in the DA and RT markets as i^{th} participant. Eq. (4.8) represents for any attack in a specific time slot, the attacker can compromise limited number of RTU's (meters) restricted to a predefined number(C_{att}). In order to avoid being detected by the ISO in BDD procedure the attacker tries to keep the FDI below the threshold limit ($\in$) is shown in Eq. (4.9). Eq. (4.11) represents total change in the demand values should be equal to zero, the injected false data can cause overloading level greater than a given threshold value equal to the 0.005, which can be ensured by constraints in the Eq. (4.11). Eq. (4.12) puts constraint on the amount of traded power in DA market should be equal to RT markets. Eq. (4.10) and Eq. (4.11) ensures the injected false data follows KCL and KVL. Eq. (4.14) and Eq. (4.15) represents the lower-level market clearing problem discussed in the previous chapter-3. The main aim behind considering the market clearing problem is to remain undetected by the ISO. In other words, the attacker follows and understands the market clearing process. Hence to consider ISO's prospective the DA and RT markets equation must be considered. Due to this the attacker's decision-making problem turn in to bi-level optimization problem. In the next section, [32] using KKT conditions and strong duality constraints, the set of equations in the lower-level problem can be turned in to MILP problem. Therefore, the above bi-level problem is turned in to single level MILP problem.



Attacker's bilevel optimization problem converting in to Single level MILP problem

Fig.4.1 Bi-level to single level MILP model

4.3.1. Bi-Level to Single level MILP Model

In simplifying bi-level optimization problem, Karush-Kuhn-Tucker (KKT) optimality conditions for multivariable inequality constrained optimization technique is used. The lower-level market clearing problem is a continuous and linear optimization problem on its decision variables i.e., it is a convex optimization problem [50]. Therefore, the market clearing problem of both EA and EP markets can be replaced by the KKT optimality conditions. Although there exist similar methods with equilibrium constraints [30,31]. Such results are not applicable here, because the upper-level problem has discontinuous and non-linearity. Moreover, the complementary slackness can be linearized using big M-method. Fig4.1 shows the block diagram process for converting bi-level attacker's model to single level MILP model.

The KKT optimality conditions of the market clearing problem is as follows

$$\emptyset_{it}^{Dual} = \{$$

$$C_{it} - \lambda_t + \mu_{it}^{max} - \mu_{it}^{min} + \sum_{l \in \Omega_n} S_{li}\left(\vartheta_{it}^{max} - \vartheta_{it}^{min}\right) \quad (4.16)$$

$$-B_{it} + \lambda_t + \gamma_{it}^{max} - \gamma_{it}^{min} - \sum_{l \in \Omega_n} S_{li}\left(\vartheta_{it}^{max} - \vartheta_{it}^{min}\right) \quad (4.17)$$

$$C'_{it} - \tilde{\lambda}_t + \tilde{\mu}_{it}^{max} - \tilde{\mu}_{it}^{min} + \sum_{l \in Cl_+} S_{li}\left(\tilde{\vartheta}_{it}^{max} - \tilde{\vartheta}_{it}^{min}\right) \quad (4.18)$$

$$-B'_{it} + \tilde{\lambda}_t + \tilde{\gamma}_{it}^{max} - \tilde{\gamma}_{it}^{min} - \sum_{l \in Cl_-} S_{li}\left(\tilde{\vartheta}_{it}^{max} - \tilde{\vartheta}_{it}^{min}\right) \quad (4.19)$$

$$0 \le \mu_{it}^{min} \perp \left(P_{it} - P_{it}^{min}\right) \ge 0 \qquad \forall i \in \Omega_g \quad (4.20)$$

$$0 \le \mu_{it}^{max} \perp \left(P_{it}^{max} - P_{it}\right) \ge 0 \qquad \forall i \in \Omega_g \quad (4.21)$$

$$0 \le \gamma_{jt}^{min} \perp \left(D_{jt} - D_{jt}^{min}\right) \ge 0 \qquad \forall j \in \Omega_d \quad (4.22)$$

$$0 \le \gamma_{jt}^{max} \perp \left(D_{jt}^{max} - D_{jt}\right) \ge 0 \qquad \forall j \in \Omega_d \quad (4.23)$$

$$0 \le \tilde{\mu}_{it}^{min} \perp \left(\Delta P_{it} - \Delta P_{it}^{min}\right) \ge 0 \qquad \forall i \in \Omega_g \quad (4.24)$$

$$0 \le \tilde{\mu}_{it}^{max} \perp \left(\Delta P_{it}^{max} - \Delta P_{it}\right) \ge 0 \qquad \forall i \in \Omega_g \quad (4.25)$$

$$0 \le \tilde{\gamma}_{jt}^{min} \perp \left(\Delta D_{jt} - \Delta D_{jt}^{min}\right) \ge 0 \qquad \forall j \in \Omega_d \quad (4.26)$$

$$0 \le \tilde{\gamma}_{jt}^{max} \perp \left(\Delta D_{jt}^{max} - \Delta D_{jt}\right) \ge 0 \qquad \forall j \in \Omega_d \quad (4.27)$$

$$0 \le \vartheta_{lt}^{min} \perp \left(F_{lt} - F_{lt}^{min}\right) \ge 0 \qquad \forall l \in \Omega_l \quad (4.28)$$

$$0 \le \vartheta_{lt}^{max} \perp \left(F_{lt}^{max} - F_{lt}\right) \ge 0 \qquad \forall l \in \Omega_l \quad (4.29)$$

$$0 \leq \tilde{\vartheta}_{lt}^{min} \perp \left(\Delta F_{lt} - \Delta F_{lt}^{min}\right) \geq 0 \qquad \forall l \in Cl_{-} \qquad (4.30)$$

$$0 \leq \tilde{\vartheta}_{lt}^{max} \perp (F_{lt}^{max} - F_{lt}) \geq 0 \qquad \forall l \in Cl_{+} \qquad (4.31)$$

Equalities in the Eqs. (4.16) to (4.19) are obtained by taking derivatives of the Lagrange function of the lower-level market clearing problem with respect to the decision variables and are defined over $\forall i \in \Omega_n$. The conditions are said to be KKT conditions. Constraints in the Eq. (4.20) to Eq. (4.31) are the complementary constraints regarding inequalities in the Eq. (3.3) to (3.5) and Eq. (3.12) to (3.15). Note that the complementary slackness has the form of $0 \leq X \perp Y \geq 0$, equivalent to $X, Y \geq 0$ and the slackness condition $X \cdot Y$. These conditions can be linearized using big-M method as discussed in the previous chapter. Reference [50] elucidates how to formulate the Lagrange function of a LP problem as well as shows how to derive KKT optimal KKT conditions.

$$\max_{\Delta P_{it}, \Delta D_{jt}} Profit_{Att} = \sum_{i=1}^{\Omega_n} \sum_{t=1}^{T} [LMP_{it}^{DA}(\Delta P_{it} - \Delta D_{it}) + LMP_{it}^{RT}(P_{it} - D_{it})] \qquad (4.33)$$

$$\text{S.t} \qquad \begin{cases} constraints\ Eq.(4.8) - \ Eq.(4.13\ ) \\ constraints\ Eq.(4.16) - \ Eq.(4.31\ ) \end{cases} \qquad (4.34)$$

This problem is generally known as MPEC model. Note that the Eq. (4.33) objective function is same as in Eq. (4.7), while the constraints include upper-level constraints of bi-level model and the KKT conditions of market clearing problem.

In order to solve a MILP, it is required to have continuous and linear objective function. The non-linearity in the objective function Eq. (4.33) is possible to replace with the terms by the exact equivalent mixed-integer linear expressions. Using KKT conditions and imposing strong duality theorem linear formulation for non-linear terms is possible. The objective function in the Eq. (4.33) can be obtained by multiplying KKT conditions from Eqs. (4.16) to (4.19) with $P_{it}, D_{it}, \Delta P_{it}, \Delta D_{it}$ respectively and then summed up. The resultant equation is as follows

$$\begin{bmatrix} C_{it} - \lambda_t + \mu_{it}^{max} - \mu_{it}^{min} + \sum_{l \in Nline} S_{li}\left(\vartheta_{it}^{max} - \vartheta_{it}^{min}\right) \\ -B_{it} + \lambda_t + \gamma_{it}^{max} - \gamma_{it}^{min} - \sum_{l \in Nline} S_{li}\left(\vartheta_{it}^{max} - \vartheta_{it}^{min}\right) \\ C'_{it} - \tilde{\lambda}_t + \tilde{\mu}_{it}^{max} - \tilde{\mu}_{it}^{min} + \sum_{l \in Cl_{+}} S_{li}\left(\tilde{\vartheta}_{it}^{max} - \tilde{\vartheta}_{it}^{min}\right) \\ -B'_{it} + \tilde{\lambda}_t + \tilde{\gamma}_{it}^{max} - \tilde{\gamma}_{it}^{min} - \sum_{l \in Cl_{-}} S_{li}\left(\tilde{\vartheta}_{it}^{max} - \tilde{\vartheta}_{it}^{min}\right) \end{bmatrix} \times \begin{bmatrix} P_{it} \\ D_{it} \\ \Delta P_{it} \\ \Delta D_{it} \end{bmatrix} = 0 \qquad (4.35)$$

The terms in the Eq.(4.35), $\mu_{it}^{max} P_{it}, \gamma_{it}^{max} D_{it}$, $\tilde{\mu}_{it}^{max} \Delta P_{it}$, $\tilde{\gamma}_{it}^{max} \Delta D_{it}$ can be replaced by $\mu_{it}^{max} P_{it}^{max}, \gamma_{it}^{max} D_{it}^{max}$, $\tilde{\mu}_{it}^{max} \Delta P_{it}^{max}, \tilde{\gamma}_{it}^{max} \Delta D_{it}^{max}$ respectively based on the duality theorem, similarly, the other terms $\mu_{it}^{min} P_{it}, \gamma_{it}^{min} D_{it}, \tilde{\mu}_{it}^{min} \Delta P_{it}, \tilde{\gamma}_{it}^{min} \Delta D_{it}$ can be replaced by $\mu_{it}^{min} P_{it}^{min}, \gamma_{it}^{min} D_{it}^{min}, \tilde{\mu}_{it}^{min} \Delta P_{it}^{min}$, $\tilde{\gamma}_{it}^{min} \Delta D_{it}^{min}$ respectively based on the duality theorem [50]. Multiply Eq. (4.35) with unity matrix $[1 \quad 1 \quad 1 \quad 1]$ on both sides results in a linear objective function.

$$\begin{aligned}\tilde{\lambda}_t(\Delta P_{it} - \Delta D_{it}) + \lambda_t(P_{it} - D_{it}) \\ &= C_{it} P_{it} + \mu_{it}^{max} P_{it}^{max} - \mu_{it}^{min} P_{it}^{min} - B_{it} D_{it} + \gamma_{it}^{max} D_{it}^{max} \\ &- \gamma_{it}^{min} D_{it}^{min} + C'_{it} \Delta P_{it} + \tilde{\mu}_{it}^{max} \Delta P_{it}^{max} - \tilde{\mu}_{it}^{min} \Delta P_{it}^{min} - B'_{it} \\ &+ \tilde{\gamma}_{it}^{max} \Delta D_{it}^{max} - \tilde{\gamma}_{it}^{min} \Delta D_{it}^{min}\end{aligned} \tag{4.36}$$

From the above Eq. (4.36), left hand side represents LMP of both DA and RT market. And on the right-hand, linear terms are presented. Thus, it can be concluded that the nonlinear terms are equal to linear term. Therefore, the objective function is a quasi-concave.

The L-0 norm represents the number of non-zero elements in a vector and aims to minimize the error in the measurements and keep within the threshold limit after the false data is injected. But it is hard to solve L-0 norm being nonlinear and non-convex. Hence, L-0 norm is relaxed with L-2 norm (Euclidean norm) which is convex set [29]. Furthermore, the attacker must define mathematical expression0whether the m^{th} meter is compromised or not. In this context, the governing equations are as follows:

$$0 \leq \tilde{\vartheta}_{it}^{max} \leq M(1 - U_{mt}) \tag{4.37}$$

$$-M(1 - U_{mt}) \leq \sum_{i=1, l \in Cl_+}^{\Omega_n} S_{lj} \left(\sum_{i=1}^{\Omega_g} \Delta P_{it} - \sum_{j=1}^{\Omega_d} \Delta D_{jt} \right) \leq 0 \tag{4.38}$$

$$0 \leq \tilde{\vartheta}_{it}^{min} \leq M(1 - U_{mt}) \tag{4.39}$$

$$0 \leq \sum_{i=1, l \in Cl_-}^{\Omega_n} S_{lj} \left(\sum_{i=1}^{\Omega_g} \Delta P_{it} - \sum_{j=1}^{\Omega_d} \Delta D_{jt} \right) \leq M(1 - U_{mt}) \tag{4.40}$$

$$0 \leq \vartheta_{mt}^{a} \leq M(U_{mt}) \tag{4.41}$$

$$-M(U_{mt}) \leq \Delta Z_{mt} + \Delta F_{lt} + F_{lt} - F_l^{max} \leq 0 \quad (4.42)$$

Where $U_{mt} \in \{0,1\}$,The above equations Eqs. (4.37)- (4.42) show the relation between the attacker's decision variables and electricity market variables. For a particular attack the attacker decides to choose a meter to manipulate the data by injecting false data ΔZ and its corresponding variable ϑ_{mt}^{a}. If $U_{mt} = 1$, this indicates that the attacker injected manipulated data in to the meter. If $U_{mt} = 0$, then the respective meter is not attacked by the adversary. These equations are required to inject fake data into the market clearing problem, and hence, included in the attacker's profit maximization problem.

$$0 \leq P_{it}^{max} - P_{it} \leq M(1 - \overline{U}_{it}) \quad (4.43)$$

$$0 \leq \Delta P_{it}^{max} - \Delta P_{it} \leq M(1 - \overline{U}_{it}) \quad (4.44)$$

$$0 \leq \mu_{it}^{max} \leq N(\underline{U}_{it}) \quad (4.45)$$

$$0 \leq \tilde{\mu}_{it}^{max} \leq N(\underline{U}_{it}) \quad (4.46)$$

$$0 \leq D_{jt}^{max} - D_{jt} \leq M(1 - \overline{U}_{jt}) \quad (4.48)$$

$$0 \leq \Delta D_{jt}^{max} - \Delta D_{jt} \leq M(1 - \overline{U}_{jt}) \quad (4.50)$$

$$0 \leq \gamma_{jt}^{max} \leq N(\underline{U}_{jt}) \quad (4.51)$$

$$0 \leq \tilde{\gamma}_{jt}^{max} \leq N(\underline{U}_{jt}) \quad (4.52)$$

$$0 \leq P_{it} - P_{it}^{min} \leq M(1 - \overline{U}_{it}) \quad (4.53)$$

$$0 \leq \Delta P_{it} - \Delta P_{it}^{min} \leq M(1 - \overline{U}_{it}) \quad (4.54)$$

$$0 \leq \mu_{it}^{min} \leq N(\underline{U}_{it}) \quad (4.55)$$

$$0 \leq \tilde{\mu}_{it}^{min} \leq N(\underline{U}_{it}) \quad (4.56)$$

$$0 \leq D_{jt} - D_{jt}^{min} \leq M(1 - \overline{U}_{jt}) \quad (4.57)$$

$$0 \leq \Delta D_{jt} - \Delta D_{jt}^{min} \leq M(1 - \overline{U}_{jt}) \quad (4.58)$$

$$0 \leq \gamma_{jt}^{min} \leq N(\underline{U}_{jt}) \quad (4.59)$$

$$0 \leq \tilde{\gamma}_{jt}^{min} \leq N(\underline{U}_{jt}) \quad (4.50)$$

$$0 \leq F_{lt}^{max} - F_{lt} \leq M(1 - \overline{U}_{lt}) \quad (4.51)$$

$$0 \leq \vartheta_{lt}^{max} \leq N(\underline{U}_{it}) \quad (4.52)$$

$$0 \leq F_{lt} - F_{lt}^{min} \leq M(1 - \overline{U}_{lt}) \quad (4.53)$$

$$0 \leq \vartheta_{lt}^{min} \leq N(\underline{U}_{it}) \quad (4.54)$$

$$0 \leq \tilde{\vartheta}_{it}^{max} \leq M(1 - U_{lt}) \quad (4.55)$$

Note that the complementary constraints in KKT optimality constraints in the above final MPEC problem are in written after linearized using big M-method discussed in the chapter-3. From the above discussion, non-linear complimentary in Eq. (4.20) to (4.31) are linearized and are formulated in the Eqns. (4.4.3) to (4.55). The problem can finally be rewritten as the following mixed integer linear programming (MILP) equation:

$$\begin{aligned} \textit{Obj:} \quad & \max_{\Delta P_{it}, \Delta D_{jt}} Profit_{Att} \\ & = C_{it}P_{it} + \mu_{it}^{max}P_{it}^{max} - \mu_{it}^{min}P_{it}^{min} - B_{it}D_{it} + \gamma_{it}^{max}D_{it}^{max} \\ & \quad - \gamma_{it}^{min}D_{it}^{min} + C_{it}\Delta P_{it} + \tilde{\mu}_{it}^{max}\Delta P_{it}^{max} - \tilde{\mu}_{it}^{min}\Delta P_{it}^{min} \\ & \quad - B_{it} + \tilde{\gamma}_{it}^{max}\Delta D_{it}^{max} - \tilde{\gamma}_{it}^{min}\Delta D_{it}^{min} \end{aligned} \tag{4.56}$$

$$\text{S.t} \quad \begin{cases} upper\ level\ constraints\ Eq.(22) - Eq.(27) \\ KKT\ optimality\ \ constraints\ Eq.(30) - Eq.(45) \\ attacks\ own\ constraints\ Eq\ (53) - Eq.(58) \end{cases} \tag{4.57}$$

4.4. Simulation Results

The proposed method is implemented on PJM-5 bus system. We empirically investigate the proposed method of financially motivated FDI attacks and can be extended to the larger systems. The data is taken from the MATPOWER packages

As shown in the Fig-4.2, the PJM-5 bus system consists of 4 generation meters, 2 load meters and 6 branch flow meters. According to the proposed method, the attacker need not compromise all the meters. Power system is large widespread network operates with different zones have different communication systems to send data to the system operator, hence it is difficult for an attacker to attack entire system. For any FDI attack, attacker needs to estimate network parameters including thermal limits. The results for five different scenarios i.e., attack on five-line flow meters are illustrated. In each case the attacker can compromises two meters, the attacker has provision of attacking more meters, in this work, attacker is limited to attack two meters. Load forecast error is small, and the injected fake data at the loads are limited to $\tau = 0.05$, and change in flow limits is set as σ = 0.5. The constant positive value M is set to 5×10^4 . The proposed financially motivated FDI attacks are implemented in GAMS softwareousing CLPEX solver on a PC with an Intel i7 3.6GHZ CPU and 8-GB RAM.

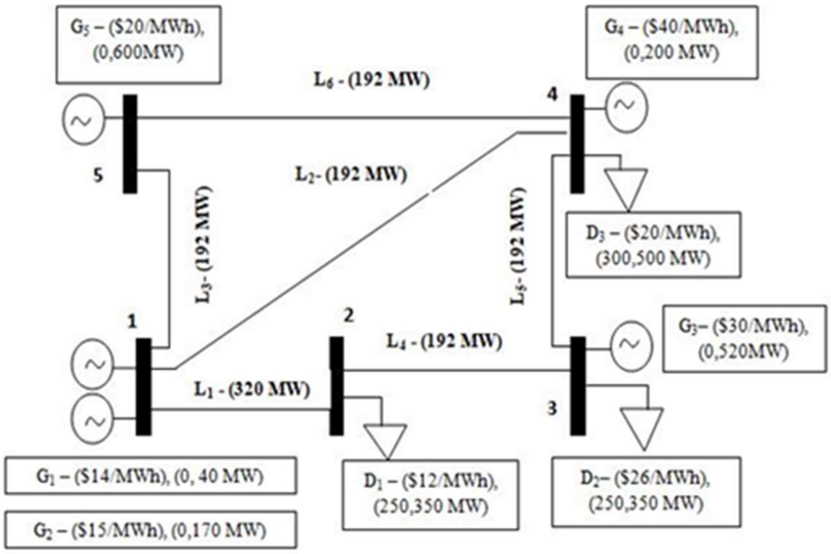


Fig.4.2. PJM-5 Bus system

4.4.1. Financial investigation of the attack on meters (RTU's):

In this section, different scenarios are demonstrated to attack the network measurements. In the proposed attack, attack on line flow meters is considered, there are 6 potential line flow meters and all the meters can be compromised among the total 13 meters. Under no attack condition($\mathrm{C}_{att}= 0$), Line-6 is congested between the bus 4 and 5. The adversary as virtual participant in the market buys power at cheap generating station in the DA market and sell it for higher prices in RT market. For example, a market participant (attacker) wants to make profit, So, the attacker buys 24MW at 31.61 ($/ MW h) power from generating plant-5 at bus-5 in DA market, and sells the same amount of power at different bus number wherever LMPs are high in the RT market. It is assumed that the participant (attacker) sells the power at bus-1 at 49 $/ MWh. The total profit gained by the attacker is $24MW(49-31.61)\$/\mathrm{MWh} = 417.39)\$/\mathrm{hour}$. So, behind any attack made by the attacker there is a financial motivation. In order to successfully launch finically motivated FDIs the attacker need to change the congestion pattern in the system. This can be achieved by the compromised power flow meters. Therefore, for any attack in a time period the attacker runs the optimization problem in Eq. (4.55). According to the presented attacker's decision-making problem, attacker can only compromise line flow meters the rest are untouched. So, attacker can compromise 6-meters ($\mathrm{C}_{att}= 0\ to\ \mathrm{C}_{att}= 6$).

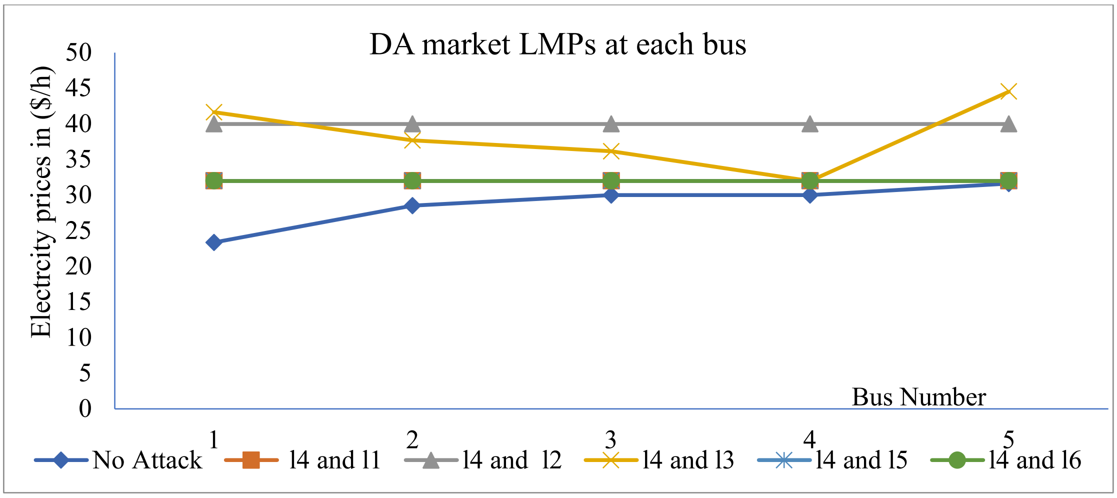


Fig. 4.3. Electricity Market prices in DA market with and without attack at individual bus number

Attacker can launch an attack for financial benefits. In the first case, the attacker compromise line-4 and line-1 meters. As a result, the congested line-6 between the bus 4 and 5 is relived and there is no congestion in the system. This leads to same LMP's at every bus. Similarly, in other case when the attacker tries to compromise line-4 and line-3 meters, it is observed that line-6 along with the line-1 are congested, as a result there will be different LMP's at each bus as shown in the Fig.4.4. Power flow meter values with and without attack are presented in Table.4.1.

Table.4.1. Power flow meters under attack and no attack condition

C_{att}	**L_1**	**L_2**	**L_3**	**L_4**	**L_5**	**L_6**
No Attack	222.8	152.71	-165.60	-27.107	-44.714	-192.00
L_4-L_1	85	124.25	0	-164.25	105.74	-127.14
L_4-L_2	73.32	96.23	40.44	-176.67	93.32	-89.73
L_4-L_3	192	157.95	-140.76	-57.18	0	-192
L_4-L_5	92.44	117.55	0	-157.55	90.11	-120.28
L_4-L_6	85	124.25	0	-164.25	105.74	-127.14

Based on the LMP's in the DA market, the attacker decides to buy/sell the power in the RT market. Figs. 4.3 and 4.4 depicts the electricity market prices variations in both DA and RT markets at each bus. In most of the cases the attacker tries to remove congestion in order to mitigate the risk of getting financial loss. And from Fig. 4.4, it can be observed that under the attack by compromising line-4 and line-1meters, the attacker will obtain loss as the difference between DA and RT market prices is negative.

During this period, the attacker tries to sell this power at bus-4 in the RT market as LMPs are same in both markets. Here the attacker is out of risk from financial losses.

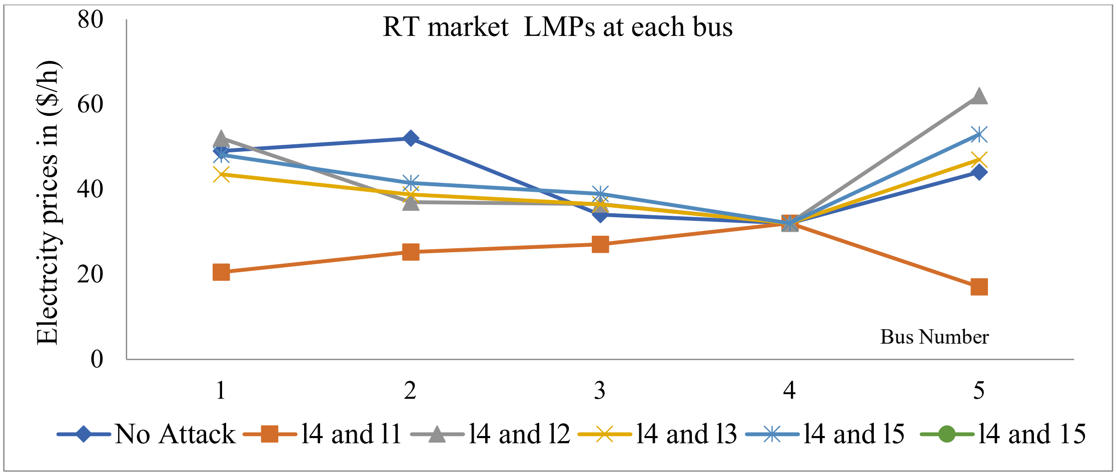


Fig. 4.4. Electricity Market prices in RT market with and without attack at individual bus number.

In the second case when the attacker tries to compromise line-4 and line-2 meters in the DA market, the LMP's at each bus are same but higher compared to the attack on line-4 and line-5 meters. In this case the attacker compromised the meters such that the generator-4 which is costly compared to the other generators is made to dispatch. Consequently, in RT market the LMP's at each bus are higher compared to the other cases. This provides the proof for best attacking strategy. Also, it can be observed that the attacker needs to compromise line-4 meter for every attack to obtain optimal attack vector, and from the Fig.4.3 and Fig.4.4 it can be observed that change in LMP's at bus-4 in both DA and RT market is very less compared to the other variations in the LMP.

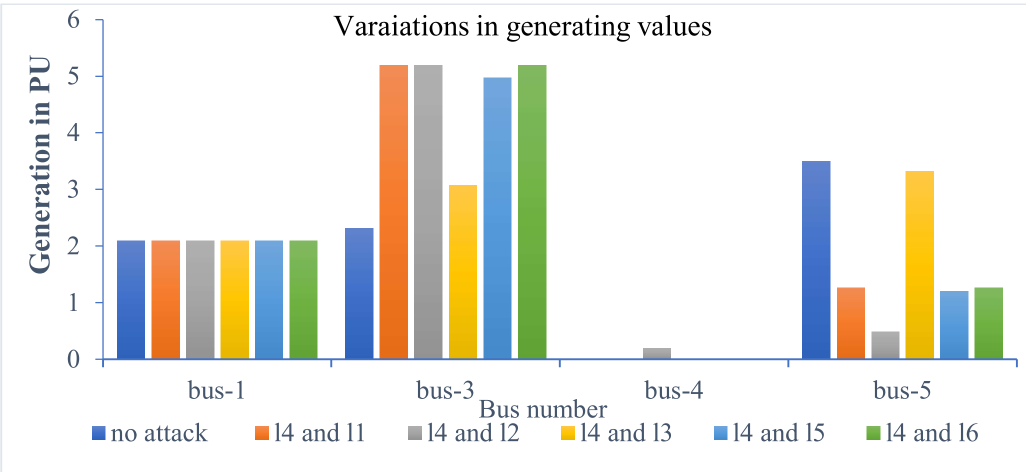


Fig.4.5. Electricity generation under attack and no attack conditions

The generation and demand variations in the DA market are depicted by the Figs.4.5 and 4.6 respectively. The generation at bus-1 under no-attack and attacking conditions is same. But, under the attack conditions the generation at bus-3 and bus-5 are varied. This reveals that the generating meters at bus-3 and bus-5 are more vulnerable compared to the meters at bus-1 and bus-4. This shows that the attacker prefers to buy/sell power at these buses more often compared to other meters to gain financial benefits.

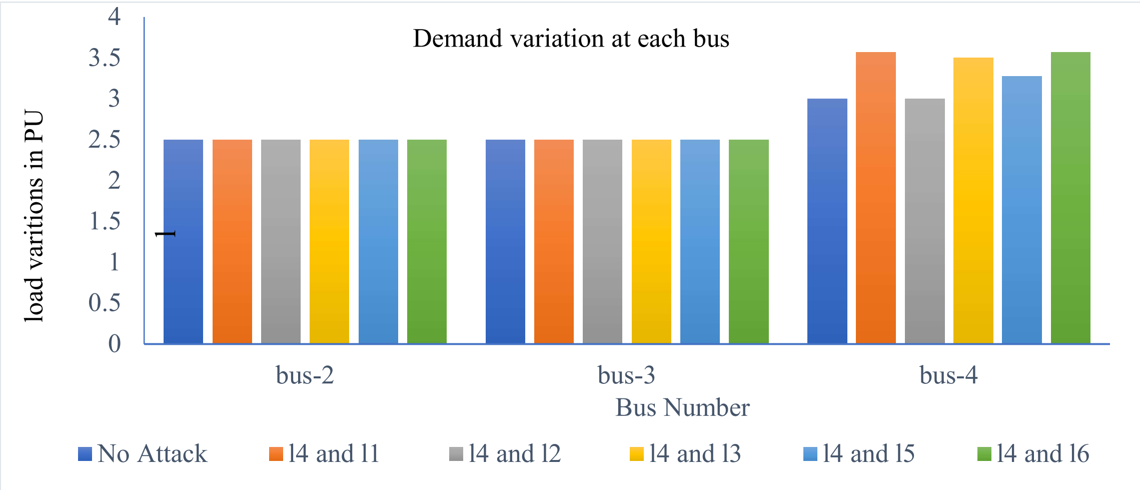


Fig.4.6. Electrcity Demand values under attack and no attack conditio

The demand variations at bus-2 and bus-3 are seen for both attacking conditions. So, the attacker may prefer to buy at these buses. But the change in the demands is observed at bus-4, here the attacker tries to buy the power. From the above discussion it can be concluded that the attacker will be interested to compromise the flow meters of line-3, line-5 and line-6 along with line-4. All these lines form node at bus 4. Hence bus-4 is more vulnerable to the attack. Compromising the above meters in the specified combination will result in financial profits in each case. Moreover, in the case of compromising line-1 and line-4 meters, the attacker can buy power at any generating bus in the network during DA market as LMP's are same. While, in the RT market the attacker has to sell at bus-4, so that the attacker will not get financial loss. This can be depicted by Figs.4.3 and 4.4. It also helps in reducing the risk of being detected by the ISO as only two meters are compromised in each case. The presented model can extend to attack more than two meters. This increases the change in error$\Delta\in$ in Eq. (4.9). As a result, the probability of launching stealthy attack may be reduced.

4.5. Conclusion

In this work we modelled the attacker's objective of profit maximization considering ISO market clearing problem of both DA and RT markets as MILP problem. According to the presented model the attacker is one of the participants in the market as a virtual bidder. Attacker will mislead ISO from its market clearing problem by injecting false data in to RTU's and results in estimating fake data along with maintaining the error within permissible limits. In conjunction to this, attacker leads the market clearing problem to gain consistent financial benefits. The presented model co-relates market prices, state variables and false data injected. The simulation results illustrated reveals the dependency of market prices on state variables and false data. These attack models investigate for the vulnerable areas (meters) in the network and tries to expose weak points in the system (as in the above results line flow meter(l_4). This provides the system operator to improve the security at vulnerable points.

Nomenclature:

sets	
Ω_g, Ω_d	Set of generators and demands respectively in the network
T	Operating time periods
Ω_n	Set of generators and demand connected to bus n
S_{lj}	Generalized shift factor matrix
N_{bus}	Number of buses in the network
Ω_l	Number of branches (lines) in the network
Parameters	
B_{it}, B'_{it}	Electricity Price $(\$/MWh)$ offered by the i^{th} demand in DA and RT markets during the t^{th} time period.
C_{it}, C'_{it}	Electricity Price $(\$/MWh)$ offered by the i^{th} generating in DA and RT markets during the t^{th} time period.
C_{att}	Minimum threshold Value
D_{jt}^{max}	Maximum demand (MW)offered by the j^{th} demand in DA market during the t^{th} time period
D_{jt}^{min}	Minimum demand (MW)offered by the j^{th} demand in DA market during the t^{th} time period
F_{lt}^{max}	Maximum capacity of l^{th} transmission line in (MW)
F_{lt}^{max}	Minimum capacity of l^{th} transmission line in (MW)
P_{it}^{max}	Maximum generation capacity (MW)offered by the i^{th} demand in DA market during the t^{th} time period
P_{it}^{min}	Minimum generating capacity (MW)offered by the i^{th} demand in DA market during the t^{th} time period

X_{DA}	Set of DA market variables
X_{RT}	Set of RT market variables
ΔD_{jt}^{max}	Maximum incremental change in demand (MW)offered by the j^{th} demand in RT market during the t^{th} time period
ΔD_{jt}^{min}	Minimum incremental change in demand (MW)offered by the j^{th} demand in RT market during the t^{th} time period
ΔF_{lt}^{max}	Maximum incremental change allowed of l^{th} transmission line in (MW)
ΔF_{lt}^{min}	Minimum incremental change allowed of l^{th} transmission line in (MW)
ΔP_{it}^{max}	Maximum incremental change in generation capacity (MW)offered by the i^{th} demand in RT market during the t^{th} time period
ΔP_{it}^{min}	Minimum incremental change in generation capacity (MW)offered by the i^{th} demand in RT market during the t^{th} time period
Variables	
D_{jt}	Demand (MW) cleared (scheduled) in the DA market during the t^{th} time period
F_{lt}	Transmission capacity scheduled for the l^{th} line during the t^{th} time period
P_{it}	Generating capacity (MW) cleared (scheduled) in the DA market during the t^{th} time period
LMP_{it}^{EP}	Locational Marginal Price in ($) at the i^{th} bus during the t^{th} time period in DA market
LMP_{it}^{EA}	Locational Marginal Price in ($) at the i^{th} bus during the t^{th} time period in RT market
R_{DA}, R_{RT}	Value of objective function in DA and RT market
ΔD_{jt}	Incremental Demand (MW) value cleared (scheduled) in the RT market during the t^{th} time period
ΔF_{lt}	Incremental change in scheduled capacity of l^{th} transmission line in (MW)
ΔP_{it}	Incremental generation (MW) value cleared (scheduled) in the RT market during the t^{th} time period
$\lambda_t, \tilde{\lambda}_t$	Locational Marginal Price in ($) at the i^{th} bus during the t^{th} time period in DA, and RT markets
ΔZ_{mt}	False data injected in the m^{th} transmission line (MW) during the t^{th} time period

CHAPTER 5

Stochastic Optimal Scheduling of Virtual Power Plants in market-based power system

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Stochastic Optimal Scheduling of Virtual Power Plants in market-based power system

5.1. Introduction

The world's power system utilities are being restructured and reformed, resulting in the loss of monopolies in the vertically integrated Power sector. The deregulated market regime has provided an enabling environment for faster expansion in generation, transmission, and distribution networks to encourage investment in the power sector. As a result, a large number of market participants, stakeholders, independent power producers, electricity traders, and regulators plays an active role. Renewable energy-based electricity generation is gaining massive traction in every country on the planet. It has had a significant impact on the deregulated power market. These developments have an impact on the financial health of incumbent fossil fuel generators, whose marginal costs of generation is comparatively high.

RE sources are incorporated in the electricity grid in one of the two ways: centralised or distributed. A stochastic model is frequently used to schedule large-scale renewable energy sources that are centralised. While RE sources that are distributed and integrated have a small capacity, they are extensively spread over the network [57]. However, the uncertainties in RE generation and market price changes can be viewed as a double-edged sword, as while RE sources offer a promising solution for reducing carbon footprints, they also impose generation-demand mismatches and adding to this increases power system's regulating burden, which leads to limited participation in the electricity markets.

The virtual power plant concept offers a centralised solution to these issues. VPP aggregate total energy production from distributed energy resources (DERs) including small to medium-scale renewable generating units such as small hydro plants, roof top solar PV systems, wind farms, flexible loads, diesel generator sets, Combined Heat and Power Producers (CHPs) and so on.

These utilities can be combined with other fossil fuel power plants to form a cluster of energy sources. VPPs, with aim to consolidate a cluster of small distributed RE-based generating units into a single entity participates in the competitive electricity market. This has brought further complexities in market operation, primarily in terms of its operation scheduling, and economic profitability, etc.

VPP acts as a link between distributed energy resources and whole-sale electricity markets, trading energy on behalf of DER owners who are unable to participate in the market directly. VPP concept enables small-scale renewable energy generators to enter the power market.

The power generation and load imbalances are dynamic in nature. Furthermore, there is unpredictability in RE generation (e.g., wind farms, solar PV plants, etc.) due to the intermittency and unpredictability of RE sources, as well as imprecise forecasting, adds to the complexity of RE integration with electrical networks. Keeping in view about the complexities, RE power is usually non-dispatchable, system operators in DAM and RTM face a difficult issue in scheduling RE generators in conjunction with CPPs.

Understanding the uncertainties in the RE generating process, which are classified as stochastic process. It is being attempted to connect RE producing utilities with other generating units such as CPPs, storage units, and flexible loads. Similar, to the other market participants VPP as a single entity tries to maximize its profits by trading its power in DA and regulating reserve (RR) markets while, optimizing its resources.

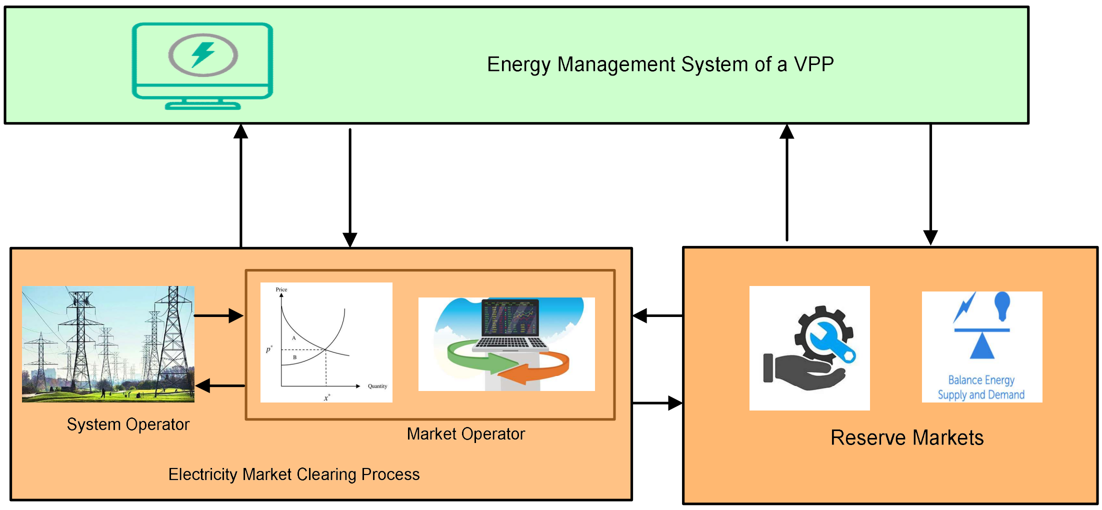

Fig.5.1. VPP energy management system showing its participation in DA and Reserve market

A two-stage stochastic programming approach is proposed to describe the uncertainties that arise during the process of integrating these VPPs with RE sources and to discover the best solution for scheduling RE units in the electricity market clearing process.

5.1.1. Impacts of Renewable Generating Units on the Electricity Markets

The market conditions have changed dramatically as a result of renewable energy generation. Historically, the cost of RES generation has decreased dramatically over time, and the per unit cost is low when compared to the cost of fossil fuel-based generating. The introduction of renewable energy into the market has resulted in lower wholesale electricity rates.

According to [45], the levelized cost of electricity (LCOE) for PVs declined by 72 percent from $304 per MWh to roughly $86 per MWh between 2009 and 2017. The LCOE of onshore wind has fallen by 27%, from $93 to $67 per MWh.

These reasons, as well as the fact that greenhouse gas emissions are negligible, are critical in establishing a renewable energy market. However, it has had a significant influence on the economic viability of traditional generators and has had a significant influence on the financial health of fossil fuel generator stakeholders. It has also been discovered that widespread adoption of renewable energy is and will continue to lead to even negative electricity costs, in which traditional generators must pay to create electricity [35].

Another important aspect that impacts grid scheduling and operation is the uncertainty of RE generation [47]. With its set of producing units (including conventional and RE sources), storage units, biomass plants, and flexible demands, VPPs can give a feasible way to minimise such concerns. These VPPs can optimise their energy sources by using conventional plants when RE production is low, and storage units are used to charge when RE production is high. It also highlights the significance of traditional sources in the system's sustenance. In the capacity markets, these typical generators can serve as capacity plants.

Stochastic and optimal scheduling of VPP is done as part of market research in the context of economic profitability of stakeholders [42-45], optimal resource utilization to fulfil end-user requirements, and minimise imbalances of load-generation dynamics in RE dominated electricity market.

5.2. Uncertainties Modelling

The information about market prices, RE intermittence generation, and reserve deployment requests is unknown and unclear during the decision-making process. As a result, VPP must deal with these uncertainties while making strategic market scheduling decisions. As a result, it's critical to deal with these uncertainties.

Using historical data and forecasting tools such as ARIMA models [48, -50], Monte Carlo Simulation tool [59], and interval approaches [51,62-64], these scenarios are generated. For the optimum realisation of the real output from WT and PV plants, a suitable set of scenarios is evaluated. A huge number of scenarios may result in a computationally infeasible task.

The uncertainties mentioned above are modelled using a set of predefined discrete scenario realizations indicated by $w \epsilon \Omega^{w}$. Therefore, in this study we use the discrete set of scenarios used in the reference [50] which are feasible and computationally efficient. Each scenario of w is defined by the parameters $\mu_{wt}^{E}, \tilde{\mu}_{wt}^{R+}, \mu_{wt}^{R+}, \tilde{\mu}_{wt}^{R-}, \mu_{wt}^{R-}, K_{wt}^{R-}, K_{wt}^{R-}$, and $P_{rtw}^{R,A}$ that indicates energy market price, power capacity price in the down-reserve market, the up and down-reserve deployment request, and the available generating levels of stochastic RE generating units respectively. Each scenario w is defined with probability of occurrence Π_{w}. The sum of overall probabilities of the scenarios is equal to 1, i.e., $\sum_{w} \pi_{w} = 1$.

5.3. Stochastic Optimal Scheduling

This section analyses the optimal scheduling problem of the electricity markets where virtual power plants (VPP) sell or buys the energy with the objective of profit maximization. On other hand, reserve markets provide the flexibility to increase or decrease the total energy production of VPPs upon the request of the system operator.

The Day-Ahead and reserve electricity markets are considered in this section to analyse the market scheduling decisions one day in advance. While making this scheduling decision the VPP faces a number of uncertainties [33,41]. Following are the uncertainties faced in the market scheduling process:

- The market prices include the day-ahead market prices and the reserve market prices (for both capacity and energy).
- Stochastic nature of the available renewable generating unit's production level.

- The requests to deploy reserve sources by the system operator.

The proposed uncertainties are modeled for obtaining optimal market scheduling decisions. As the proposed approach is probabilistic and not deterministic in nature, inappropriate modeling will result in loss or profit to the VPPs and even results in an infeasible operation of utilities/ generation and demand asset.

5.3.1. Two- Stage Stochastic optimal Scheduling Problem

The optimal decision-making problem under these scenarios is modelled as a two-stage stochastic programming model and is interpreted as follows:

$$max_{\varphi^V} \sum_{w\in\Omega^W} \Pi_w \left\{ \sum_{t\in\Omega^T} \Big((\mu_t^E P_t^E \Delta t) + (\tilde{\mu}_{wt}^{R+} + K_{wt}^{R+} \mu_{wt}^{R+} \Delta t) P_t^{R+} \right.$$
$$\left. + (\tilde{\mu}_{wt}^{R-} - K_{wt}^{R-} \mu_{wt}^{R-} \Delta t) P_t^{R-} - \sum_{C\in\Omega^C} \big(C_C^{C,F} u_{ct}^C + C_C^{C,V} P_{ctw}^C \Delta t \big) \Big) \right\} \tag{5.1}$$

Subject to:

$$\underline{P}_t^E \le P_t^E \le \overline{P}_t^E \tag{5.2}$$

$$\underline{P}_t^{R+} \le P_t^{R+} \le \overline{P}_t^{R+} \tag{5.3}$$

$$\underline{P}_t^{R-} \le P_t^{R-} \le \overline{P}_t^{R-} \tag{5.4}$$

$$P_t^E + K_{wt}^{R+} P_t^{R+} - K_{wt}^{R-} P_t^{R-} = \sum_{C\in\Omega^C} P_{ctw}^C + + \sum_{r\in\Omega^R} P_{rtw}^R + \sum_{s\epsilon\Omega^S} \big(P_{stw}^{S,D} - P_{stw}^{S,C} \big) - \sum_{d\epsilon\Omega^D} P_{dtw}^D \tag{5.5}$$

$$\underline{P}_{dt}^D \le P_{dtw}^D \le \overline{P}_{dt}^D \qquad ; \forall d \in \Omega^D \tag{5.6}$$

$$\sum_{t\in\Omega^T} P_{dtw}^D \Delta t \ge \underline{E}_d^D \qquad ; \forall d \in \Omega^D \tag{5.7}$$

$$\underline{P}_{ct}^C u_{ct}^C \le P_{ctw}^C \le \overline{P}_{dt}^C u_{ct}^C \qquad ; \forall C \in \Omega^C \tag{5.8}$$

$$0 \le P_{rtw}^R \le P_{rtw}^{R,A} \qquad ; \forall R \in \Omega^R \tag{5.9}$$

$$\underline{P}_{st}^{S,C} \le P_{stw}^{S,C} \le \overline{P}_{st}^{S,C} \qquad ; \forall S \in \Omega^S \tag{5.10}$$

$$\underline{P}_{st}^{S,D} \le P_{stw}^{S,D} \le \overline{P}_{st}^{S,D} \qquad ; \forall S \in \Omega^S \tag{5.11}$$

$$e^{S}_{stw} = e^{S}_{s(t-1)w} + P^{S,C}_{stw}\Delta t \eta^{S,C}_{s} - \frac{P^{S,D}_{stw}\Delta t}{\eta^{S,D}_{s}} \qquad ;\forall S \in \Omega^{S} \quad (5.12)$$

$$\underline{E}^{S}_{st} \leq e^{S}_{stw} \leq \overline{E}^{S}_{st} \qquad ;\forall S \in \Omega^{S} \quad (5.13)$$

Where set $\varphi^{V} = \{P^{E}_{t}, P^{R+}_{t}, P^{R-}_{t}, \forall t \in \Omega^{T}; u^{C}_{ct}, \forall C \in \Omega^{C};\ P^{C}_{ctw,} \forall C \in \Omega^{C};\ P^{R}_{rtw}, \forall R \in \Omega^{R};\ P^{S,C}_{stw},; \forall S \in \Omega^{S};\ P^{S,D}_{stw}, \forall S \in \Omega^{S};\ e^{s}_{stw},; \forall S \in \Omega^{S}\} \forall t \in \Omega^{T}, \forall w \epsilon \Omega^{W}$ are the optimization variables in the above problem. Π_{w} indicates, weight of each scenario w [39,40,41]. VPPs objective is defined in the Eq. (5.1) throughout the planning horizon and consists of the following terms:

- The term $\mu^{E}_{t} P^{E}_{t} \Delta t, \forall t \in \Omega^{T}$ represents the revenues acquired by the VPP for their participation in the DA markets. Here the variable P^{E}_{t} may be +ve (if VPPs sell power in the DA market) and -ve (if the VPPs buy power in the DA markets).
- The term $(\tilde{\mu}^{R+}_{wt} + K^{R+}_{wt} \mu^{R+}_{wt} \Delta t) P^{R+}_{t}, \forall t \in \Omega^{T}$ represents the revenue obtained by the VPP for participating in the Up-reserve markets. These revenues are again divided into $(\tilde{\mu}^{R+}_{wt} P^{R+}_{t})$ capacity payments and $(K^{R+}_{wt} \mu^{R+}_{wt} \Delta t P^{R+}_{t})$ energy payments.
- The term $(\tilde{\mu}^{R-}_{wt} - K^{R-}_{wt} \mu^{R-}_{wt} \Delta t) P^{R-}_{t}, \forall t \in \Omega^{T}$ represents the revenue obtained by the VPP for participating in the Down-reserve markets. These revenues are again classified into $(\tilde{\mu}^{R-}_{wt} P^{R-}_{t})$ capacity payments and $(K^{R-}_{wt} \mu^{R-}_{wt} \Delta t P^{R-}_{t})$ energy payments.
- Variable cost incurred by the CPPs is represented by the term $\left(C^{C,F}_{C} u^{C}_{ct} + C^{C,F}_{C} P^{C}_{ctw} \Delta t\right); \forall C \in \Omega^{C}, \forall t \in \Omega^{T}$

Where Eqs. (5.2), (5.3) and (5.4) are the constraints, representing upper and lower bounds on the amount of power traded in the DA, up, and down-reserve markets respectively. Eq. (5.5) represents the power balancing constraint. Eqs. (5.6) and (5.7) puts power consumption limits on the demands. $u^{C}_{ct} \in \{0,1\}; \forall C \in \Omega^{C}, \forall t \in \Omega^{T}$ denotes binary variable, it represents the on/off status of CPP. Constraints in the Eqs. (4.8), and (4.9) limits the power produced by the CPPs and stochastic RE generation level respectively. Eqs. (5.10) and (5.11) represents the constraints on the charging and discharging level of storage units, while the Eq. (5.12) represents the energy production level in storage units and Eq. (5.13) represents the limiting constraint on the energy level of the storage units. The above problem is a Mixed Integer Linear Programming (MILP) problem solved using CLPEX solver.

5.4. Simulation Results

The proposed two-stage stochastic model for optimal scheduling is tested on 4-hour planning horizon, and the required data is collected from [50]. The simulation results are implemented in GAMS software using CLPEX solver on a PC with an Intel i7 3.6GHZ CPU and 8-GB RAM.

The maximum power traded (sold/buy) in the energy market is limited to 100MW. The up and down reserve market capacity is limited at 50 MW. Energy Market prices along with up and down reverse market prices for the power capacity are presented in Table-5.1. Generation limits of the CPPs and their economic data along with the flexible demand data is referred from IEEE-5 bus system. The forecasted wind power production level is provided in Table-5.2. Reverse deployment request is considered to be 80% of the power capacity scheduled in down reserve market during the time period-2, similarly for up reserve market 50% and 100% of scheduling capacity are requested during the time period-1 and 3 respectively. No reserve deployment is requested during the time period-4. This data is assumed and considered based on the system operators request for the reverse deployments.

In the above two-stage stochastic programming model, the uncertainty in the RE (wind) generating levels along with the uncertainty present in the reserve deployment request are modeled by using two equiprobable scenarios in each stage. Thus 4 scenarios (two of each) are considered. For the sake of simplicity these scenarios are independent of each other.

Table 5.1. Energy and Reserve market price data

Time Period	Price [$/MWh]				
	Energy Markets	Up reserve market		Down reserve market	
		Energy	Capacity	Energy	Capacity
1	12	14	4	14	4
2	14	15	10	38	10
3	22	30	8	26	8
4	32	20	6	25	6

Table 5.2. Total Wind forecasting level for different time periods

Time Period	Wind Power Generating level [MW]			Scenario Weights
	R_1	R_2	R_3	
1	70	100	120	0.25
2	100	83	140	0.25
3	95	75	115	0.25
4	55	80	100	0.25

The proposed two stage stochastic model is run by the system operator to determine optimal scheduling for each generating unit in each time period. Considering the data presented in the tables-5.1 and 5.2, the optimal power scheduled and market prices in Day-ahead and reserve markets are presented and explained in Figs. 5.2 to 5.8.

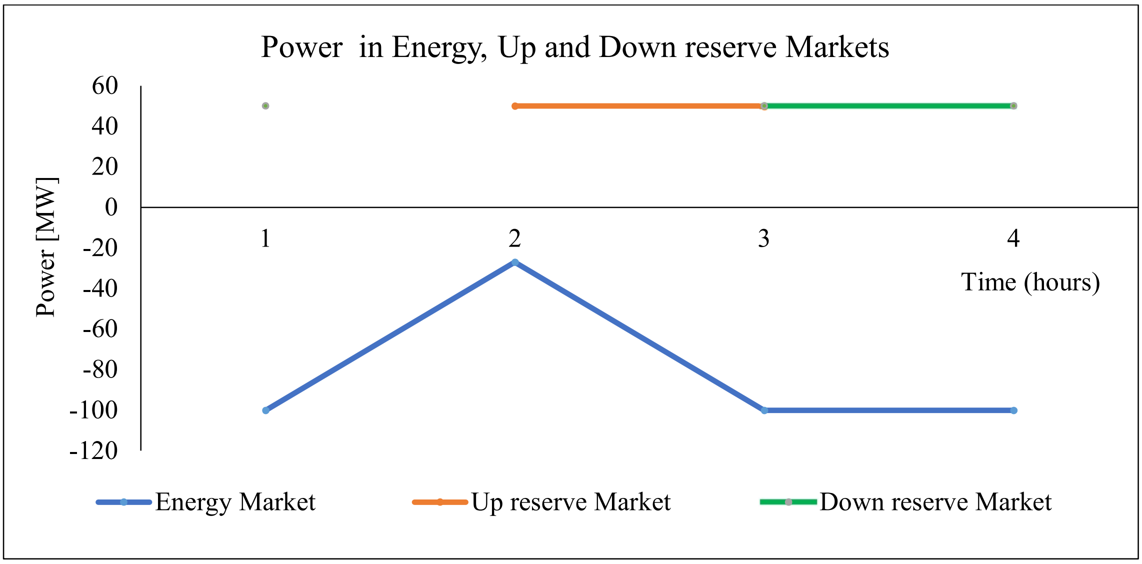

Fig.5.2. Plants Power traded in energy, up-reserve and down reserve markets

VPPs participate in the energy markets and submit their bids based upon their demand levels in the specific time period, these bids are submitted in terms of price and quantity to the system operator. Fig. 5.2 shows, the optimal amount of power traded in each time period in the energy, up and down reserve markets. In these markets the VPP decides to buy the energy, expect for the time period-2 when its demand level is being low and during this period energy is supplied by their own renewable generating units. In all other cases the VPP tries to buy the energy in the energy market. In the case of up reserve market, the power is traded in time periods 2 and 3. While in the case of down reserve market power is traded during the periods 1, 3 and 4. No power is traded during the time period-2. This is because of the maximum demand levels and low prices for the reserve deployment as explained in Table-5.2.

Based up on the amount of power traded in the energy and reserve markets, conventional power plants are scheduled. During the low demand level i.e., during the time period-2, these plants are turned off. Fig. 5.3 shows, scheduling of CPP. The power plants with highest economical prices are not scheduled for the entire market operation as shown in Fig 5.6. The renewable generation is maximum at each time period as shown in the Fig. 5.5. Power consumption levels in each time period is same expect for the time period T-2. In order to supply their demand level during the maximum demand periods, VPPs enter in to the power markets. Therefore, based on the market prices the VPP decides to buy maximum power from RE sources in the markets.

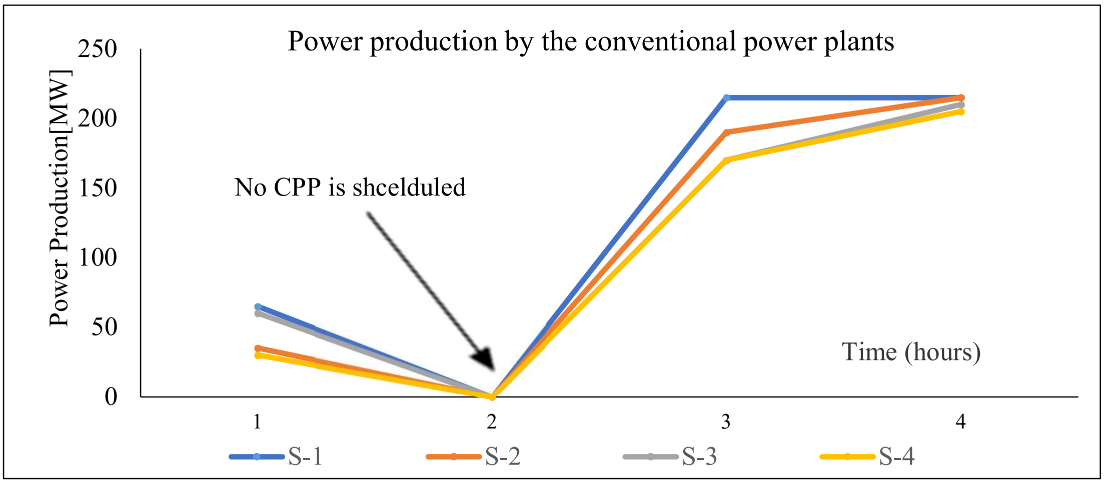

Fig.5.3. Power consumption by the conventional power plants in the market

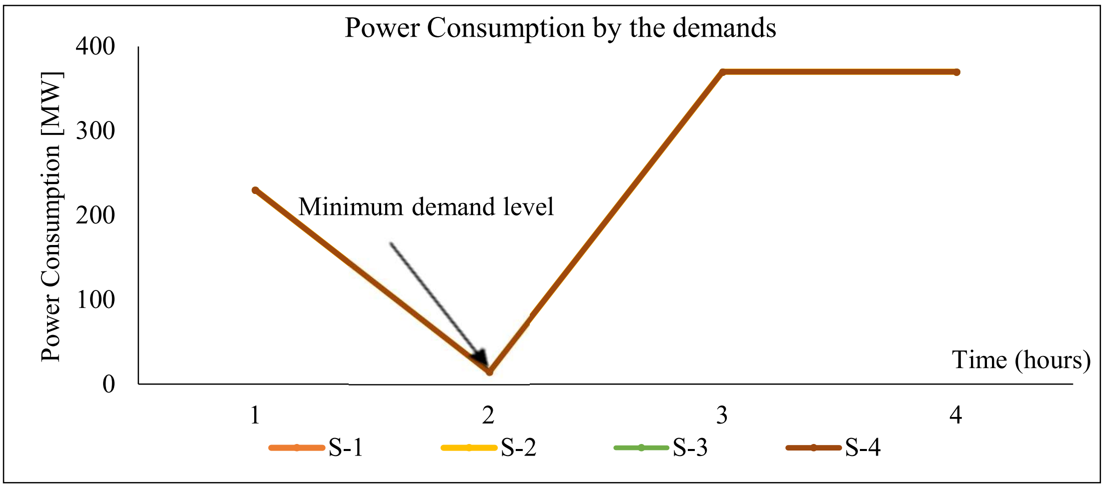

Fig.5.4. Power consumption by the demand in the market

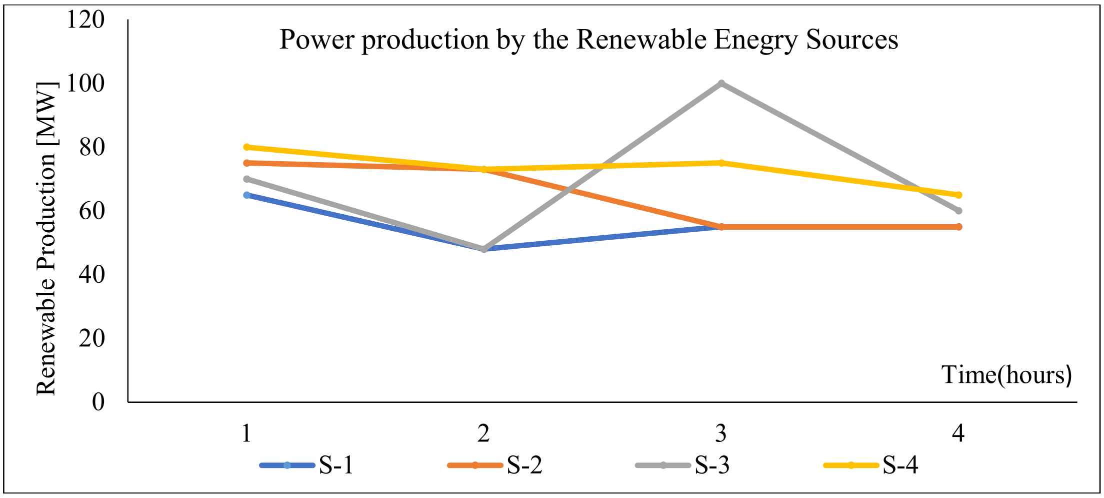

Fig.5.5. Forecasting Power generating level of Wind Power source

From the above optimal scheduling process, it is clear, that the stochastic RE sources are made to dispatch in all time periods and based on the power demand level and market prices the system operator request for up and down reverse deployments during a specific time period.

The conventional power plants are scheduled only when the required demand is more than the RE generation and reverse deployment capacity. Fig.5.6 shows scheduled dispatch of CPPs. During each hour, generator (G-4) is not dispatched. Similarly, during second period no CPP is scheduled. This puts economic burden on the conventional generators. The prices incurred during the power production is less than the revenues obtained. Hence, it is required to provide policy incentives and to take standard tariff policy mechanism for conventional generation. Updating to the current technology, increasing ramp up and ramp down rates of the generators may make their way possible to compete with the RE sources.

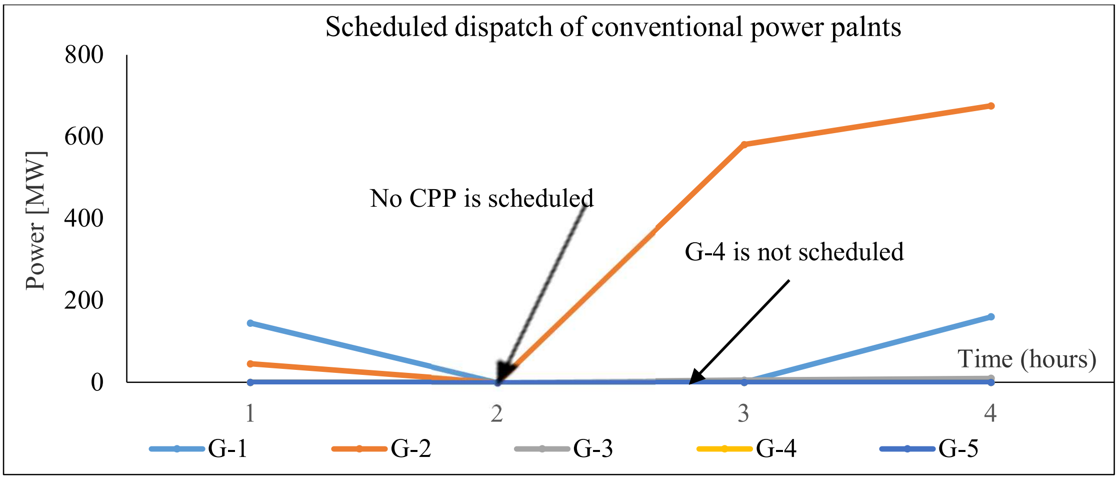

Fig.5.6. Scheduled power dispatch of conventional power plants

Fig.5.7 and Fig.5.8 represent market clearing price ($/h) variations with and without RE sources. It is observed that MCP's without RE sources is always greater than the MCP'S with RE. Therefore, it is clear that the conventional generators are forced to generate power for lesser prices. This price variations will result in economic losses. Therefore, it is required to provide cost-based policy incentives for the conventional plants. Some of the countries are following fed in tariff policy, purchase obligations and contract for difference mechanism to create a balance pricing mechanism.

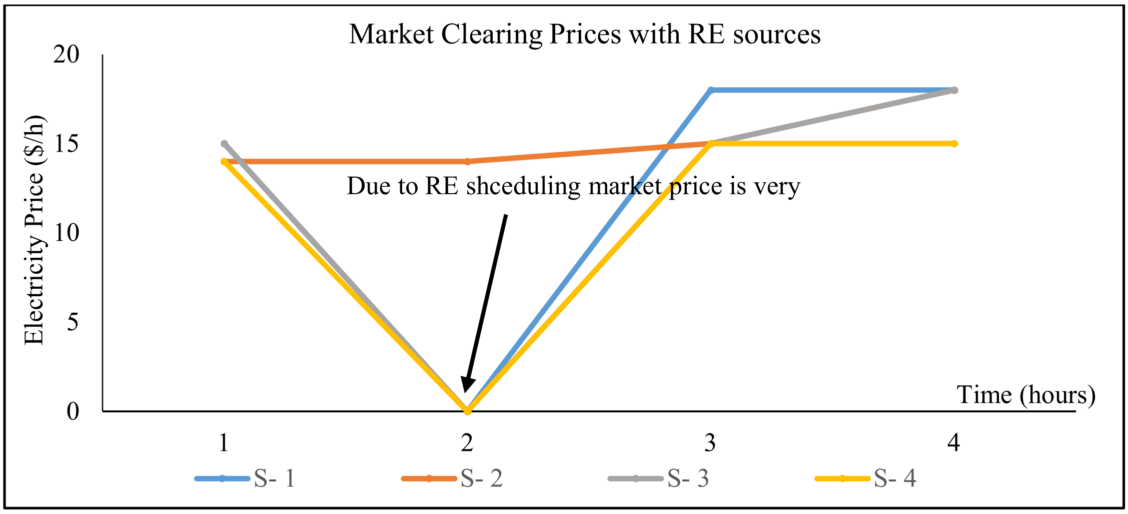

Fig.5.7. Market clearing prices in $/h with RE sources for different time periods.

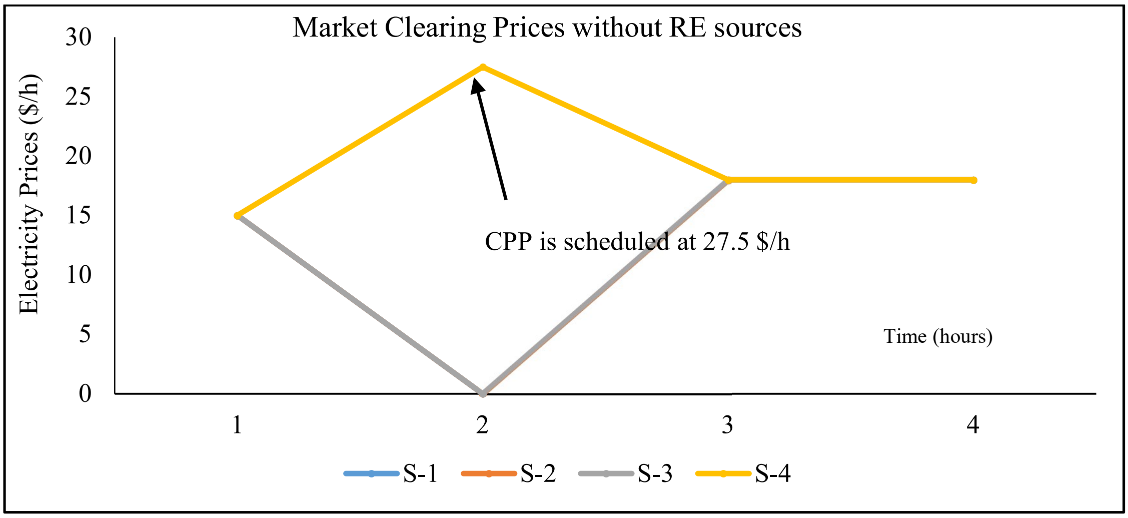

Fig.5.8. Market clearing prices in $/h without RE sources for different time periods.

The above simulation result has established that during low demand periods VPP optimizes its resources by using RE (wind) generation only. During maximum demand periods CPPs are scheduled, and reserve deployment requests are made accordingly to the system operator request. With interest participation of VPPs market price levied on the consumers is reduced but burden on the conventional generators increases. The simulation graphs shown in Fig.5.7 and 5.8 has clearly indicated the price variations with and without RE sources. This clearly indicate that the VPP in the electricity market are acting as price makers and sometimes as price takers.

The above two stage stochastic problem is executed using deterministic approach, in such case the optimal scheduling of VPP is found infeasible. This is due to the error while providing reserve deployment request. This highlights the importance of an accurate modelling of the uncertainties in the problem. Economic impact on CPPs due to RE sources can also be interpretated from the above results.

5.5. Conclusion

Power and energy balancing mechanisms are evolutionary in market operation from the cost economic angle. It depends on RE policies, power sector reform strategies, price discovery mechanisms, generation scheduling economics, load management techniques, role of VPPs, etc. Like every generator looking for its profitability and services to the system operation. VPPs with its resources look for maximization of their profits. The proposed two-stage stochastic modelling for optimal scheduling of VPP in electricity markets has established the merits of its generation scheduling to mitigate certain uncertainties as explained above. The simulation work provides impressive results for accurate optimal scheduling of the generating units of VPP. This method may be extended to large scale market operations and big power system networks by dividing the system into several subsystems.

Nomenclature:

Sets	
Ω^C	Set of Conventional Power Plants
Ω^D	Set of Demands
Ω^R	set of renewable energy generating units
Ω^S	Set of storage units
Ω^T	Scheduling Time periods
Ω^W	Set of discrete scenarios
Parameters	
$C_C^{C,F}$	Online cost of conventional generating unit c [$/MWh]
$C_C^{C,V}$	Variable cost of conventional generating unit c [$/MWh]
K_{wt}^{R+}	Up-reserve requirement request factor in time period *t* [pu]
K_{wt}^{R-}	Up-reserve requirement request factor in time period *t* [pu]
$\overline{P}_{dt}^{D}, \underline{P}_{dt}^{D}$	Upper and lower bounds of the power consumption of the d^{th} demand [MW] in time period *t*

$\underline{E}_{d}^{D}$	Minimum energy consumption of the demand d^{th} throughout the planning horizon [MW]
$\overline{P}_{dt}^{C}, \underline{P}_{ct}^{C}$	Upper and lower bounds on the power generation of the c^{th} conventional generating unit [MW] in time period t
$P_{rtw}^{R,A}$	Available RE generating limit of unit r in the time period t
$\underline{P}_{st}^{S,C}, \overline{P}_{st}^{S,C}$	Upper and lower bounds on the charging capacity of storage unit s [MW]
$\underline{P}_{st}^{S,D}, \overline{P}_{st}^{S,D}$	Upper and lower bounds on the discharging capacity of storage unit s [MW]
$\underline{E}_{st}^{S}, \overline{E}_{st}^{S}$	Upper and lower bounds on the energy stored in the storage unit s [MW]
Δt	Duration time period in hours
P_{ct}^{C}	Power generation of the conventional power plants in time period t [MW]
P_{dt}^{D}	Demand d power consumption level in the time period t [MW]
P_{rt}^{R}	RE generating unit r production level during the time period t
$P_{st}^{S,D}$	Power discharging level of storage unit s in the time period t
$P_{st}^{S,C}$	Charging level of storage unit s in the time period t [MW]
e_{st}^{S}	Energy stored by the storage unit s in the time period t [MWh]
P_{t}^{R+}	Power capacity traded in up-reserve market in time period t
P_{t}^{R-}	Power capacity traded in down-reserve market in time period t
P_{t}^{E}	Amount of Power traded in the market during the time period t
Parameters	
$C_{C}^{C,F}$	Online cost of conventional generating unit c [$/MWh]
$C_{C}^{C,V}$	Variable cost of conventional generating unit c [$/MWh]
P_{ct}^{C}	Power generation of the conventional power plants in time period t [MW]
P_{dt}^{D}	Demand d power consumption level in the time period t [MW]
P_{rt}^{R}	RE generating unit r production level during the time period t
$P_{rt}^{R,A}$	Available RE generating limit of unit r in the time period t
$P_{st}^{S,D}$	Power discharging level of storage unit s in the time period t
$P_{st}^{S,C}$	Charging level of storage unit s in the time period t [MW]
e_{st}^{S}	Energy stored by the storage unit s in the time period t [MWh]
P_{t}^{R+}	Power capacity traded in up-reserve market0in0time period t
P_{t}^{R-}	Power capacity traded in down-reserve market0in0time period t
P_{t}^{E}	Amount of Power traded in the market during the time period t

Chapter 6

Security constrained Bi-level Strategic Scheduling of Virtual Power Plant in Electricity markets

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Security constrained Bi-level Strategic Scheduling of Virtual Power Plant in Electricity markets

6.1. Introduction

Virtual Power Plant concept allows distributed energy sources, and small utilities to participate in the electricity markets. It is well known fact that the each and every market participant tries to maximize their profit through trading electricity in the markets. Similar to the other market participants, VPP also tries to make profits. Hence, strategic bidding is necessary to sustain against the fluctuating market prices. VPP as an aggregator of different energy sources optimize its internal demands and then participate in the electricity market.

In the system modelling, the VPP that is considered as a single entity in the electricity market of DERs for electricity generation and flexible load duration profiles. The DERs include solar PV plants, wind turbines, CHPs, diesel generating sets (DGs), and energy storage/discharge systems (ESSs). Uncertainties in scheduling and making decision are modelled using scenario realization technique (refer chapter-4). The VPP uses the flexibility of its energy assets and participate in the DA energy and reserve markets to increase its profitability. This decision is made before the scenario '*w*' is actually realised, it is termed '*here and now'* decision. It schedules its energy assets after forecasting and modelling the data related to uncertainties as well as information regarding up and down reserve deployment requests made by market participants to the market operator, and this act of taking dispatch decision is termed as *'wait and see'* decision with respect to the scenario.

Thus, knowing the actual requirements of electricity markets, VPP takes strategic decision about its scheduling of energy assets. Therefore, VPP emerges as leader in deciding market price. Thus, VPP acts as price maker in the market followed by the market clearing process. A bi-level programming is suitable for modelling leader and follower models and is developed for optimal scheduling of the VPP, with the objective to maximise profit by serving as price maker.

Network flow constraints are included in the optimization problem. Therefore, the optimization model is converted into security constrained power flow model. The congestion on the transmission line is realized along with congestion prices. The impact of congestion on VPPs profit is worked out.

6.2. Mathematical Modelling of VPP's strategic behaviour

The VPP considered here participates in DA, and Reserve market. The0bi-level model consists of upper level and lower level as explained earlier in the previous Chapter-3. The upper-level problem is said to be leader whereas the lower-level problem is considered as follower.

VPP as a price maker decides the market price decision by participating in the DA and reserve markets. The VPP strategic decision in scheduling its energy assets is followed by the utilities participating in DA and reserve markets. Hence bi-level modelling is suitable for investigating the VPP's strategic behaviour. The mathematical formulation is explained as follows:

6.2.1. Upper-level Problem:

The objective function in the upper-level model is to maximize the profits obtained by the VPP and minimize the cost of generation of VPP. It consists of three components which includes profit obtained by participating in DA and reserve market, and revenues obtained from scheduling VPP components.

$$P^{DAM} = \sum_{t=1}^{24} \lambda_t^{DA} \left[P_t^{DA+} - P_t^{DA-}\right] \qquad \forall \Gamma_{DAM} \quad (6.1)$$

$$P^{RM} = \sum_{t=1}^{24} \left[\lambda_t^{RU} P_t^{RU} + \lambda_t^{RD} P_t^{RD}\right] \qquad \forall \Gamma_{RM} \quad (6.2)$$

$$C^{VPP} = \sum_{w \epsilon \Pi^{DAM,RM}} \Pi_w \sum_{t=1}^{24} C_{tw}^{PV} + C_{tw}^{WT} + C_{wt}^{CHP} + C_{wt}^{DG} + C_{wt}^{CPP} - C_{wt}^{d} \qquad \forall \Gamma_{VPP} \quad (6.3)$$

Eq. (6.1) represents the profit acquired by selling and bidding power by the VPP designated by P^{DAM}. Eq. (6.2) represents the profit acquired by offering reserve capacity for balancing the system in the reserve market. Finally, Eq. (6.3) indicates the revenues obtained in scheduling the components of VPP. This objective function is subjected to the constraints related to different VPP components and includes network flow constraints at the end. These constraints are for formulated below, corresponding to the each VPP component and constraints related to VPP participation in the DA and reserve market.

Subject to

$$\sum_{i} P_{itw}^{G,VPP} + \sum_{i\in\Omega^S}\left(P_{stw}^{S,C} - P_{stw}^{S,D}\right) - \sum_{j} P_{jtw}^{D,VPP} = \overline{P}_t^{DAM} - \underline{P}_t^{DAM} + K_{tw}^{DRM+}P_t^{URM+} - K_{tw}^{DRM-}P_t^{DRM-} \quad \forall i \in \Gamma_{VPP,} j \in \Gamma_{DEM,} t \qquad (6.4)$$

$$\underline{P}_{itw}^{G,VPP} \leq P_{itw}^{G,VPP} \leq \overline{P}_{itw}^{G,VPP} \qquad \forall i \in \Gamma_{VPP,}\, t, \qquad (6.5)$$

$$P_{i(t-1)w}^{G,VPP} - P_{itw}^{G,VPP} \leq R_i^{G,VPP,DW} \qquad \forall i \in \{CPPs, DGs, CHPs\} \qquad (6.6)$$

$$P_{itw}^{G,VPP} - P_{i(t-1)w}^{D,VPP} \leq R_i^{G,VPP,UP} \qquad \forall i \in \{CPPs, DGs, CHPs\} \qquad (6.7)$$

$$\underline{P}_{jt}^{D,VPP} \leq P_{jtw}^{D,VPP} \leq \overline{P}_{jt}^{D,VPP} \qquad j\epsilon\Gamma_{DEM,}, \forall t \qquad (6.8)$$

$$P_{j(t-1)w}^{D,VPP} - P_{jtw}^{D,VPP} \leq R_j^{D,VPP,DW} \qquad j\epsilon\Gamma_{DEM,_d}, \forall t, \qquad (6.9)$$

$$P_{jtw}^{D,VPP} - P_{j(t-1)w}^{D,VPP} \leq R_j^{D,VPP,UP} \qquad j\epsilon\Gamma_{DEM,}, \forall t \qquad (6.10)$$

$$\sum_{t} P_{jtw}^{D,VPP}\,\Delta t \geq E_j^{min} \qquad j\epsilon\Gamma_{DEM,}, \forall t \qquad (6.11)$$

$$\underline{P}_{st}^{S,C} \leq P_{stw}^{S,C} \leq \overline{P}_{st}^{S,C} \qquad ; \forall S \in \Omega^S \qquad (6.12)$$

$$\underline{P}_{st}^{S,D} \leq P_{stw}^{S,D} \leq \overline{P}_{st}^{S,D} \qquad ; \forall S \in \Omega^S \qquad (6.13)$$

$$e_{st\vartheta}^{S} = e_{s(t-1)w}^{S} + P_{stw}^{S,C}\Delta t \eta_s^{S,C} - \frac{P_{stw}^{S,D}\Delta t}{\eta_s^{S,D}} \qquad ; \forall S \in \Omega^S \qquad (6.14)$$

$$\underline{E}_{st}^{S} \leq e_{stw}^{S} \leq \overline{E}_{st}^{S} \qquad ; \forall S \in \Omega^S \qquad (6.15)$$

$$\overline{P}_t^{DAM+}, P_t^{URM} \leq \overline{P}_t^{VPP+} \qquad \forall t \qquad (6.16)$$

$$\overline{P}_t^{DAM-}, P_t^{DRM} \leq \overline{P}_t^{VPP-} \qquad \forall t \qquad (6.17)$$

$$\overline{P}_t^{DAM+} + P_t^{URM} \leq \overline{P}_t^{VPP+} \qquad \forall t \qquad (6.18)$$

$$\overline{P}_t^{DAM} + P_t^{DRM} \leq \overline{P}_t^{VPP-} \qquad \forall t \qquad (6.19)$$

$$\overline{P}_t^{DAM+}, \overline{P}_t^{DAM-}, P_t^{URM}, P_t^{DRM} \geq 0 \qquad \forall t \qquad (6.20)$$

$$V_t^{DAM+}, V_t^{DAM-}, V_t^{URM}, V_t^{DRM} \geq 0 \qquad \forall t \qquad (6.21)$$

$$\lambda_t^{DAM}, P_t^{DAM+}, P_t^{DAM-} \epsilon\, \psi_t^{DAM} \qquad \forall t \qquad (6.22)$$

$$\lambda_t^{URM}, P_t^{URM},\, \lambda_t^{DRM}, P_t^{DRM}\, \epsilon\, \psi_t^{RM} \qquad \forall t \qquad (6.23)$$

$$P_{ijtw}^{flow} = B_{ij}^{line}\left(\delta_{itw} - \delta_{jtw}\right) \qquad \forall i, j\, \epsilon N_{bus}, w \qquad (6.24)$$

$$\sum_{i\in \Omega_n} P_{itw}^{VPP} + \sum_{i\in \Omega_n}\left(P_{stw}^{S,C} - P_{stw}^{S,D}\right) - \sum_{j\in \Omega_n} P_{jtw}^{VPP} + \sum_{i\in \Omega_n} P_{it}^{G,DAM} - \sum_{j\in \Omega_n} P_{jt}^{D,DAM} + \sum_{i\in \Omega_n} P_{it}^{URM} + \sum_{i\epsilon\in \Omega_n} P_{it}^{DRM} = \sum_{j\epsilon\in \Omega_n} P_{ijtw}^{flow} \qquad ; \forall t, w \qquad (6.25)$$

$$-P_{ij}^{flow} \leq P_{ijtw}^{flow} \leq P_{ij}^{flow} \qquad \forall i, j, w \qquad (6.26)$$

Where, $\Gamma_{VPP} \in \{CPPs, DGs, WT, PV, and\ CHPs\}$ ie., set of VPP components. Eq. (6.4) governs balancing constraints, the demands should be equal to generation in specific time period. Eqs. (6.5) and (6.8) imposes upper and lower bounds on the power generation and demand consumption by the VPP components respectively. Constraints in Eqs. (6.6) and (6.7) formulates ramping constraints related to CPPs, CHPs and DG sets of VPP. Similarly, constraints in the Eqs. (6.9) and (6.10) are ramping limits related to flexible demands, while Eq. (6.11) imposes minimum demand consumption in each time period. Eqs. (6.12) and (6.13), limits maximum and minimum charging and discharging level of storage units, while the Eq. (6.14) represents the energy production level in storage units and Eq. (6.15) limits the amount of energy stored in the storage units.

Constraints in the Eqs. (6.16) and (6.17) represents upper limit on the power quantity that is offered and bid by the VPP in the DA and reserve electricity markets respectively. These limiting bounds are based on the VPP scheduling capacity in each time period. Eqs. (6.18) and (6.19), govern the limiting constraint on sum of capacities offered and bidded by the VPP in the DA and RMs. Constraints in Eqs. (6.20) and (6.21) define the quantity and price offers and bid decisions as a positive variable respectively. Constraints in Eqs. (6.22) and (6.23) states that the both scheduled power of the VPP and the market cleared prices are the results of market clearing problem of DA energy and reserve electricity markets represented by the set ψ_t^{DAM}, ψ_t^{RM} respectively.

Finally, network flow constraints are defined in Eqs. (6.24) and (6.25). These constraints are defined at each bus i.e., difference between the generated power and consumed power is flowed through the transmission lines (6.25). The constraint in the

Eq. (6.26) limits the power flow through each transmission line in the network. Note, these constraints can be included in the lower level market clearing problem according to [18, 34]. The Variables $P_{it}^{G,DAM}$, P_{it}^{URM}, P_{it}^{DRM}, $and\ P_{jt}^{D,DAM}$ ~~are~~ belong to lower-level problem.

6.2.2. Lower-level problem

In a bi-level model, lower-level problem follows the upper-level problem. In this case, VPP as a price maker with the objective of profit maximization is followed by the market clearing process in which VPP participates. Here, VPP participates in DA and reserve markets. In particular, VPP participates in regulation reserve markets for balancing the market requirements. The reserve deployment requests made by the system operator are modelled using the scenario realization technique. The detailed formulation of DA and reserve regulation is explained in Chapter-3. With few additions to the present context of VPP, the power flow model of the market clearing process is as follows:

$$min_{\Gamma_{DAM,RM}} Obj = Obj1 + Obj2 \tag{6.27}$$

$$\text{Obj1:} \quad min_{\Gamma_{DAM}} S_t^{DAM+} P_t^{DAM+} + \sum_{i\epsilon\Omega_G} C_{it}^{G,DAM} P_{it}^{G,DAM} - S_t^{DAM-} P_t^{DAM-} - \sum_{j\epsilon\Omega_D} B_{jt}^{D,DAM} P_{jt}^{D,DAM} \tag{6.28}$$

$$\text{St:} \quad P_t^{DAM+} + \sum_{i\epsilon\Omega_G} P_{it}^{G,DAM} = P_t^{DAM-} + \sum_{j\epsilon\Omega_D} P_{jt}^{D,DAM} \qquad \forall t;\ \lambda_t^{DAM} \tag{6.29}$$

$$\underline{P}_{it}^{G,DAM} \le P_{it}^{G,DAM} \le \overline{P}_{it}^{G,DAM} \qquad \forall t, i\epsilon\Omega_G\ ; \overline{\mu}_{it}^{G,DAM}, \underline{\mu}_{it}^{G,DAM} \tag{6.30}$$

$$\underline{P}_{jt}^{D,DAM} \le P_{jt}^{D,DAM} \le \overline{P}_{jt}^{D,DAM} \qquad \forall t, j\epsilon\Omega_D, \overline{\mu}_{jt}^{D,DAM}, \underline{\mu}_{jt}^{D,DAM} \tag{6.31}$$

$$0 \le P_t^{DAM+} \le \overline{P}_t^{DAM+} \qquad \forall t; \overline{\varphi}_t^{DAM+}, \underline{\varphi}_t^{DAM+} \tag{6.32}$$

$$0 \le P_t^{DAM-} \le \overline{P}_t^{DAM-} \qquad \forall t;\ \overline{\varphi}_t^{DAM-}, \underline{\varphi}_t^{DAM-} \tag{6.33}$$

$$\text{Obj2:} \quad min_{\Gamma_{RM}} S_t^{URM} P_t^{URM} + \sum_{i\epsilon\Omega_{URM}} C_{it}^{URM} P_{it}^{URM} - S_t^{DRM} P_t^{DRM} - \sum_{i\epsilon\Omega_{DRM}} B_{it}^{DRM} P_{it}^{DRM} \tag{6.34}$$

$$\text{St:} \quad P_t^{URM} + \sum_{i\epsilon\Omega_{URM}} P_{it}^{URM} = \overline{P}_t^{URM} \qquad \forall t;\ \lambda_t^{URM} \tag{6.35}$$

$$P_t^{DRM} + \sum_{i\epsilon\Omega_{URM}} P_{it}^{DRM} = \overline{P}_t^{DRM} \qquad \forall t;\ \lambda_t^{RD} \tag{6.36}$$

$$\underline{P}_{it}^{URM} \le P_{it}^{URM} \le \overline{P}_{it}^{URM} \qquad \forall t, i\epsilon\Omega_{URM}\ ; \overline{\mu}_{it}^{URM}, \underline{\mu}_{it}^{URM} \tag{6.37}$$

$$\underline{P}_{it}^{DRM} \le P_{it}^{DRM} \le \overline{P}_{it}^{DRM} \qquad \forall t, i\epsilon\Omega_{DRM}\ ; \overline{\mu}_{it}^{DRM}, \underline{\mu}_{it}^{DRM} \tag{6.38}$$

$$0 \leq P_t^{URM} \leq \overline{P}_t^{URM} \qquad \forall t; \overline{\omega}_{it}^{URM}, \underline{\omega}_{it}^{URM} \tag{6.39}$$

$$0 \leq P_t^{DRM} \leq \overline{P}_t^{DRM} \qquad \forall t; \overline{\omega}_{it}^{URM}, \underline{\omega}_{it}^{DRM} \tag{6.40}$$

The objective function in Eq. (6.28) is related the system operator's objective to maximize the social welfare in the DA market. It consists of four terms including VPP generation offering and bidding terms. Balancing constraints is formulated in Eq. (6.29). Eqs. (6.30) and (6.31) limits bidding and offering capacity of each market participant including VPP's capacity. Constraints as denoted in Eqs. (6.32) and (6.33), impose limits on the amount of power offered and bidded by the VPP in DA energy market respectively.

Similar to the DA market, VPP participates in the reserve regulation market based upon its requirements and system operator request for reserve capacity deployment. The objective function in Eq. (6.34) is related to the system operator's objective to minimize the cost for reserve deployment. Constraints denoted in Eqs. (6.35) and (6.36) represents the balancing constraint on the up and down reserves respectively. Eqs. (6.37) and (6.38) impose limits on the reserve capacity offered by each market participant other than VPP's respectively. Limits are imposed on up and down reserve capacity offered by the VPP in the reserve market using Eqs. (6.39) and (6.40) respectively. The overall clearing process of DA and reserve markets with respective to their objective is considered as lower-level problem.

The dual variables are defined for each constraint separated by using semicolon, where, $\Gamma_{DAM}\ and, \Gamma_{RM}$ represent the set of optimization variables $\{P_{it}^{G,DAM}, P_{jt}^{D,DAM}, P_t^{DAM}\ , P_t^{DAM-}\}, \{P_{it}^{URM}, P_{it}^{DRM}, P_t^{URM}, P_t^{DRM}\}$ respectively. The variables $\left\{\overline{P}_t^{DA+}, \overline{P}_t^{DA-}\right\}, \left\{\overline{P}_t^{RU}, \overline{P}_t^{RD}\right\}$ belong to upper-level problem. Now, the overall bi-level problem is together with upper-level and lower-level problems. The complete bi-level problem is shown in the Fig. (6.1).

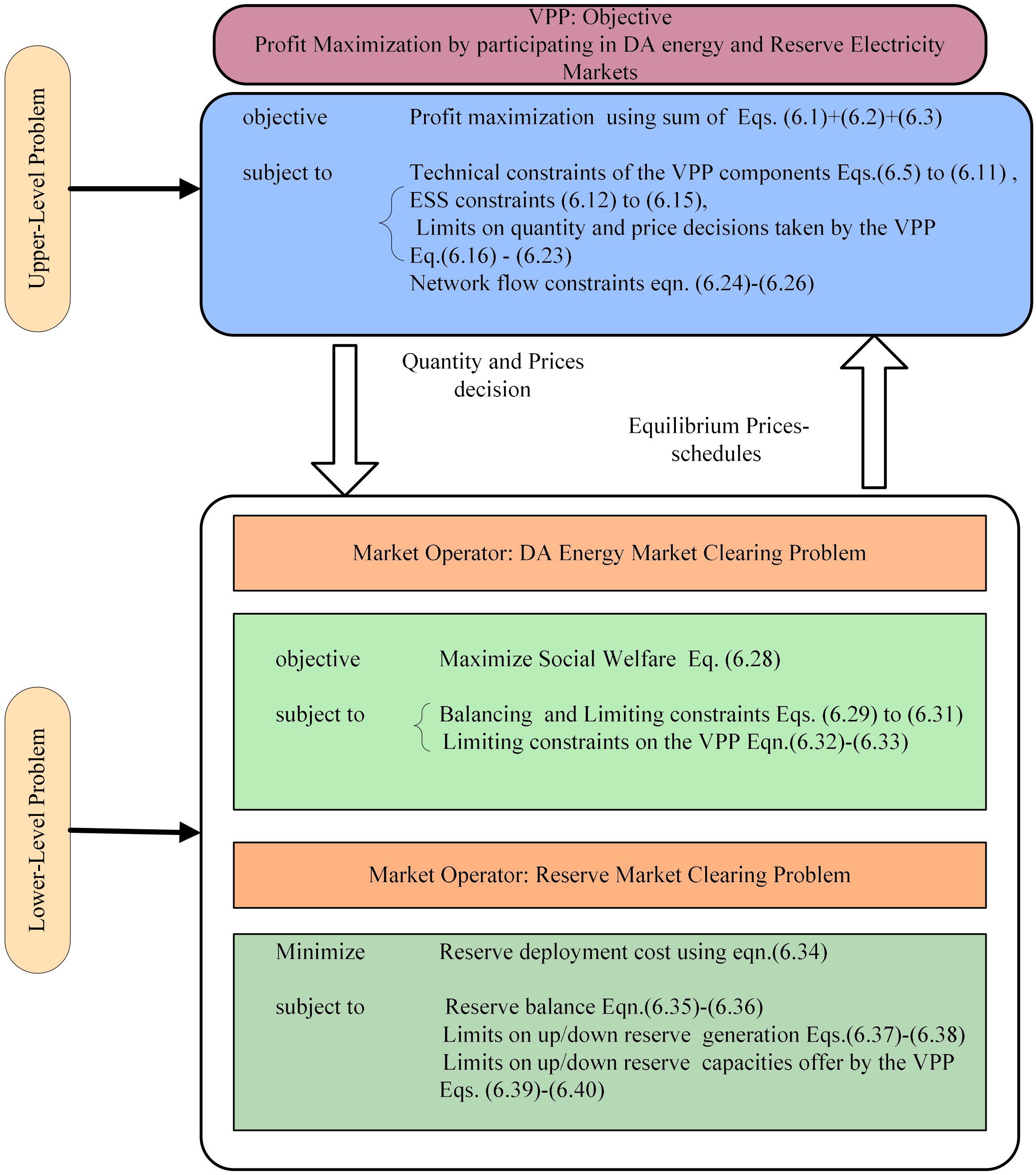

Fig.6.1. Complete Bi-level optimization problem

The above bi-level problem is then converted into single level mixed integer linear program using KKT and duality constraints. The process of converting lower level into dual problem is explained in the Chapter-3. The non-linearities in complementary slackness are linearized using big-M method as explained in the Chapter-3.

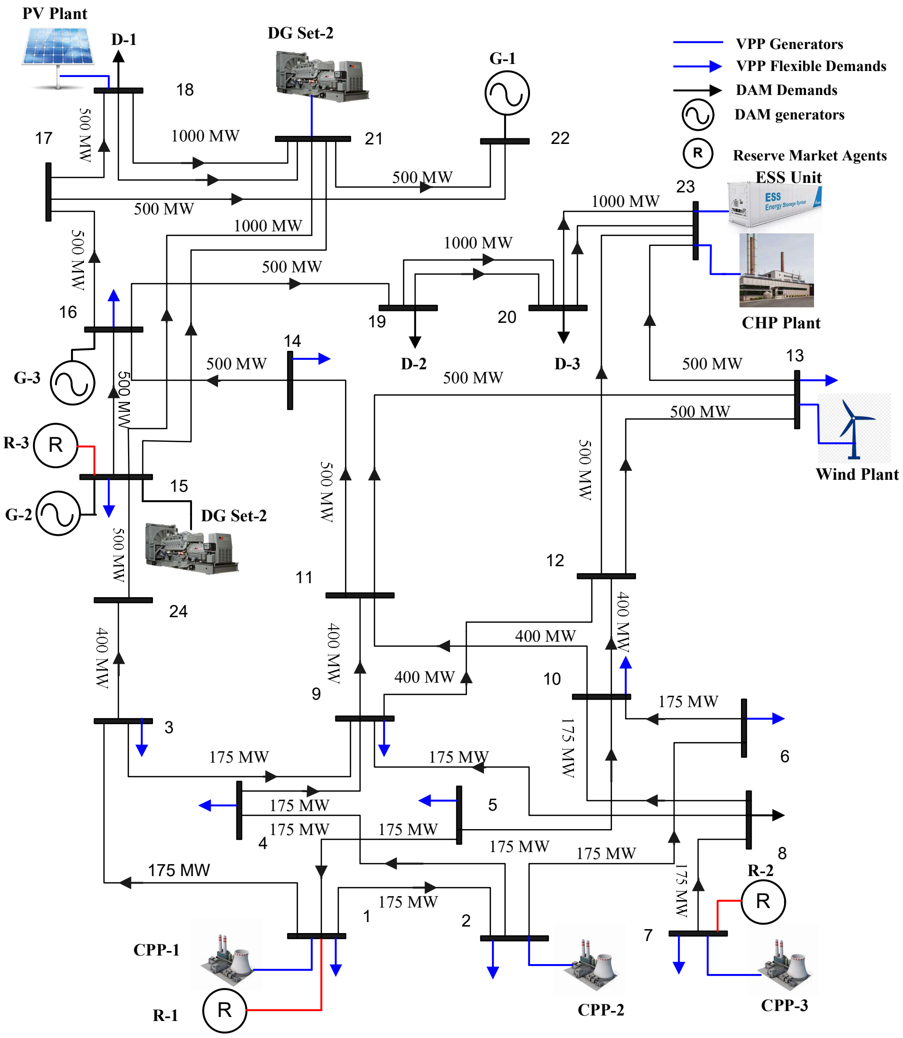

Fig.6.2. Study results of IEEE-24 reliability test bus systems during scenario-I

6.3. Simulation Results

The proposed has been implemented using modified IEEE -24 bus reliable test system. The test system has VPP components distributed across the network shown in the Fig (6.2). Network data is obtained from the Matpower [51]. CPLEX solvers in GAMS software are used to simulate the suggested model on intel i7 core PC.

The VPP is a price-maker in this study, and it is always focusing on improving its profit by making strategic decisions. Four equiprobable scenarios are ~~being~~ used to characterize market pricing and RE generation uncertainty. To cope with these uncertainties, data on hourly electricity prices, as well as RE generation, are forecasted.

The data related to the generating units in the DA and reserve market along with the data related to VPP components is provided in Appendix-A

The VPP optimises its assets for its own demand during peak demand hours and low market prices in the DA and RMs, and does not participate in the market scheduling process. We investigate two different operating instances to examine the strategic decision-making of price-maker VPP using the suggested model. Profit maximisation and bidding decisions are compared in each situation. The two separate cases that are considered are listed below.

i. VPP with flexible loads
ii. VPP without flexible loads

VPP with flexible loads obtain more profits compared to the case without flexible demands. This is due to the flexibility in loads; VPP can shift its maximum peak demand to some other hour where sufficient generation is available. As a result, VPP participates in the DA market and reserve markets for most of the time periods. This is clearly shown in Figs. (6.3) and (6.4). The optimal VPP generation vis-a-vis demand is shown in Figs. (6.5) and (6.6). It can be observed that VPP generation ~~flows~~ follows the demand curve during flexible demands while in the case of VPP without flexible loads no such relation is seen.

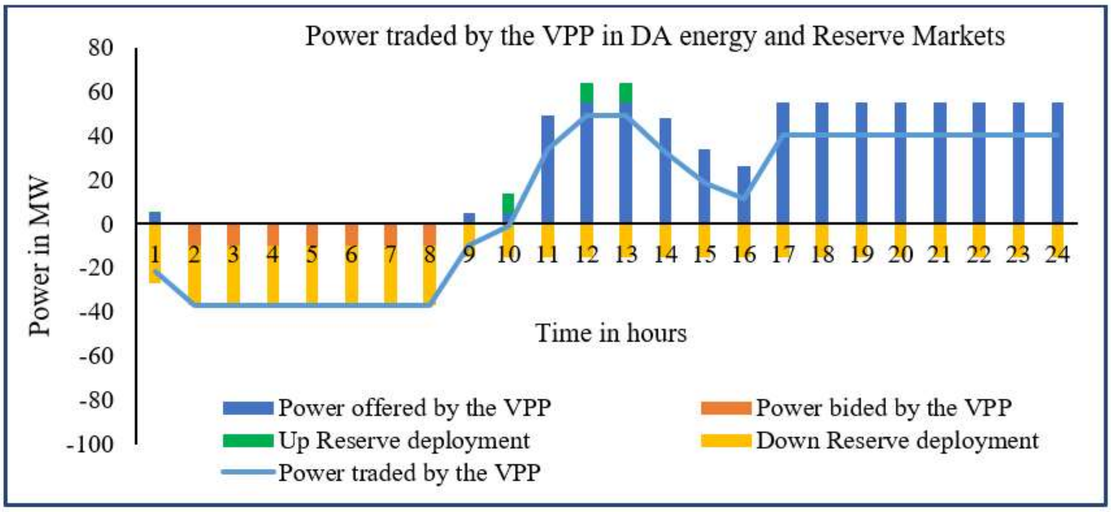

Fig. 6.3. Net power traded by the VPP in the DA and RMs in all time periods with flexible loads

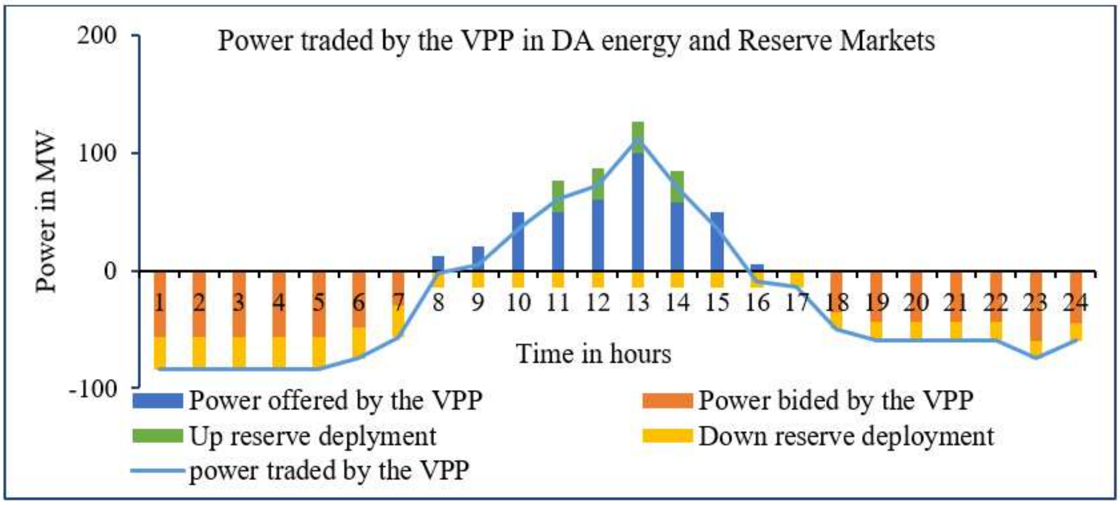

Fig.6.4. Power traded in DA and RMs in all time periods without flexible loads

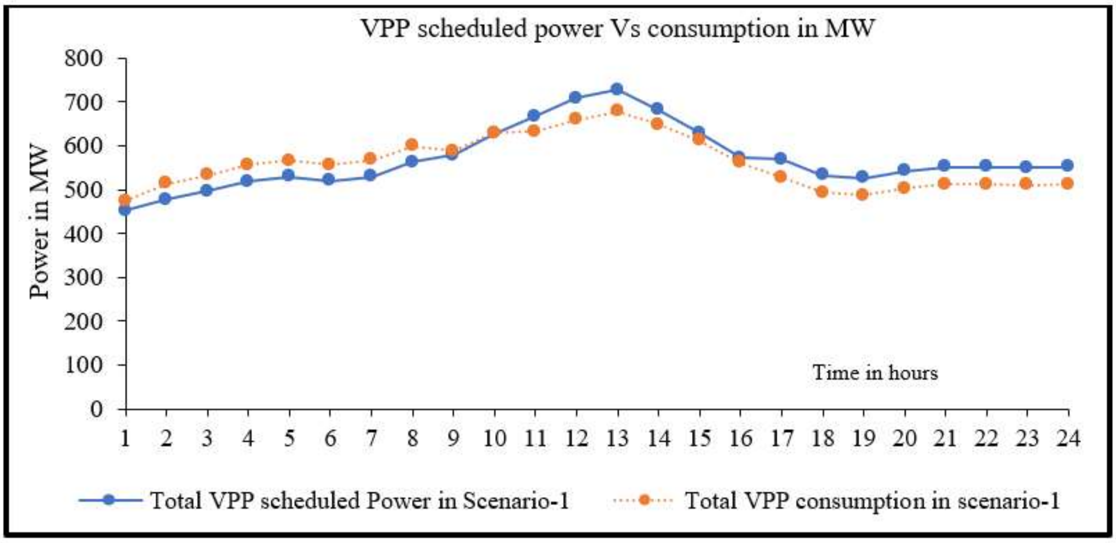

Fig. 6.5. VPP scheduled Power Vs VPP consumption in MW in all time periods during scenario-1

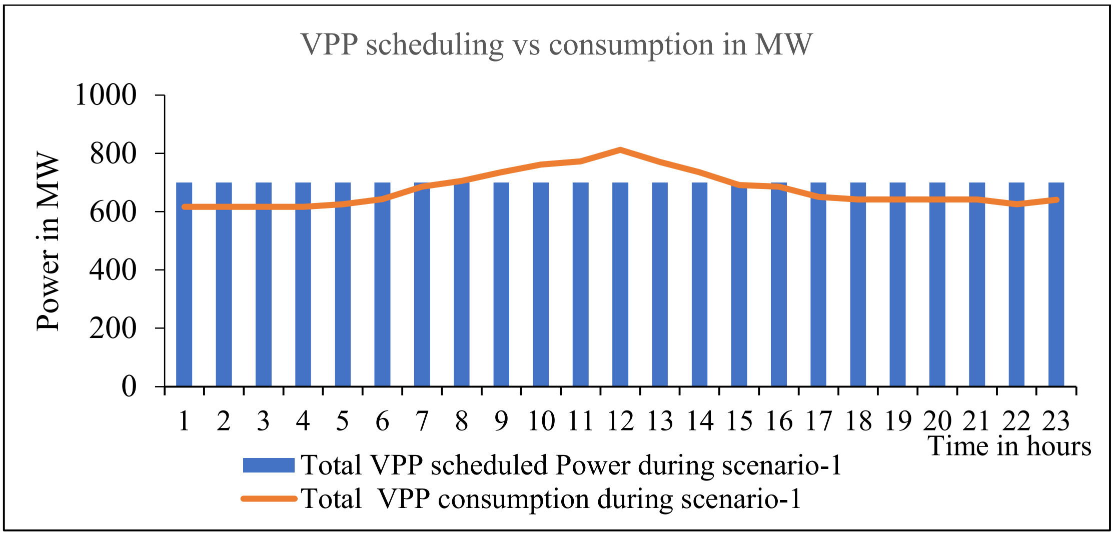

Fig.6.6. Total power scheduling of the VPP during scenario-1 without flexible demand.

6.3.1. Case-I: VPP with flexible demands

Now, we will investigate the participation of VPP in DA and reserve markets. Let us consider the time period -17th hour in the Fig.6.5. During this time period VPP generation is greater than the demand i.e., 40 MW. While in the DA energy market the energy is deficient about 55 MW. During this period the VPP offers it excess generation in the DA energy market. The energy is balanced by offering its reserve capacity. VPP decides to offer its 55 MW of excess power generated in DA market, but only 40 MW is required in the DA market. The remaining 15 MW is offered by participating in the reserve markets. This can be observed from the Fig.6.3. Based on the VPP offer, the down reserve capacity is cleared for 30 MW. Here, 30 MW is the maximum limit allowed for making reserve deployment requests or offers. Due to the uncertainty in the reserve deployment, the cleared capacity is multiplied by the uncertain parameter ($\phi_{tw}^{RU} = 0.5$). The VPP sells this power at the market price $\lambda_t^{DA} = 45\ \$/MW$, and it offer down reserve capacity for balancing the load at $\lambda_t^{RD} = 10\$/MW$. The profit obtained for this time period is $45 \times 55 + 30 \times (10) = 2775\$$. The net profit obtained in this time period is equal to 2775\$. In this case the profit obtained from the DA energy market is 2475\$ and in the reserve market the profit obtained is 300 \$. Here, if we observe the DA market, price is more and the VPP strategically offers its excess generation in that higher price and in the case of reserve market participation, the excess 15MW is reduced from its generation as its down reserve capacity offer.

6.3.2. Case. II: VPP without flexible demands

In this case the DA market offering of the VPP is greatly affected, since VPP demands doesn't have flexibility to shift their peak demand hours to the maximum generating hours. This can be depicted in the Fig. 6.6. In this case, participation of VPP in the DA and reserve market during the time period 13th hour is taken as example. During this time period VPP generation is greater than VPP demand consumption. The difference in the power generation and demand is $112\ MW$. Here, the VPP has sufficient power to optimize its demand. Hence, VPP decides to sell the power in the DA energy market. In the DA energy market, as there is a requirement of $100\ MW$ from the demands other than VPP components shown in the Fig.6.4. The VPP sells this power at the market price $\lambda_t^{DA} = 20\ \$/MW$, and it offer both of its up and down reserve capacities for balancing the load generation at $\lambda_t^{RU} = 10\$/MW$, and $\lambda_t^{RD} = 10\$/MW$

respectively. The profit obtained for this time period is $100 \times 20 + 30 \times (10 + 10) = 2600\$$. Here, the VPP gain the profit from the DA and RMs. During this case, the profits obtained by the VPP are greatly affected comparted to the previous case.

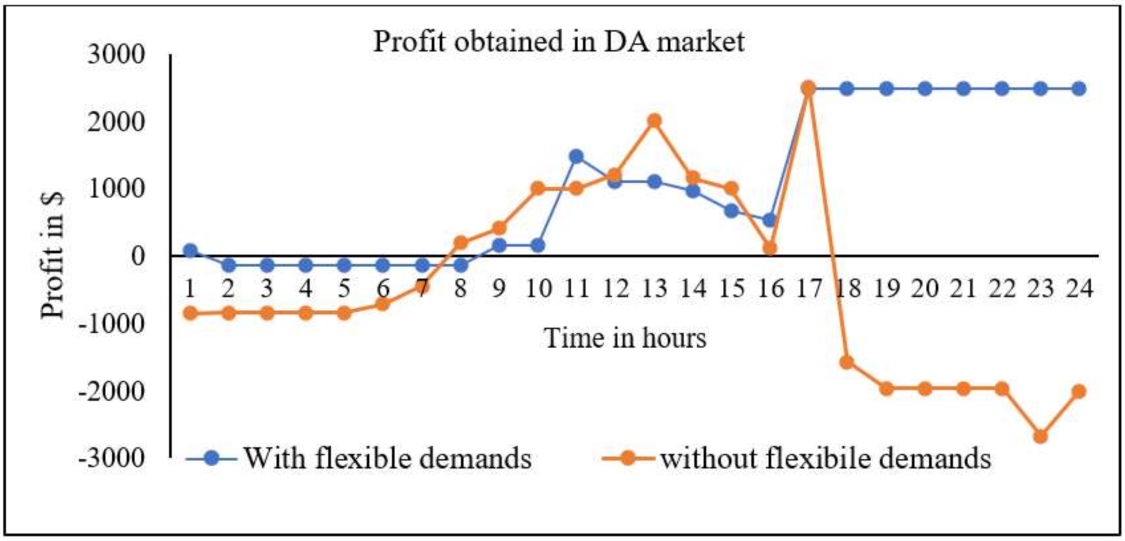

Fig.6.7 Comparing profit obtained by the VPP through participating in DA market with and without flexible loads

6.3.3. Impact of flexible demands on the profits obtained by the VPP:

In this section, we will analyse the impact of flexible demand on the VPP profits in DA and reserve market. Figs. 6.3 and 6.4 shows the amount of power traded by the VPP in both DA and reserve market. It is clearly visible that, the VPP offers in the DA market for the case without flexible demand is greatly reduced while, VPP bid for optimizing its demand is increased. Hence, the profit obtained by the VPP is also reduced. Fig. 6.7. compares the profit obtained by the VPP in the DA market for both cases. From this figure, it is observed that VPP obtains the profit during the time periods 8^{th} to 17^{th} hours, and in the remaining periods VPP pays to optimize its resources. Whereas, in the case of VPP with flexible demand, it can be observed that VPP obtains profit in all the time periods except for the hours 2^{nd} to 8^{th} time periods.

The time periods where VPP obtain profit can be correlated with the VPP scheduling in the Figs. (6.5) and (6.6). The VPP makes profits during the hours whenever, generation is greater than demand consumption. This can be related to flexibility of the demands. Since flexible demands can shift their consumption from one period to other periods, the VPP generation is greater than the demand in most of the periods except for few periods when, RE sources are unavailable (solar PV generation is zero during early morning hours and night times). As a result, VPP profit is increased. The percentage values of VPP traded power and profit difference is compared in the Table-6.1.

VPP offers in the DA market, for the case-I is recorded as 721.19 MW where as for the case-ii, it is limited to 406.71. The percentage share of the VPP power offered in the DA market is reduced by -43.6% when VPP supplies constant demands (Case-II). But in the case of reserve market, the VPP participation is increased by 1.31% compared to the case-I, this clearly states the balancing reserve are utilised more in the case-II. The profit obtained by the VPP followed same trend similar to DA market participation. The VPP obtains -47.94% reduced profit in the case-II when compared with the case-I. Thus, the profit obtained by the VPP is greatly reduced.

6.3.4. Comparing strategic and non-strategic case

In order to investigate the power of market participant as price maker, VPP participation in DA and reserve market is modelled as strategic and non-strategic case. It is assumed that the VPP objective during the non-strategic case is to maximize the social welfare. While for the strategic case, the VPP's objective is to maximize profit. Table-6.2, shows the comparison between the strategic and non-strategic case. When VPP as a non-strategic player in the market, the total profit obtained by the VPP is reduced by -20.99% compared to the strategic case. Similarly, VPP obtains less profit in DA market. The dependency on the reserve market for balancing the system is reduced by a slight value of -0.98%. While social welfare is increased by 25.57%. This clearly indicates that VPP excises the market power to alter the prices during the strategic case. Hence VPP as a single entity acts as price maker. During the non-strategic case social welfare value is increased.

Table.6.1. Simulation result of DA and Reserve market participation of VPP comparing with and without flexible demand cases for all the time periods

Case	Total DA offered Power (MW)	Total DA bidded Power (MW)	Total reserve market offered power (MW)	Expected profit ($)	Objective value
Case-1	721.19	70	827.83	69103	430425
Case-2	406.71	675.82	838.88	35972	601541
Percentage difference	-43.6%	89.6%	1.31%	-47.94%	-28.44%

Table.6.2. Strategic and non-strategic operation of VPP

Case	Total Profit obtained in DA and RMs ($)	Profit obtained in DA Market ($)	Profit obtained in the reserve markets ($)	Social Welfare
Strategic	31954.02	24448.48	7505.54	430425.48
Non-Strategic	26409.49	18977.12	7432.37	578355.09
Percentages Difference	-20.99%	-28.88%	-0.984%	25.57%

6.4. Conclusion:

The concept of VPP as a prospective market participant in the energy market has been discussed in this chapter. VPP as a promising solution to incorporate DERs as a single entity can act as both a price and profit maker. The 24-IEEE test bus system has been used to study optimal scheduling strategies with varied energy sources, flexible and non-flexible load demands. The primary VPP components, such as WT, solar PV plants, DG sets, CHP units, ESSs, electrical loads, have been considered as distributed over the test bus system. A bi-level stochastic optimization model with network constraints is presented in this research. This model investigates the possibility of VPP to act as market power for its own gain. Using KKT and the strong duality theorem, the proposed bi-level model has been restated as a MILP problem. The profit obtained by the VPP is examined using simulation results that incorporated demand flexibility into account. Flexible loads, as deduced, can increase the VPP's profit in DA and RMs. While in the case of constant demands, the profit curve shrinks. Flexible demands have an impact on the VPP scheduling and profit making during specified time periods, as shown by the simulation results. It has been observed that the strategic behaviour outperforms the non-strategic behaviour. The proposed strategic optimal scheduling methodology is appealing because it increases profits while ~~also~~ positioning the VPP as a price maker also among market participants.

Nomenclature:

sets	
Π_w	Scenario's sets; $\sum_w \Pi_w = 1$
$\Gamma_{VPP,}$	Set of VPP components
Ω^S	Set of energy storage systems in the VPP

Ω^{n}	Set of units connected to a bus
ψ_{t}^{DAM}	Set of DA market variables
ψ_{t}^{RM}	Set of reserve market variables
Π_{w}	Scenario's sets; $\sum_{w} \Pi_{w} = 1$
Parameters	
$B_{jt}^{D,DAM}$	Cost associated by the i^{th} demand other than VPP in the DA energy market [$/MWh
$C_{it}^{G,DAM}$	Cost associated by the i^{th} power producers other than VPP in the DA energy market [$/MWh]
C_{tw}^{PV}	Cost of i^{th} Solar PV plant in VPP[$/MWh]
C_{tw}^{WT}	Cost of i^{th} WT generating plant in VPP[$/MWh]
C_{wt}^{CHP}	Cost of i^{th} generating plant in VPP[$/MWh]
C_{wt}^{DG}	Total cost of i^{th} DG set in VPP[$/h]
C_{wt}^{CPP}	Total cost of i^{th} CPP units in VPP[$/h]
C_{wt}^{d}	j^{th} Utility demand price in the time period t in VPP [$/h]
$\underline{E}_{st}^{S}, \overline{E}_{stw}^{S}$	Lower and upper limits on the energy stored in the i^{th} storage unit in the time period t [MWh]
E_{j}^{min}	Minimum daily energy consumption of j^{th} demand [MW]
$\underline{P}_{jt}^{D,VPP}, \overline{P}_{jt}^{D,VPP}$	Upper and lower bounds on demand consumption of j^{th} demand of VPP in the time period t [MW]
$\underline{P}_{it}^{G,VPP}, \overline{P}_{it}^{G,VPP}$	Upper and lower bounds on generation of i^{th} unit of VPP in in the time period t [MW]
$\overline{P}_{st}^{S,C}$	Maximum charging limit of the i^{th} storage unit in the time period t [MW]
$\overline{P}_{st}^{S,D}$	Maximum dis-charging limit of the i^{th} storage unit in the time period t [MW]
$\underline{P}_{it}^{G,DAM}, \overline{P}_{it}^{G,DAM}$	Lower and upper limits on the Power offered by the i^{th} generating plant in the time period t other than VPP in [MW]
$\underline{P}_{jt}^{D,DAM}, \overline{P}_{jt}^{D,DAM}$	Lower and upper limits on the Power bided by the j^{th} demand in the time period t other than VPP in [MW]
$\underline{P}_{it}^{URM} \overline{P}_{it}^{URM}$	Lower and upper limits of Up reserve capacity offered by the i^{th} market agent in the time period t in Reserve market [MW/h]

$\underline{P}_{it}^{DRM}\overline{P}_{it}^{DRM}$	Lower and upper limits of down reserve capacity offered by the i^{th} market agent in the time period t in Reserve market [MW/h]
P_{ij}^{flow}	Maximum power flow in transmission line connecting i^{th} bus and j^{th} bus during time period t [MW]
$R_j^{D,VPP,DW}$	Down Ramping rate of j^{th} demand of VPP in [MW]
$R_j^{D,VPP,UP}$	Up Ramping rate of j^{th} demand of VPP in [MW]
$R_i^{G,VPP,DW}$	Down Ramping rate of i^{th} generating unit of VPP in [MW]
$R_i^{G,VPP,UP}$	Up Ramping rate of i^{th} generating unit of VPP in [MW]
B_{ij}^{line}	Admittance of transmission lines connecting i^{th} and j^{th} bus
$\eta_s^{S,C}\eta_s^{S,D}$	Charging and discharging efficiency of i^{th} storage unit [%]
Δt	Time period duration i.e., 1hour
Variables	
e_{stw}^{s}	Amount of energy stored in the i^{th} storage unit in time period t and scenario w [MWh]
$P_{jtw}^{D,VPP}$	Amount of Power consumed by the j^{th} demand in the VPP in the time period t [MW]
P_t^{DAM+}	Power sold by the VPP to the DA market in the time period t [MW]
P_t^{DAM-}	Power brought by the VPP to the DA market in the time period t [MW]
$P_{itw}^{G,VPP}$	Amount of Power generated by the i^{th} VPP component in the time period t scenario w [MW]
P_{ijw}^{flow}	Power flow in the transmission lines connecting i^{th} and j^{th} bus during time period t and scenario w [MW]
$P_{it}^{G,DAM}$	Amount of Power generated by the i^{th} producer in the DA market in the time period t [MW]
$P_{jt}^{D,DAM}$	Amount of Power consumed by the j^{th} demand in the DA market in the time period t [MW]
P_{it}^{URM}	Up- reserve capacity sold to the reserve market by the i^{th} market agent in the time period t [MW]
P_{it}^{DRM}	Down- reserve capacity sold to the reserve market by the i^{th} market agent in the time period t [MW]

$\overline{P}_t^{URM} \overline{P}_t^{DRM}$	Up and Down reserve capacity offered in the reserve market in the time period t in [MW/h]
$P_{stw}^{S,C}$	Power charging level of the i^{th} storage unit in time period t and scenario w [MW]
$P_{stw}^{S,D}$	Power discharging level of the i^{th} storage unit in time period t and scenario w [MW]
λ_t^{DAM}	DA energy market price in the time period t [$/MWh]
λ_t^{URM}	Up- reserve market price in the time period t [$/MWh]
λ_t^{DRM}	Down - reserve market price in the time period t [$/MWh
δ_{itw}	Voltage Bus angle of the i^{th} bus in degrees
S_t^{DAM+}, S_t^{DAM-}	The offer and bid price submitted in the DA market by the VPP in the time period t [$/MWh]
S_t^{URM}, S_t^{DRM}	The Up and Down reserve offer price submitted in the reserve market by the VPP in the time period t [$/MWh]

CHAPTER 7

Conclusion and Future Work

CHAPTER 7
Conclusion and Scope for Future Research

7.1. Conclusion

In this thesis work, we have analysed false data injection attacks in the electricity market where, attacker acquire financial profits by trading electrical power in the DA and real time markets. This work also analyses the optimal scheduling of VPP generation as two stage stochastic processes, where VPP acts as a price maker in the electricity market.

At first, the structure of electricity markets and its principles are reviewed. Integrating market driven new technologies and its complexities are studied to investigate the proposed model, wherein state estimation and cyber threat to the power system are the major areas of being focussed. Market based power system is formulated based upon the social welfare maximization objective. Day Ahead, Real time and reserve markets and their market clearing process is presented as DC optimal power flow model.

Cyber-attacks are great threat to the integrity of the power system. In this work, attacker objective is to obtain financial profits. This attacking strategy is modelled as bi-level mathematical model, and is formulated for launching a stealthy attack. Attacker as a virtual participant, knowing the system topology, and market clearing process the adversary designs an attack vector. The changes brought by the attacking values are not detected in the BDD process in the state estimation run by the ISO. The designed stealthy data is injected into the measuring devices deployed at various locations. Due to the errors in measuring devices, attacker always tries to attack less meters that cause more changes in the congestion pattern. Thus, attacker manipulates system operator and market clearing process.

The proposed stealthy false data attack is tested using IEEE-5 bus test system. From the simulation results, it is observed that the attacker alters the congestion in the transmission lines, as a result Locational Marginal Prices (LMPs) at each bus are different. Knowing this the attacker buys power in the DA market at lesser LMPs and then sell the same amount of power at higher LMPs in the Real time markets. Thus, the attacker acquires profits. The results show that the attacker can manipulates two meters at a time to change congestion in the transmission line. In each and every attack the attacker manipulates the line-4 flow meter indicated in the Figs. (4.3) and (4.4). The impact of attacking transmission lines connecting bus-4 is more when compared to other cases. Hence, it can be concluded that node at bus-4 is critical node to launch the attack. So, it is desirable to provide strong security at this node in order to avoid such financially motivated cyber intrusions. Here, the proposed model is converted into single level MILP model using KKT and duality conditions.

Integrating new technologies such as RE sources and DERs has brought further complexities in the market clearing process. In order to eliminate the disadvantages in integrating these technologies, the concept of VPP is studied. VPP as a single entity aggregates the production from different DERs and participates in the electricity markets.

In this work, optimal scheduling of VPP in the DA and reserve market is investigated. Uncertainties related to the intermittence and variability of RE generation, market prices and reserve deployment request for balancing the system are considered as stochastic process, and are modelled using scenario realization technique. In this technique for each uncertain parameter different scenarios are realized as probability of occurrence. A two- stage stochastic model is formulated for optimal scheduling of VPP in the DA and reserve markets.

The proposed two-stage stochastic model is implemented on 4-hour planning horizon and the VPP considered here, consist of WT and CPPs as its components. The simulation results indicate that the VPP generating utilities are scheduled for the most of the time period while, CPPs with low generation costs are utilized to supply for the remaining loads. It can be observed that the CPPs with high marginal costs are not being scheduled. As a result, market clearing prices are at low values, which are less than the marginal cost of generation of the CPPs. This has large impact upon the income acquired by the CPPs. The reserve deployments are scheduled when the market operator request to deploy, these are also scheduled based upon the prices. The simulation results clearly indicate the VPP as a single entity can alter the prices. However, these effects the income of CPPs. This work provides impressive results for accurate optimal scheduling of the generating units in the VPP.

Since the VPP can alter the prices in the electricity markets, a bi-level model has been proposed to investigate the power of the VPP in the electricity market. The VPP considered in this work consist of diversified RE sources, CHPs, DG sets, small scale CPPs, and flexible electrical loads. The proposed model formulates VPP as strategic market participant with the objective to maximize its profits. The bi-level model is then reformulated into single-level MILP problem using KKT optimality conditions and duality theorem.

The proposed model finds out strategic optimal scheduling of VPP in the DA and reserve market. This model is implemented on IEEE modified-24 reliability test bus system. From the simulation results, it is deduced from the table-6.4 that VPP strategic participation obtains 20.99% more profits compared to the non-strategic operation. Also, the flexibility in the demand increases the participation of VPP in DA market to obtain profits. The results show that the profit obtained by the VPP with flexible demands is more than the case of the VPP scheduling without flexible demands. The proposed strategic optimal scheduling methodology is suitable because it increases profit from the DA and reserve markets, positioning the VPP as a price maker also among the market participants.

7.2. Research Papers Published on the dissertation work:

(1) M. Indeevar Reddy, Radheshyam Saha and Sudharshan K Valluru, "Modelling Financially Motivated Cyber Attacks on Electricity Markets using MILP Program", *2nd IEEE International conference on power, Energy, control and transmission systems*, Chennai, India, pp:1-6, 10th-11th December, 2020. (*Best Paper Award*)

(2) M. Indeevar Reddy, Radheshyam Saha and Sudharshan K Valluru "Two Stage Stochastic programming model for optimal scheduling of RE based Virtual Power Plants in Electricity Markets ",. *IEEE 6th International Conference for Convergence in Technology (I2CT),* Pune, India, pp. 1-6, 2nd - 4th April, 2021.

(3) M. Indeevar Reddy, Radheshyam Saha and Sudharshan K Valluru, "Bi-level Optimal Strategic Generation Scheduling with Flexible Demands under Uncertainties and Improving Profitability of VPP in Day Ahead and Reserve Electricity Markets" *International Journal of Electrical Power and Energy Systems*, Elsevier **(Communicated)**

7.3. Scope for Future Research

In the power system generation, transmission, distribution, and security issues remain as a challenge. For example, integrity of the data related to measuring devices in the power system is important to ensure the validity and consistency of data in state estimation. The enormous large amount of data that need to be handled is a big ongoing difficulty. Indeed, data analysis should extract information from the vast data set generated by smart metres and convert it into a comprehensible structure that a control centre may utilise for a variety of purposes, including speedy defect identification in distribution systems.

At present, data analytics and deep learning techniques are used in analysing the large data. This task of digitalising power system network is a big challenge. Meanwhile, these techniques are more reliable in detecting and defending cyber intrusions, which is an ongoing and highly potential research work. In future, developing a model to mitigate the cyber intrusions using deep learning-based techniques ~~is~~ could be investigated; in addition to this, we are to plan and integrate large numbers of VPPs in the electricity grid and electricity market as well. It would be very essential to study the roles of the VPPs, ESSs and dominant REs of the various independent VPPs in the electricity markets and importantly to provide remedial measures when such models are subjected to cyber-attacks.

The optimal scheduling of RE based VPPs in the electricity market is ongoing research work mainly in two directions. One group of researchers are trying to find out the more accurate predictive models in realising precise outputs, so that the uncertainties are minimized. The other group of researchers are finding out the optimal scheduling solution for the VPPs without violating network security constraints.

Microgrids are low-voltage supply networks designed to supply electrical and heat loads to small customers in a defined area such as academic institution, public communities, manufacturing firms, etc. In the event of a power outage, these microgrids can be disconnected from the main grid and can provide appropriate electricity to the customers. These micro grids are largely dependent on communication systems for efficient and reliable operation. This increases the risk of cyber intrusions. Developing new protocols and cyber-drill for vulnerable assessments were limited in securing the grid from such attacks. Hence, it is important to advance the defending and detection mechanism against the attacks. On other hands, microgrids hold enormous promise in terms of integrating renewable resources with other distributed energy sources, smart grid and peak demand, significant obstacles are being faced in terms of real-time power management and control systems. The risk in scheduling these distributed energy sources is to be analysed. Some of these issues can be handled by solving optimization problems with various objectives, such as power demands, fuel consumption, environmental emissions, costs, dispatchable loads, and so on. Developing a model considering these objectives and risk assessment can be further investigated.

APPENDIX-A

Appendix-A

Table A1		
Wind Turbine Generating Unit parameters [34]		
Parameter	Value	Unit
ϑ_{cin}	3	m/s
ϑ_{co}	25	m/s
ϑ_{rated}	14	m/s
G_R^{WT}	400	MW
C_{it}^{WT}	3	\$/MWh

Table A2		
Solar PV Plant parameters [34]		
Parameter	Value	Unit
n^{PV}	3560	-
S^{PV}	1.28	m^2
$\eta^{r,PV}$	0.255	-
$\eta^{r,pc}$	1	-
T^{ref}	27	℃
C_{it}^{PV}	2	$\$/kWh$
$G_{it}^{PV,max}$	300	MW

Table A3		
CHP unit Parameters [50]		
Parameter	Value	Unit
$A(A_P, A_Q)$	$A(26,0)$	-
$B(B_P, B_Q)$	$B(23,20)$	-
$C(C_P, C_Q)$	$C(10,20)$	-
$D(D_P, D_Q)$	$D(12,11)$	-
$C_{it}^{fix,P,CHP}, C_{it}^{Var,P,CHP}$	0,5	\$/kWh
$P_{it}^{CHP,max}, P_{it}^{CHP,min}$	150,15	MW
$C_{it}^{fix,th,CHP}, C_{it}^{Var,th,CHP}$	0.5,5	\$/MWh
$Q_{it}^{CHP,max}, Q_{it}^{CHP,min}$	27,5	MW
L_{it}^{CHP}	10	MW

Table A4			
DG sets parameters			
Parameter	Value		Unit
	DG set-1	DG set-2	
$P_{it}^{DG,max}$	80	85	MW
$P_{it}^{DG,min}$	5	5	MW
$R_i^{DG,U}$	25	25	MW/h
$R_i^{DG,D}$	25	25	MW/h
$C_{it}^{fix,DG}$	2	2	\$/MWh
$C_{it}^{Var,DG}$	5	5	\$/MWh

Table A5				
Conventional Power Plant parameters [50]				
Parameter	Value			Unit
	CPP-1	CPP-2	CPP-3	
$C_{it}^{fix,CPP}$	2	5	4	\$/MWh
$C_{it}^{var,CPP}$	20	10	20	\$/MWh
$P_{it}^{CPP,max}$	100	100	100	MW
$P_{it}^{CPP,min}$	0	0	0	MW
$R_i^{CPP,U}$	15	15	15	MW/h
$R_i^{CPP,D}$	15	15	15	MW/h

Table A6		
ESS parameter [50]		
Parameter	Value	Unit
$\eta_i^{s,ch}$	0.95	-
$\eta_i^{s,dis}$	0.9	-
$P_{it}^{s,ch,max}$	140	MW
$P_{it}^{s,dis,max}$	140	MW
$E_{it}^{s,max}$	160	MWh
$E_{it}^{s,min}$	125	MWh
E_{int}^{s}	130	MW

Table A7				
Generating Units other than VPP [18]				
Parameter	Value			Unit
	Gen-1	Gen-2	Gen-3	
$\chi_{it}^{G,DA}$	30	15	25	\$/MWh
$\underline{P}_{it}^{G,DA}$	75	75	55	MW
$\overline{P}_{it}^{G,DA}$	0	0	0	MW

Table A8				
Demand Units other than VPP [18]				
Parameter	Value			Unit
	D-1	D-2	D-3	
$\chi_{jt}^{D,DA}$	70	70	73	\$/MWh
$\underline{P}_{jt}^{G,DA}$	75	75	25	MW
$\overline{P}_{jt}^{G,DA}$	0	0	0	MW

Table A9				
Reserve market agents other than VPP [18]				
Parameter	Value			Unit
	C-1	C-2	C-3	
$\chi_{it}^{G,RU}$	10	20	10	\$/MWh
$\chi_{it}^{G,RD}$	10	20	10	MW/h
$\overline{P}_{it}^{G,RU}$	20	20	30	MW/h
$\underline{P}_{it}^{G,RU}$	0	0	0	MW/h
$\overline{P}_{it}^{G,RD}$	20	20	30	MW/h
$\underline{P}_{it}^{G,RD}$	0	0	0	MW/h

Table A10								
Flexible Demand utilities data								
Parameter	Value of each Demand							Unit
	D-1	D-2	D-3	D-4	D-5	D-6	D-7	
$P_{jt}^{d,max}$	70	75	35	75	74	50	70	MW
$P_{jt}^{d,min}$	10	25	07	10	10	10	10	MW
$R_{j}^{d,DW}$	10	10	10	10	10	10	10	MW/h
$R_{j}^{d,UP}$	10	10	10	10	10	10	10	MW/h
C_{jt}^{d}	45	40	43	42	32	32	33	\$/MWh
$P_{j,int}^{d}$	40	30	05	20	40	20	20	MW
Parameter	D-8	D-9	D-10	D-11	D-12	D-13	D-14	Unit
$P_{jt}^{d,max}$	50	35	55	26	54	80	100	MW
$P_{jt}^{d,min}$	15	10	12	5	20	20	10	MW
$R_{j}^{d,DW}$	10	10	10	10	10	10	10	MW/h
$R_{j}^{d,UP}$	10	05	10	10	10	05	10	MW/h
C_{jt}^{d}	44	45	42	42	42	45	45	\$/MWh
$P_{j,int}^{d}$	20	05	15	10	24	40	55	MW

Table A11								
Scenarios related to the Up and Down Reserve Market deployment request in all the time periods								
Time periods	Up regulation Market				Down regulation Market			
	S-1	S-2	S-3	S-4	S-1	S-2	S-3	S-4
1-8 hours	0.5	0.8	0.5	0.8	0.9	0.5	0.7	0.6
9-16 hours	0.9	0.5	0.7	0.6	0.5	0.8	0.5	0.8
17-24 hours	0.6	0.6	0.6	0.6	0.5	0.8	0.5	0.8

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