DESIGNING OF MARKET MODEL, EFFECTIVE PRICE FORECASTING TOOL AND BIDDING STRATEGY FOR INDIAN ELECTRICITY MARKET

THESIS SUBMITTED TO THE DELHI TECHNOLOGICAL UNIVERSITY IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

BY

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Dedicated to …

My family

Certificate

This is to certify that the thesis entitled "Designing of market model, effective price forecasting tool and bidding strategy for Indian electricity market" is being submitted by **Mr. Neeraj Kumar (2K16/PHD/EE/18)** for the award of degree of Doctor of Philosophy to the Delhi Technological University is based on the original research work carried out by her. She has worked under the supervision of **Prof. M. M. Tripathi** and has fulfilled the requirements, which to; our knowledge has reached the requisite standard for the submission of this thesis. It is further certified that the work embodied in this thesis has neither partially nor fully submitted to any other university or institution for the award of any degree or diploma.

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List of Publications

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3. Neeraj Kumar, M.M. Tripathi "Design of a solar Energy Market model for Indian Scenario" Journal of Electrical Engineering Technology,2021, ISSN Print: 1975-0102, ISSN online: 2093-7423, Doi: 10.1007/s42835-021-00802-9 *(*SCI-E, IF 0.73*)*.
4. Rachna Pathak, Arnav Wadhwa, Poras Khetarpal, Neeraj Kumar "Comparative assessment of regression techniques for wind power forecasting" IETE Journal of Research, 2021, ISSN Print:0377-2063 ISSN online:0974-780X, Doi: 10.1080/03772063.2020.1869591 (SCI-E, IF 1.12)
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6. Neeraj Kumar, M. M. Tripathi "Impact Exploration of wind energy on electricity price using regression techniques" Electric power systems and components, ISSN No. 1532-5016 (Revision Submitted) (SCI-E, IF 0.82) Submission ID: 213296373.

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1. Neeraj Kumar, M.M. Tripathi “Evaluation of Effectiveness of ANN for feature selection-based Electricity Price Forecasting” 2017 IEEE International Conference on Emerging Trends in Computing and Communication Technologies (ICETCCT), Dehradun Electronic ISBN: 978-1-5386-1147-0. Doi: 10.1109/ICETCCT.2017.8280298. Added to IEEE Xplore: 05 Feb 2018.
2. Neeraj Kumar, M.M. Tripathi “Impact analysis of wind energy on electricity price using Deep Neural Network” 2021 8th international conference on computing for sustainable global development, Indiacom-2021, Delhi, Electronic ISBN:978-93-80544-43-4 DOI: 10.1109/INDIACom51348.2021.00026. Added to IEEE Xplore: 03 June 2021.

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Abstract

The Development scenario for renewable energy across the globe is changing rapidly in terms of capacity addition and grid interconnection. Penetration of renewable energy resources into grid is necessary to meet the elevated demand of electricity. In view of this penetration of solar and wind power growing enormously across the globe. Solar energy is widely escalating in terms of generation and capacity addition due its better predictability over wind energy. Electricity pricing is one of the important aspects for power system planning and it felicitates information for the electricity bidder for exact electricity generation and resource allocation. The important task is to forecast the electricity price accurately in grid interactive environment. This task is tedious in renewable integrated market due to intermittency issue.

As renewable energy penetration into the grid is enhancing swiftly. An appropriate market model addressing the issues of related to renewable energy specially wind and solar is necessary. A novel solar energy-based market model is proposed for state level market along with the operating mechanism. The different component associated with grid and their functionality in the operation of grid is discussed. Challenges and possible solutions are addressed to implement the market model.

Energy trading plays a crucial role in the economic growth of country. Renewable energy trading opens a new avenue for the economic growth. India is blessed with a rich solar energy resources, the solar power producers tapped the potential of solar up to appreciable extent, but due to lack of trading models and specific regulatory mechanism in context of renewable energy generation is main hurdle in competition among generators. Various market model developed for solar energy trading at state level electricity along with their trading mechanism is presented. Also features of the models are also addressed.

A Rigorous literature review on price forecasting is conducted with focus on impact of solar and wind energy on electricity price. The data of Australia electricity market is collected for price forecasting. The correlation among the inputs for price is calculated using correlation coefficient formula and selected the highly corelated input with price. Artificial Neural Network (ANN) is implemented to forecast the price by using historical data. The price is predicted for January to June month and weekly forecast of price for the same month is executed. The minimum MAPE is 1.94 for April month and 1.03 for third week of January.

The research work is continued to investigate the impact of solar and wind energy on electricity price. The Long short-term memory (LSTM) is designed to forecast the electricity price considering the solar power penetration. The raw data of Austria market consists of actual day ahead load, forecasted day ahead load, actual day ahead price and actual solar generation is used. The reliability of forecasting model is analyzed by computation of confidence interval on MAPE.

The research work is extended to investigate the impact of wind energy on electricity price. The Austria electricity market data is used for investigating the potential impact of wind energy on rice. The statistical analysis of the data is conducted for finding the suitability of the model. Decision tree model is designed and implemented and significant reduction in the forecasting accuracy of 5.802 is achieved for the data set using wind energy as input parameter.

The future of solar energy in India is positive. The growth of solar energy in terms of capacity addition and grid interconnection programme is expanding day by day. To promote the solar energy trading in open market a suitable bidding mechanism must be designed for solar power producers. It becomes pertinent to design the bidding strategy for solar power producers to maximize their profit considering the uncertainty in the energy output. Hybrid Particle Swarm Optimization – Gravitational Search Algorithm (HPSO - GSA) is proposed for designing the optimal bidding strategy for solar PV power producer for designed solar energy based Indian electricity market. The objective function is designed considering the constraint of uncertainty and energy imbalance in price. The proposed algorithm shows highest profit when compared with Real Coded Genetic Algorithm (RCGA), Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA).

In the light of continual renewable energy growth and grid interconnection, a novel solar energy-based electricity market model addressing the issues of solar energy is proposed to make the system effective and reliable. This novel market may fill the promise of providing electricity at competitive cost for all in India. The various market models are proposed for trading the solar energy in competitive market for maximum utilization of untapped potential of solar energy. The various trading models may be implemented based on the application and suitability. The electricity price forecasting is an important aspects of power system planning and for renewable energy interactive grid price forecasting is crucial task due its intermittent nature. ANN model is proposed for price forecasting and significant improvement in MAPE is reported for Australia electricity market data. Further the investigation has been done on the impact of solar energy generation on electricity price using machine learning techniques (DT, RF, LASSO, XGBOOST and LSTM). The LSTM model accuracy is good in price forecasting with consideration of solar energy as input parameter. The investigation is extended for impact of wind energy on electricity price and Decision tree model accuracy is superior as compared to RF, LASSO, LR, SVR and DNN model. The bidding strategy for the designed solar based electricity model is proposed using HPSO-GSA method and profit calculation has been done for solar PV producers on real time data. The maximized profit has been obtained through HSPO-GSA method for two different sets of datasets.

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Acronyms

MNRE	Ministry of New Renewable Energy
WPF	Wind Power Forecasting
PV	Photo Voltaic
EPF	Electricity Price Forecasting
DT	Decision Tree
SVM	Support Vector Machine
ANN	Artificial Neural Network
LR	Linear Regression
SVR	Support Vector Regression
RF	Random Forest
XGB	Xtreme Gradient Boost
LASSO	Least Absolute Square Selector Operator
DNN	Deep Neural Network
CI	Confidence Interval
RCGA	Real Code Genetic Algorithm
PSO	Particle Swarm Optimization
GSA	Gravitational Search Algorithm
HPSO	Hybrid Particle Swarm Optimization
MLP	Multilayer Perceptron
STPF	Short Term Price Forecasting
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Squared Error
SPV	Solar Photovoltaic
RE	Renewable Energy
PGCIL	Power Grid Corporation India Limited
ISO	Independent System Operator
SLDC	State Load Dispatch Centre
SEB	State Electricity Board
NLDC	National Load Dispatch Centre

RLDC	Regional Load Dispatch Centre
SDU	State Distribution Utility
CERC	Central Electricity Regulatory Commission
SERC	State Electricity Regulatory Commission
PX	Power Exchange
SC	Scheduling Coordinator
SPP	Solar Power Producer
PPA	Power Purchase Agreements
DA	Day Ahead
MLP	Marginal Locational Price
RPO	Renewable Purchase Obligation
SPF	Solar Power Forecasting
REC	Renewable Energy Certificate
WPF	Wind Power Forecasting
CEA	Central Electricity Authority
MCP	Market Clearing Price
DISCOM	Distribution Company
SDU	State Distribution Utility
IPP	Independent Power Producer
SGU	State Generating Utility
CGU	Central Generating Utility
VPP	Virtual Power Plant
NSM	National solar Mission
JNNSM	Jawahar Lal Nehru national Solar Mission
FERC	Federal Energy Regulation Commission

Chapter 1

INTRODUCTION

1.1 Overview of renewable energy

The momentum of renewable energy generation (solar and wind) development across the globe is satisfactory and met the expectations of energy demand. Renewable energy resources are prime choice due to abundance availability in nature, environment friendly and economical. RE resources are promoted all over the world to meet the energy demand and to make the environment pollution free, in addition some countries energy generation has shifted from coal based to renewable based to ensure the sustainable and energy secure future.

The wind and solar energy capacity addition initiatives helps to achieve the sustainability in energy sector. 2537GW is the global renewable energy generation by the end of 2019, out of which 90% share is from wind and solar share of new capacity [1]. Renewable power capacity addition growth is positive across the globe and government policies and regulations are becoming more favorable for RE sources.

India is blessed with an adequate solar exposed area and balanced wind energy resource, and the growth in solar and wind energy generation is positive signal towards the clean and sustainable energy future. National institute of solar energy has accessed the potential of solar to only 748 GW. National solar mission (NSM) is one of the key initiatives toward the climate change by adding up more and more capacity to grid. The future goals and recent developments of in solar energy for India were discussed [2]. To meet the increasing demand of electricity grid interactive solar and wind program is promoted by MNRE and in this direction several initiatives have been taken. By the end of year 2022 MNRE has set target of achieving 100GW capacity grid connected solar power plant. India secured 5th position in the world in renewable energy installed capacity. In largest installed capacity of world India is 4th in wind and at 5th

position in solar power. 6529.20MW power grid connected power added during 2018 – 2019 financial year. 39083.71 MW is the total installed capacity of grid connected capacity from solar and 38789.15 MW from wind as on February 2021 [3]. The status solar photovoltaic (SPV) development is maximum among others technologies available the data of recent development in SPV is presented [4]. Government is focused on addition of off grid and on grid capacity continually to make the environment pollution free and achieve energy security. The Indian government actively working on the development of RE and policies are being framed for maximum RE integration [5].

With continual effort towards promotion of RE for energy demand and environmental concern, but there is a long way to go for maximum utilization of the untapped RE sources. still some barrier exist in the holistic growth of RE sectors in India are RE power producers are very less, results into lesser competition among generators, market model is not suitable for RE integration, RE trading options are very limited and electricity market for RE bidding is not flexible due to variability in the power. The technical challenges in RE grid interconnection and their solutions have been suggested in [6].

This chapter attempts to explore the bibliographical updates in RE market development, trading of RE, impact of RE on electricity price and RE bidding. This survey motivates researchers working in the field of RE and its impact on the grid.

The major highlights of this chapter are as follows

- Literature review on the RE market development for Indian context
- Review on available trading models for RE with emphasis on solar energy trading models for Indian electricity market
- A comprehensive review is presented on price forecasting and effect of renewable energy on electricity price is discussed
- The effect of solar energy generation on electricity price is explored

- The effect of wind energy generation on electricity price is explored
- A brief literature review is presented on bidding strategy for renewable energy power producer to maximize their profit in uncertainty of generation.

1.2 Renewable energy market model

Appropriate market model for Renewable energy auction is important aspect to ensure the healthy competition among generators to supply quality of power at competitive price to the consumer end. This task is only possible by designing proper non-discriminatory operation mechanism, where regulatory body closely observe the power procurement, demand and dispatch management, optimal resource allocation and effective transmission and distribution of the power to the consumer end. By adopting proper market mechanism and operating mechanism for RE based electricity market the energy demand can be fulfilled in effective the only challenges are to cope with the variability in the RE generation and demand.

The literature available for RE based market development is none to fewer. After the restructuring process of power system comes into play the few researchers presented the market model for fuel-based power plants [7] considering the competition on generation side because transmission is wholly owned by PGCIL in India. Some of the competitive models also suggested for distribution side [8]. The market model for solar energy is proposed [9]. The impact of RE on electricity market has been discussed [10]. The market model and operating mechanism has been proposed for combined wind and solar energy [11]. The RE market development is in early stage in India, more research needs to done in the market development for RE sources and certain additional changes have to make to make the system reliable. Three key factors to make the RE integrated system reliable is discussed below.

Storage system: storage system plays a vital role in maintaining the reliability and balance of grid connected renewable energy system. It allows flexibility to system for managing the resources, improve power quality, and reduce peak demand and grid stability. The available technologies for energy storage in RE integrated system techno economic analysis and benefits associated with energy storage system discussed [12]. The list of available and being developed are battery based, controller based and non-battery storage system which can be interfaced with techno economic advantages are given in [13] – [14]. The energy management is important aspects in RE integrated grid to cope with the variable generation. The methods of optimization of renewable energy resources and energy management for effective operation of the grid are presented [15].

Advanced forecasting: to compensate the uncertainty in generation of power from solar and wind it is important to adopt advanced forecasting to meet the desired demand. In this unique method system planner use 5 minutes interval forecasting of generation instead of conventional 15 minutes interval to ensure the grid stability. Advanced machine learning techniques can be employed on past data for accurate forecasting of power to match the load and demand [16].

Virtual power Plant: primary goal of VPP is to integrate the renewable energy resources into conventional electricity market to improve the capacity to meet the demand. Secondly it coordinates with RE generation, and demand side management to supervise the forecast and optimize the generation and demand. The VPP is one of best promising solution for mitigating the issues arises due to intermittent nature of solar PV system. The design aspects of VPP and its analysis are presented in [17]. The case study for evaluation of potential and implication of VPP for Punjab state power corporation limited (PSPCL) has been presented [18].

1.3 RE trading models

Solar and wind are two prominent RE resources are being used in grid interactive mode to meet the escalating demand of power in India. Depending on the suitability of location new RE based State level dispatch center may propose power trading flexible for consumer and power producers. Models needs to be designed to mitigate the flaws in the coal-based trading mechanism such as uncertainty issue and storage system facility.

Concept of solar aggregator model was introduced and various models for trading of solar power in pool electricity market for state level are proposed [19] for Indian scenario. The aggregator model for trading solar power is shown in Fig.1.1. The functions and responsibility of the components of the restructured power market is explained and based on practical experience of restructuring various models of fuels-based power trading has been suggested [20]. VPP is appropriate option to integrate the solar and wind energy with gird because it can cope with variability of power the real time implementation of VPP integrated with wind and solar is proposed [21]. The microgrid is widely used to tap the potential of RE sources. the energy management in microgrid for multi residential apartment is analyzed [22]. The usage of storage devices to make the system reliable and effective will add economic burden. The resource allocation and pricing of the storage system for SPV is discussed for multi apartment solar grid [23].

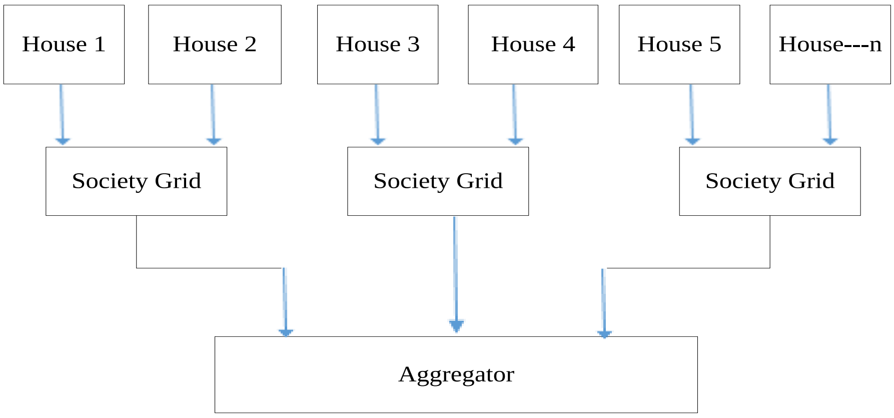

Fig.1.1: Aggregator model for solar power trading

1.4 Price forecasting

The adequate literature is available on electricity price forecasting for various type of electricity market and with different accuracy rate. However, the literature for price forecasting is very rich the most cited paper covers different types of EPF and bibliographical updates in this filed adequately [24]. The most cited and based on advanced AI techniques is listed in table 2. With their major outcomes and features. Recent seven-year papers from reputed journals have been included in literature review to analyse the impact of latest techniques on price forecasting accuracy.

Forecasted Price is used to design an optimal bidding strategy for a generator according to degree of risk. The forecasted price gives an idea regarding the previous electricity market price. So, price forecasting is the basis for optimal bidding in the electricity market. [25] – [46]. The bibliographical updates in electricity price forecasting is presented in Table 1.1.

Table 1.1: Bibliographical updates in Electricity price forecasting

Year of publication and Reference no.	Forecasting Horizon	Type of Test System	Tool used	Features and Major Outcomes
2020 [25]	STPF	New York USA	Hybrid Deep neural network consisting of Variational Mode Decomposition (VMD), Convolution neural network and Gated Recurrent Unit	VMD is used to decompose complex time series of price signal into intrinsic mode function with different centre frequency.
2020 [26]	STPF	Penselvaniya New Jersey Maryland (PJM)	GA-CNN	Spatiotemporal data used for lower error in forecasting accuracy.
2019 [27]	STPF	New England Electricity Market	Relevance vector machine and XGBoost	Highly accurate Mean absolute error and computationally cheap
2019 [28]	STPF	New south wales of Australia and French	Wavelet Transform-adam-LSTM	More stable variance and capable in capturing the non-linearity and stochasticity in efficient manner to hybridization of WT and Optimizer. way.
2019 [29]	MTPF	European energy exchange	Weighted nearest neighbour, TBATS and Deep feed forward neural network	29 day ahead forecasting for production planning stage in advance

2019 [30]	STPF	Ontario Electricity market	Mixed Integer Linear Programming	Detection of price spike and extreme price variation
2019 [31]	STPF	Global Energy Forecasting Competition (GEFCoM 2014)	ARX and NARX	Averaging of DA electricity price using different calibration window
2019 [32]	STPF	Ontario Electricity market	Hybrid ANN and Artificial cooperative algorithm	Feature selection based on mutual information and neural network is used.
2018 [33]	STPF	European Power system	ANN with kalman filter	Stability analysis of forecasting method using Lyapunov method and one step ahead and n step ahead prediction done.
2018 [34]	STPF	Deep learning approach	Deep Learning approach	Statistically significant improvement in accuracy and results compared with 27 state of the art methods
2017 [35]	STPF	Ontario and Australia	Extreme Machine Learning and Wavelet Neural Network	Bootstrapping technique is used to overcome the uncertain spike in price
2017 [36]	STPF	Merchant Compressed Energy Storage Plant	Information Gap Decision Theory	Consideration of Risk constrained Bidding
2017 [37]	Medium Term PF	PJM, Spanish Electricity and New York Electric Utility	Quantile Regression	Accurate Tail Risks, Feature selection of load and Price
2017 [38]	STPF	Australia Electricity Market	extreme machine learning and non – dominated sorting genetic algorithm	Importance of reliability and sharpness for generating Quality PIs.
2016 [39]	Short Term and Medium Term	U.K Electricity Market	Six Different Autoregressive Model	For the forecasting of Base load Electricity Price inclusion of Natural Gas price, Coal Price and CO2 Price

2016 [40]	Short Term	European Electricity Market	Regression integrated with Lasso Estimation Method	Consideration of price of same day and previous day
2015 [41]	Short Term	Spanish Electricity market	Modified order weighted Average combined with ANN, ANFIS and Autoregressive Moving Average	Hybridisation of multiple forecast engines based on Data Fusion Training efficiency and forecasting accuracy is considerably good. Convergence speed is high
2015 [42]	Short Term	New England	Relevance Vector Machine with Genetic Algorithm	RVM is capable to capture the various dynamics of Electricity Price
2015 [43]	STPF	Ontario and PJM	PSO-SVM	High quality PI generation for uncertainty characterization of price signal with lesser computational time.
2014 [44]	Short Term	Ontario Electricity Market	SVM with Radial Basis Kernel function	Generation of quality PIs for Price and load
2014 [45]	Mid Term MCP Forecasting	PJM Electricity Market	Multiple least square support vector Machine	Pre-processing of data corresponding to price zone and forecasting with four parallel LSSVM.
2014 [46]	Austria Electricity market	Extreme machine learning	Extreme machine learning and maximum likelihood method	Reliability and sharpness are considered in calculation of Particle Interval for accurate forecasting.

1.5 RE generation forecasting and its impact on price

Forecasting of renewable generation is important task for system planner to ensure the reliability of power being fed to the grid. Due to variability in the output power of RE sources forecasting is necessary to maintain the grid stability. In Forecasting future value of expected power is predicted from the past metrological and generation data of RE sources. In case of RE sources forecasting of power is more important due to intermittent nature of solar and wind. To cope with uncertainty advanced forecasting is adopted by the system planner to ensure the reliability of power and grid stability in RE integrated market [report for forecasting].

Price forecasting is important aspects for power system economics as it gives information to the producer to bid optimally in the market to gain profit. As the marginal cost in RE generation is very low RE power producers can maximise their pay off by adopting suitable bidding strategy. Different machine learning algorithm proven to be good for forecasting of price renewable energy scenario because it can capture the stochasticity of price and variability in the output with time efficiently. Demand, weather factors, geographical horizon and variable RE generation are major factors in variability of price for different hours.

The RE integration into grid to meet the demand is escalating due to availability of clean energy at lower marginal cost. Due to comparative low marginal cost of wind and solar energy the energy supplied to the consumer is competitive low. Due to higher demand and limited generation the cost of electricity is high especially in peak hours. In order to compensate the cost incurred for electricity by user and rising demand RE is possible solution for energy security. In this section the potential effect of solar and wind energy generation on electricity price forecasting is discussed.

1.5.1 Solar power forecasting

Solar power forecasting is an important factor in the achievable solar energy deployment for supporting reliable and cost-efficient operation and control of grid. Short-term forecasting of solar power is an important aspect for the management of security and cost control of power industry. This has great significance in improving the accuracy of forecast. Thus, forecasting of solar provides the participants of market and prospect to balance their generation/ consumption needs and other obligations in advance**.**

Deep neural networks are proven to be accurate for forecasting of solar power. Hybrid model of LSTM, auto encoder and Deep belief networks algorithm has been used to predict the solar power various solar plants were discussed [47]. Inherent variability in the solar power generation is the major drawback, due to which grid interconnection with grid to meet the demand is not reliable. To cope with this problem forecasting of solar generation to maintain grid stability is important. A comprehensive review on solar power forecasting methodologies and analysis on performance of machine learning models with their success rate was presented [48]. ANN is also one of the most extensively used tool for forecasting problems, apart from metrological and electrical parameters affecting solar power, satellite image and ground telemetry used as input for accurate forecasting of solar power[49].Geographical location tracking technologies are gaining popularity for identifying the potential of solar energy and its forecasting for grid interconnection [50] - [51]

1.5.2 Solar energy generation impact on price

The analysis of impact of solar energy generation on electricity price is an important task to ensure the price imbalances penalties to the producers. The market electricity price is affected majorly by demand, metrological data, solar energy generation and type of market. RE integration to grid plays will an important role in meeting demand, reducing the cost of electricity, securing pollution free environment and energy security as of now and in future. In this section a brief literature review of solar energy impact on price is presented to motivate researchers working in this area.

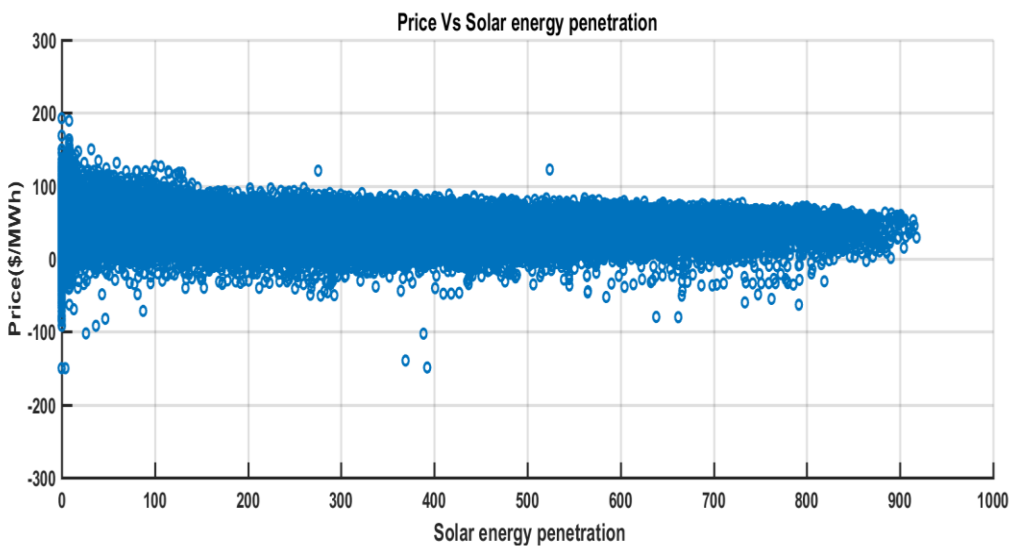

Fig.1.2: Scatter plot for solar energy penetration impact on electricity price

In Fig. 1.2. the impact of solar energy generation on electricity price for Austria electricity market data is clearly visible. For higher penetration level of solar energy, the electricity price is dropped and this effect if more visible for peak as this time solar generation at its peak and demand is high. To compensate the high demand effect RE integration is best possible and economical solution to meet the demand effectively. Flexibility and suitability evaluation for Nigerian electricity market to handle large penetration of PV is presented [52]. The impact of RE on electricity price has been evaluated for Germany market and technical solutions suggested to cope with the high penetration of PV [53] – [54].

1.5.3 Wind power forecasting

Power generation from renewable resources like wind and solar is popular choice to meet the rapidly increasing demand. The reason for wide acceptance of wind as renewable resource is abundance in nature, economic and environmental advantages. But main issue associated with the wind power generation is uncertain and intermittent nature. So, wind power forecast is essential for effective operation and maintains the grid stability.

The literature availability for wind power forecasting is comparatively lower due to lesser capacity addition and lower predictability rate over solar. The history of short wind power forecasting is divided in three categories is before 1990, after 1990 and since year 2000. The extensive literature survey about models used and major outcome were outline in a precise manner [55]. The wind power forecasting is important for grid interconnection to ensure security of power. Due to intermittent nature of wind expected power output from wind needs to predict to commit the demand. Long term wind power forecasting using different machine learning algorithms for specific geographical location were implemented and result was analyzed for setting upwind power plant [56]. A comparative review on application of intelligent predictors, ensemble learning methods and metaheuristic approaches have been discussed for short term wind power forecasting. Critical comments on merits and limitation have been outlined [57]. To mitigate the challenges in wind such as randomness and inherent non linearity a hybrid forecasting model were proposed and experimental analysis was done for real time data for validation of results [58]. Ensemble learning methods demonstrated to be an accurate for short term wind power forecasting as it captures the non-linearity effectively and improves the accuracy at each stage [59].

1.5.4 Wind energy generation impact on electricity price

In this section the literatures review on the potential impact of wind energy on electricity price in renewable integrated electricity market. The Development scenario for renewable energy across the globe is changing rapidly in terms of capacity addition and grid interconnection. The impact of wind energy on electricity price is significant and it is an important task for power system planners to forecast the price in light of its variability. The opportunities (lower carbon emission and energy security etc) and challenges (stability and reliability issues) associated with interconnection of solar and wind into the grid is discussed for 9-bus system [60].into the grid .In Australia the wind energy production surpasses 20% of total energy production, it greatly impacts the electricity price but authors claims no clear relationship between wind energy generation and demand. Due to inherent variability in the output of wind energy [61]. The potential impact of wind generation forecast on electricity price using regression methods for Spanish electricity market claims accuracy and additionally week days factors considered for better feasibility of model [62]. Impact of over forecasting and under forecasting of wind energy on electricity price is analyzed for real time data [63]. Wind energy generation marked a positive impact on spot market prices but at the same time econometric analysis indicates that higher initial cost burden plays major hurdle in growth [64]. The impact of wind energy generation on price is described using statistical analysis for real time data of generation and price for Portugal electricity market on wind energy data has been performed for analysis [65]. in future the mix capacity of RE and coal based is used to serve the electricity demand but the share of RE will certainly dominate to secure the environment. The long-term prediction analysis of high RE penetration in electricity market is necessarily a discussion point. The future equilibrium of the high wind energy penetration and its impact on price and capacity, possible challenges and mitigation techniques were given [66]. The authors conducted survey for north pacific region and US for hydro-wind plant and conventional coal-wind plant and pointed out that hydro-wind coordinated plant is economically more beneficial as compared to direct investment in the wind power [67]. To maintains the stability of the grid probability density function have been used to model the uncertainties associated with wind power and day ahead (DA) price and correlation between the day ahead (DA) and real time (RT) price established analytically to ensure the price stability [68]. Optimization based approach proposed on real time data for detection of price imbalance, penalties and impact of wind energy generation on electricity price. Proposed approach may benefit the wind power producer to maximize the profit in wind coordinated electricity market [69]. The real time pricing tariff proposed to cope the challenges (non dispatchability, variable generation and generator constraints) of wind energy for large scale integration into the grid [70] – [71]. The quantitative analysis on impact of large wind integration on LMP has been done [72].

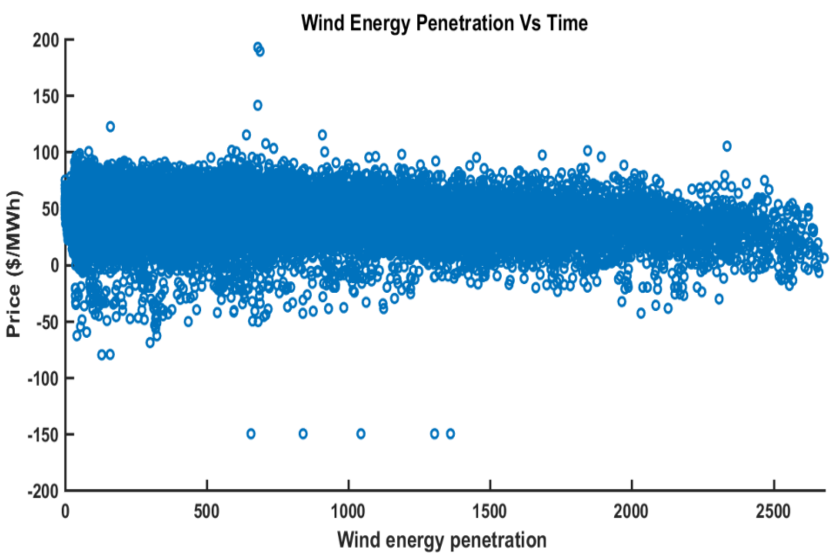

Fig.1.3: scatter plot for wind energy penetration impact on electricity price

In Fig. 1.3. the potential impact of wind energy penetration on electricity price for Austria electricity market data is evident. However, the impact of wind energy is not following any pattern which helps in demand side management and maximize the resource utilization. The two major points from above graph derived compared to solar energy, one is the degree of variability in the wind output is comparatively higher and predictability of wind is complex task which leads to mismatch in demand and supply.

1.6 Bidding strategy for renewable energy market

Due to large capacity addition in generation of power from RE sources, the penetration rate into gird is also enhancing to meet the demand. The major concern in penetration for RE into grid is intermittent nature of solar and wind. For RE producers it is a challenging task to participate in bidding process and maximize their profits. The major factors affecting the bidding strategy for RE producers are, RE generation, time horizon, demand, capacity of plant and rival bid. The RE producers have to bid optimally to gain profit in such scenario to avoid penalty and dispatch committed power to load Centre. The only difference lies in the bidding of RE power is variability in the output, due to which consumer may face price spike for specific time and if the all favorable conditions exist then electricity price will be marginally low for specific time periods for RE integrated grid. The concept of RE trading is not new for some countries but the literature availability in this area is very fewer. For mitigating the variability in the output and financial penalties issues the wind-photovoltaic coordinated operation is suggested for reliable and profitable operation of the grid [73]. To maximise the pay off and cope with variability and penalty coalition bidding implemented on Belgium power transmission data for hybrid RE system [74]. The hybrid of solar-wind system can be useful to make system reliable in terms power dispatch using compressed air energy storage(CEAS) device[75], for specific time when output from solar and wind source is zero then power from CEAS can be utilized to bid to rid of frequent issues like penalty and price imbalance issues. The compressed air energy storage based bidding for hybrid solar-wind energy system has been suggested The RE trading in India is at an early stage the data of real time experiences of JNNSM for competitive bidding of solar and wind power for Indian scenario and recent developments in the regulatory and policies has been highlighted [76]. A report on development of RE auction for developing countries, comprises RE auction experience of Brazil, China, Morocco, Peru and South Africa including, best practices, policies and regulations followed to benefit the producers and consumers have been discussed [77]-[78]. Wind generation forecast plays a major role in maximization of profit for power producers, a stochastic bidding model used for higher revenue [79]. Colonel search algorithm was implemented [80] for the optimization of resources for generation and maximizing the profit of producers for combined wind, hydro and pumped storage system considering pumping constraints, pumped storage unit will maintain the stability of the system. Bi-level optimization technique proposed for wind power bidding in short term electricity market [81]-[82]. The optimal bidding strategy for wind power producer considering uncertainties (real time wind power generation, real time LMP, DA LMP and price imbalance penalties)

Designing of rival bidding strategy also be included in the RE based bidding to get more accurate figure of price and volume to be quoted in future to minimize the resources and maximize the profit. However, the market of RE is not competitive yet in India, the design of appropriate and suitable bidding strategy is one of the emerging research areas.

1.7 Research gaps

With above literature survey, the research gaps found listed below.

- With increasing growth of solar energy, electricity market is necessary to promote solar energy expansion.
- Existing market mechanism is not suitable for renewable energy to cope up with uncertainty issue.
- No suitable market for trading of renewable energy to promote competition among solar power generator

- Effective price forecasting tool is necessary for real time electricity market
- In renewable interactive grid scenario, the effect of renewable energy on electricity market price could be investigated.
- Machine learning models are not completely explored in analysing the effect of solar and wind energy penetration on electricity price.
- Utilization of statistical models for study the reliability of forecasted price is not considered.
- Fewer research work done on bidding of solar PV for profit maximization
- The work shall be done to improve the convergence rate.
- Many authors tested and validated the forecasting models developed using the data of one location. Further, the location dependency of the model requires verification using the data from more than one location.
- Most of the research on wind power forecasting shows models developed for short term forecasting, but not much for long term forecasting.
- In case of grid integration of large capacity renewable energy sources, more work can be carried towards wind power forecasting (WPF) at grid level.
- To identify the reliability of a forecasting tool, a comparison study can be carried between physical model and statistical model in forecasting.
- The effect of wind direction on the prediction of wind power can be evaluated.

1.8 Main objectives of the research proposal

After rigorous literature review in the relevant areas above research gaps are identified. To proceed with the research, work the following objectives are defined.

- To design a suitable market model for solar energy for Indian electricity market.
- To design a market mechanism favourable for solar energy electricity market

- To design solar power trading models for solar energy market.
- To design a suitable model for price forecasting.
- To explore the impact of solar energy generation on electricity price.
- To explore the impact of wind energy generation on electricity price.
- To analyse the uncertainty in the prediction of price forecasting renewable integrated market.

1.9 Key research outcomes

The outcomes of the research work are listed below.

- Design of solar energy market model and operating mechanism are proposed for state level electricity market for Indian scenario.
- Different solar power trading (SPT) models and their mechanism are proposed for Indian Electricity market.
- Feature selection-based price forecasting reduced the complexity of ANN model and improves the forecasting accuracy.
- As the penetration of renewable energy to grid is growing rapidly, the investigation of solar energy penetration on electricity price is done using LSTM. To examine the effectiveness of the proposed model the result is compared with Decision tree, Random forest, LASSO and Xtreme gradient boost model.
- Investigation on effect of wind energy on electricity price forecasting is analyzed and it is understood that with the consideration of wind energy generation the forecasted price is reduced and forecasting accuracy is also improved for the dataset used.

- with continual increase in the capacity addition of solar energy generation and grid integration programme leads to the design of Optimal bidding strategy for solar power producers using Hybrid particle swarm optimization – Gravitational search algorithm. The profit calculation for power producer using optimization method is performed.
- Reliability of the forecasting methods is analyzed with confidence intervals of errors.

1.10 Organization of thesis

One of the objectives is to design a suitable market model for solar energy-based electricity market. Chapter 2 describes the work carried in order to achieve this objective. The work proposes a solar energy market model for Indian scenario. The market mechanism for operation of the market is also proposed. In one day ahead WPF, the SVR approach is more consistent and reliable. The methods to maintain the grid stability amid uncertainty is discussed and challenges in practical implementation of such markets are also outlined in this chapter.

Chapter 3 explores the trading models for solar power trading in restructured electricity market. The work proposes the operating mechanism for solar power trading at state level electricity market. The five different solar power trading models namely solar power trading with aggregator model, solar power trading model for rural area supply, solar power trading model for generation side competition model, solar power trading for retailer fixed model, and solar power trading for retailer flexible model. The operating mechanism is also proposed along with the function of each entity for solar power trading in electricity market.

In chapter 4, the work carried for designing of effective electricity price forecasting tool. This work mainly implements ANN model for electricity price forecasting (EPF) of Australia electricity market. The co relation coefficient formula is used to find the correlation of input parameters and highly co related input is used for training and testing the model. The results indicate improvement in forecasting accuracy of ANN model for April month and second week of January.

Chapter 5 Describes the Impact of solar energy generation on electricity price. This work is carried by LSTM model, Decision Tree, Random Forest, LASSO and XGBOOST. the impact of solar energy generation on electricity price for Austria Electricity market is Investigated. For the available data developed LSTM model showing best accuracy in comparison with Decision Tree, Random forest, LASSO and XGBOOST model. Reliability of the forecasted price is evaluated using Confidence Interval value.

Chapter 6 provide price forecasting in electricity market influenced by wind energy in renewable energy integrated grid. Decision Tree, Random Forest, Linear Regression, LASSO Support vector Regression and Deep Neural Network used to investigate the impact of wind energy generation on electricity price for Austria electricity market data. In price forecasting of Day ahead data Decision tree model outperform and best accuracy is achieved.

Chapter 7 in this chapter, design of optimal bidding strategy for solar PV power producer is carried using Indian Electricity market data. The RCGA, PSO, GSA and HPSO – GSA is proposed for designing the optimal bidding strategy. The objective function is designed to maximize the profit of solar power producers (SPP) with constraint of price imbalance and uncertainty in the solar output. HSPO – GSA shows best profit for the data set used over RCGA, PSO and GSA. The computation time is also lower as compared to rest three algorithm used for designing the bidding strategy.

Chapter 8 concludes the work.

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Chapter 2

DESIGN OF A SOLAR ENERGY MARKET MODEL

2.1 Introduction

The Indian Electricity Act (EA) 2003 triggered the restructuring of Power system in India helping it changing from monopoly to competitive market. After enforcement of this Act many electricity board all across the country got restructured and named as separate company for generation and distribution in India. EA 2003 opens a new path for the power producer to trade power in competitive manner and consequently improves the way of operation and gave a better tariff structure. As per the data of 18th Electricity Power Survey (EPS) from Government of India, the predicted country's peak demand will surpass 285 GW by the end of year 2022. This will resemble to nearby 8% of power demand being met by solar power throughout the country in 2022.Grid interactive solar power capacity targeted to reach 10 GW by 2017 under Jawaharlal Nehru National Solar Mission [1].

Solar energy is one of the amplest renewable sources of energy and Indian government has taken path breaking steps towards development of solar energy by providing policy and platforms. As per the reports from Ministry of New and Renewable Energy (MNRE), solar generation has increased by 370% in the last three years form 2.6 GW to more than 12.2 GW. Some of the largest solar power plants are mentioned in Fig. 2.1. which indicates that largest solar power plant is working in India [2]. The price of solar power generation is reducing and a record low solar tariff of 2.44 rupees per unit was achieved in Bhadla Rajasthan. India has launched the world largest renewable expansion programme of creating capacities of 175 GW capacities by the year 2022[3].

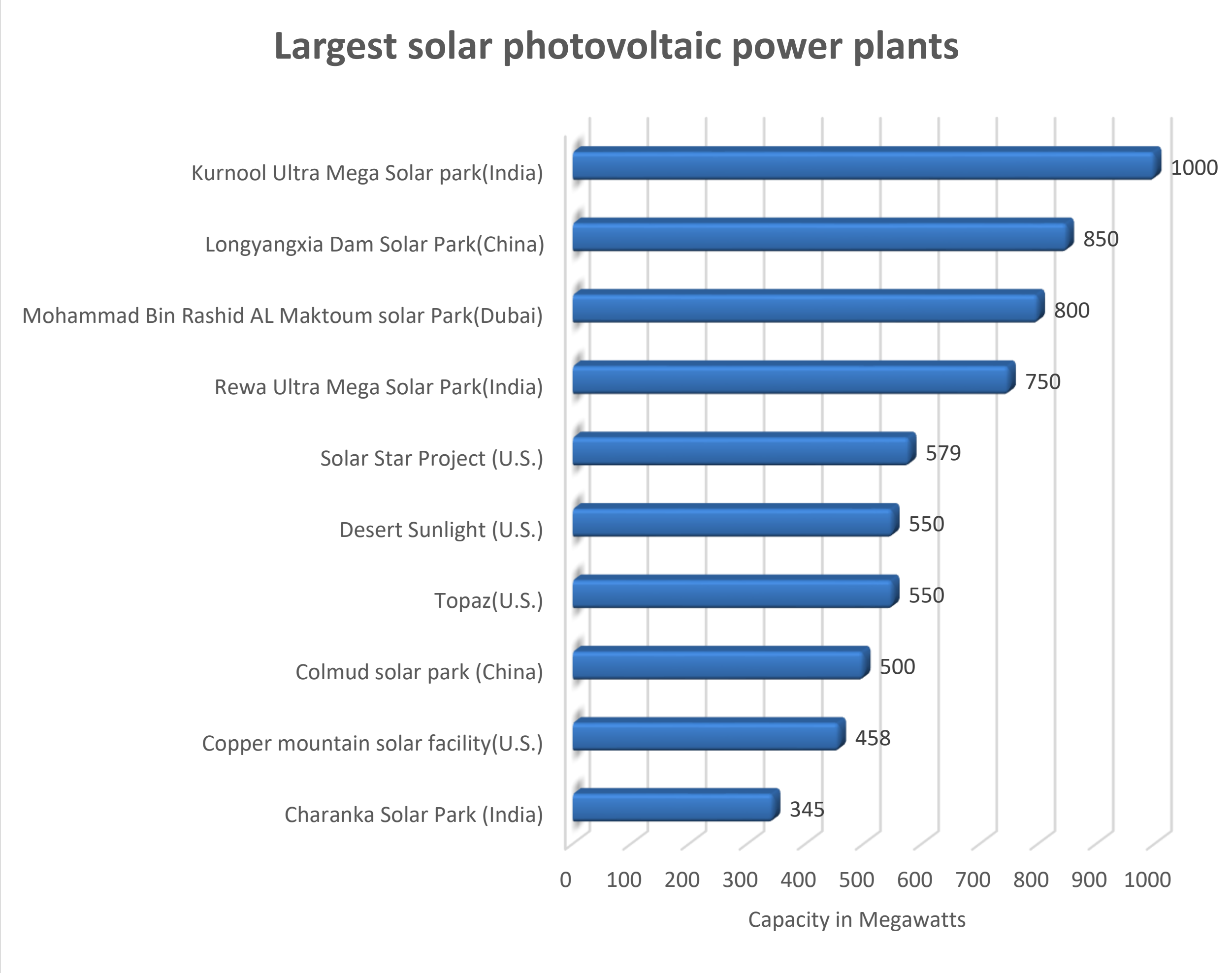

Fig. 2.1: Largest Solar Photovoltaic Power Plants Worldwide as on June 2017

According to the data availability from ministry of power, India is the sixth leading energy consumer with 3.4% of global energy consumption [4]. Maharashtra is one of the highest electricity generator states in India. Owing to economic rise the demand for energy consumption is increasing rapidly. To meet this rising demand India is moving forward to rely on the green energy generation. The largest solar photovoltaic power plant in is indicted in fig.1. The MNRE is implementing the development of solar cities program. Under this scheme 37 cities have been sanctioned to develop as the solar cities with the implementation of this scheme, reliance on the conventional sources for electricity is expected to reduce. According to the data available eight states in India have installed over GW of solar power as shown in Fig. 2.2 [5].

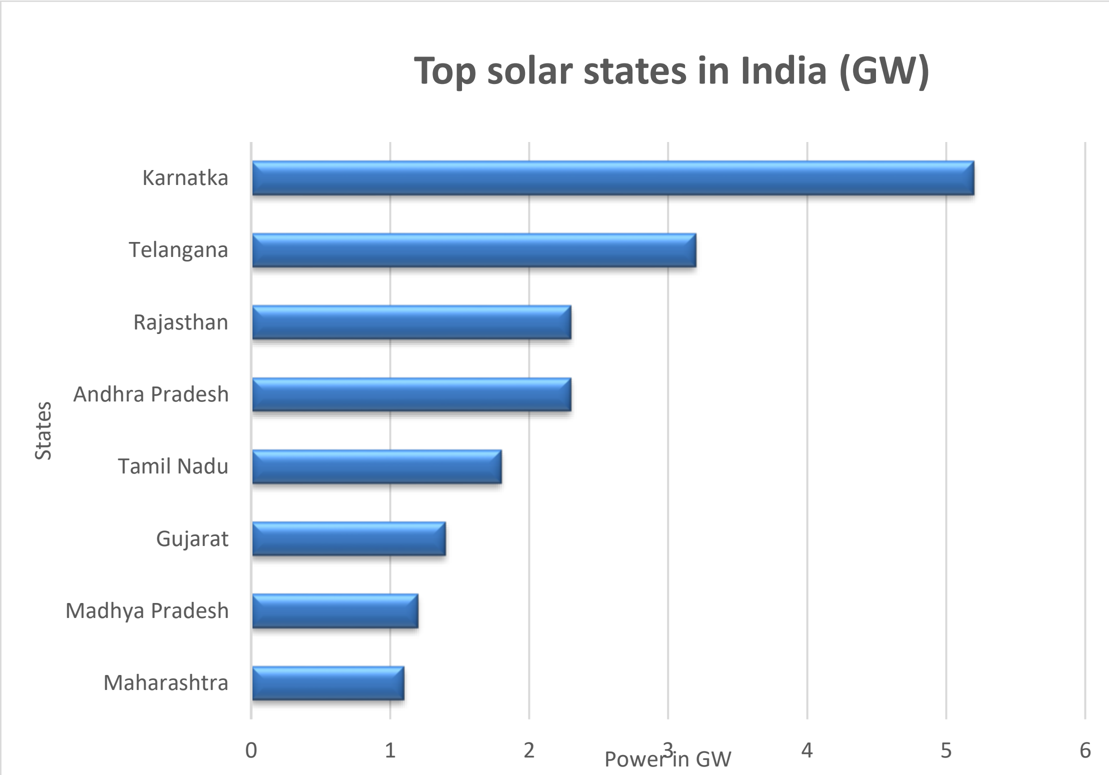

Fig. 2.2: Top solar states in India as on 31.03.2018

According to the load generation balance report released by Central Electricity Authority (CEA) for 2016-2017 year many states are identified as the power deficit states in India as presented in Table 2.1 [6].

It indicates that there must be a provision for setting up individual grid for independent states with solar generation so that they can meet the requirement of electricity and consequently becomes power surplus state and can export power to the other area as well. In India, investments in improving the solar PV capacities are now speedily rising in both on grid and off grid mode. Indian government is planning for solar cities, and the master plan is being prepared for its implementation [7].

This paper proposes a solar energy-based grid to meet the electricity for all targets. This is a unique concept for market-based trading of solar energy for Indian scenario. Due to better predictability over wind, solar is considered for the market modelling and bidding for achieving the target. Integration of solar energy with conventional sources may raise various issues such as power fluctuation, power quality, grid stability, forecasting power generation and one major concern with the solar energy is intermittent in nature. The different challenges in solar energy penetration into grid were addressed and possible solutions such as by adopting advanced forecasting methodology, suitable management of reserve capacity and flexible market design are recommended. Also, market model for solar energy is proposed, various component of this market model was discussed.

Table 2.1: Electricity deficit states in India

S. No.	State/ UT	Peak Demand (MW)	Peak Met (MW)	Surplus (+)/Deficit (-) (MW)	Deficit (-) %
1.	J &K	2,650	2231	- 419	- 15.8
2.	Uttar Pradesh	16,000	14454	- 1546	- 9.7
3.	Chandigarh	350	343	- 7	- 2.0
4.	Uttarakhand	2,075	2,058	-17	- 0.5
5.	Goa	520	518	-2	-0.4
6.	Andhra Pradesh	7,859	6773	-1086	-13.8
7.	Karnataka	11,152	9905	-1247	-11.2
8.	Telangana	8,381	7321	-1060	-12.7
9.	Pondicherry	395	387	-8	-2.0
10.	Bihar	3,900	3183	-717	-18.4
11.	Jharkhand	1,250	1160	-90	-7.2
12.	West Bengal	8,439	8138	-301	-3.6
13.	Assam	1,560	1360	-254	-16.3
	Total	**64531**	**57831**	**- 6754**	**-113.6**

2.2 New initiatives of govt. of India

Solar power generation has been a viable source for delivering electricity in regions without access to the grid for long distance. In last decade the penetration level of solar has increased considerably in grid connected mode. Consequently, the overall contribution in total energy generation in 2015 still at low pace at only 1% worldwide and is possible only to increase in future. The marginal cost of energy production with solar are falling consistently, technological advancement and a wide range of growing applications are up comings to boost the solar energy sector. Therefore, solar energy is going to be an inexpensive and environment friendly energy source in coming future with massive investments being attracted to this sector. Affordability can be seen as a key concern wherever energy storage is needed to meet the demand, as energy storage technologies are not significantly good, and commercial appropriateness is not explored so far. It is known from available locations, in some of them grid peak is experienced during day time only, so broader scene solar power sector becomes competitive. To increase the harness of solar energy Govt. of India has taken many new initiatives as presented below [8].

a. International solar alliance (ISA): the objective of ISA is to achieve 1000 GW globally from solar generation by 2030, and mobilisation of investment of $1000 billion.
b. To encourage the green energy Government of India (GOI) has launched National Solar Mission in 2010 with target of 20,000 MW solar power generations. Now this capacity is scaled up to 1, 00,000 MW through grid interconnected solar power.
c. JNNSM with viability gap funding (VGF)
d. Development of solar cities Programme
e. State Distribution companies (Discoms) to buy Minimum 20% of power from solar park.
f. Establishment of Solar cell capacities companies
g. Solar Rooftop projects

h. Installation of 25 Solar Parks by MNRE targeting to add 20,000 MW solar power in next five years.

i. REC trading platform through The Indian energy exchange (IEX) and The power exchange India limited (PXIL)

j. India has planned for investing $ 1.8 billion in transmission lines sector to transmit solar power.

k. Development of solar cities programme.

l. Implementation of Solar power policy for states.

m. In India total of 2311.88MW of on grid power generation capacity addition from solar and wind.

n. The Government of India (GOI) has revised the renewable energy capacity to 175GW by 2022. Out of 175GW 5GW from small Hydro power plants, 10GW from Bio- Power, 60 GW from wind and 100GW from solar [9].

o. State nodal agencies (NDA) and National bank for agriculture and rural development (NABARD) has taken a new initiative to install 0.1 million solar pumps for providing drinking water and irrigation facility in rural areas.

p. With the financial grant of Rs 4050 crore from central government, government has approved 12500MW capacity solar parks in different states. The number of sanctioned parks is 25, which will be added in next five years.

q. Execution of scheme for setting up 1000 MW of on connected solar PV power projects by Government of India (GOI) organization's and central Public Sector Undertaking (CPSUs)from 2015-16 to 2017-18 with viability gap funding.

r. This fiscal, the Government of India has set a target of adding 4,460 MW of power generation capacity from renewable energy sources.

s. Renewable purchase obligation (RPO) under this scheme states pool has to purchase power mandatorily from renewable source.

2.3 Proposed solar power grid structure

The Electricity Act 2003 is the major milestone in the reformation of electricity market. Some of the main features of this act are license free power generation, no long-term Power Purchase Agreement (PPA) requirement for merchant power plant, open access to distribution system, non-discriminatory access to transmission system, open up the new competitive environment in the sector of generation transmission and Distribution.

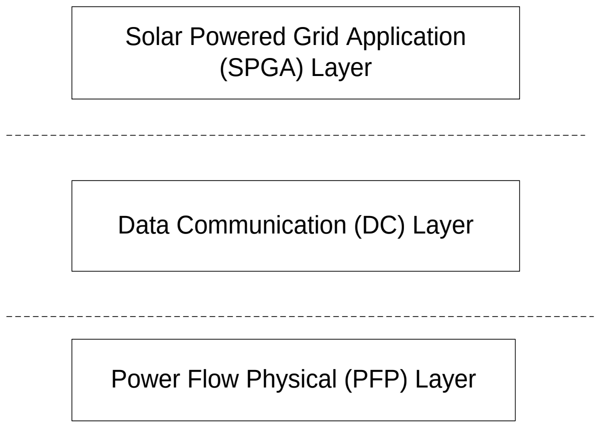

Fig. 2.3: Layered structure of grid

In Fig.2.3 the complete layered structure for proposed power delivery scheme in the solar power grid is shown. In the proposed solar power grid structure, first layer is solar powered grid application (SPGA) layer which is consisting of various software applications for management of solar grid. Second layer is the internet protocol (IP) based communication layer which provides the communication architecture for the solar power grid. The third layer is the bottom layer for the physical delivery of the power in which the power delivery mechanism from generation to consumer is organized. The three layers are discussed in detail below.

2.4 **Physical power flow architecture**

After implementation of electricity reform sand bringing new green energy policy, the power sector is ready for integration of solar power to grid and trading of it in a competitive manner [6]. The proposed architecture may have a state level solar power grid, where independent solar power producers and different government initiatives (solar park, rooftop solar etc.) may participate and inject the power into the grid. This unique concept of solar energy-based grid provides a non-discriminatory and efficient solar power trading platform within a state. However, the designing of market for trading of solar power will be challenging task due to the factors like intermittent nature of supply, transmission constraints and changing penetration of solar power producers with time. The proposed grid may be created in each state and state load dispatch centres (SLDCs) may manage the trading of the power. Power pool already exists at state level, so surplus power can be transferred to or from other states as per the need. Such implementation may facilitate a conducive environment for investor to invest in the state solar power projects.

The solar power can be fed directly to grid as indicated in Fig.2.4, or it can be operated in islanding modes of operation. But due to the additional cost of battery the islanding mode may not be economical so, grid connected mode may be adopted for the proposed model. Due to intermittency involved with the solar radiation some of the generator can be operated in islanding mode for back up supply thereby provisioning the additional power to meet contingencies and uncertainties in demand and supply. This will make the power system network reliable. In present scenario entire solar power plant (SPP) in India is being operated in grid mode to serve the cheaper power to the customer. The other advantage associated with the on grid solar power system is that the surplus energy can be fed back to the grid through net metering.

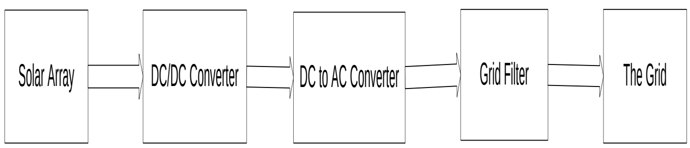

Fig. 2.4: Basic grid connected structure of solar PV

Following are the requirements for state for implementing and promoting the grid connected solar roof top system.

- States should adopt a conducive solar policy towards grid connectivity.
- State regulators have issued tariff order for the grid connectivity, net-metering defining suitable tariff, feed-in tariff etc.
- The Discoms decided to permit grid connectivity and procure the power through net metering arrangement or on feed-in-tariff.

The proposed solar grid may be monitored by a State Independent System Operator (SISO) which may be an independent body not participating in the trading of solar power. The SISO for proposed grid shall have the following responsibilities [9]-[10].

- Issues dispatch instructions;
- Monitors the economic power dispatch schedules;
- Ensures the reliability of the system, transmission line maintenance and proper pricing;
- Ensures proper system planning;
- Ensure grid interconnection and Energy Management System (EMS);
- Provides protection from the exercise of market power;
- Work for minimization of congestion and reflection of line losses;
- Enhances inter-state power transfer facilities;
- Creates an equitable regulating structure for all gencos and consumers.

2.5 Communication architecture

Communication is an acute function for the Solar Energy Grid System (SEGS). Due to day-by-day addition in capacities of solar PV system and so the penetration into grid, the role of the communication is becoming more important. The primary task of the communication is to establish end to end communication with transmission and distribution system for insuring a safe, secure and reliable operation of grid. In order to offer widespread applicability solar system should use protocol, which is based on open system. Development of efficient communication capabilities devices which are compatible with national standards will help in developing market for SEGS. Use of Supervisory Control and Data Acquisition (SCADA) for monitoring the operation and control of grid can enhance the market acceptability of SEGS. Virtual Private Networks (VPN) can be a better option for specifying security features and reducing the traffic over SCADA system [11]-[12]. Some components of proposed communication system are discussed below.

2.5.1 Anti-islanding Control

The inverters in presents PV systems can continually capture grid parameters and cut off when those parameters are beyond the threshold values. Though, as the number of interconnected inverters surges, a more collaborative method integrated with SEGS required, to ensure that inverters will disconnect when essential and it is flexible enough to adjust ride-through variation in utility operating parameters produced due to rise in demand. The distance over which this information transmitted is possibly long, but the amount of information required is small consequently it is required that the communication of the signal to disconnect must be quick and certain (always happen when connection with utility is lost).

2.5.2 External Communication

In order to optimize the grid parameters, the system must be reciprocated to external data such as pricing signal, dispatch signal response and weather forecast. Many critical data related to frequency synchronization and area regulation, voltage regulation, peak savings (Demand response), feedback control, spinning reserve (replacement of lost capacity) being externally transported to the grid must be received in real time in a secure manner because consequences of a cyber-attack in concurrent disconnect of large number of systems.

2.5.3 Internal Communication: For maintaining the system safety within permissible limit internal communication plays an important role by controlling of loads and storage for optimizing the system values for grid security. For ensuring safe and secure operation of grid the data which are transmitted must be updated over a specified time for balancing the available energy with solar generation. Other coupled distributed generation sources, and storage devices with variations in loads and utility pricing. While solar output is intermittent because it changes with weather conditions on the other side change in loads is just one switch away, measurement of utility demand charges is typically observed over a fixed interval of time (15-30 minutes) approximately, thus the system has time to respond. But in case of off-grid operation, the system must respond quickly to prevent load from exceeding to its maximum system capacity at any given time.

2.5.4 Communication Methods and Protocols

Following are the characteristics of a various types of communications methods and protocol [12].

- Copper wiring.
- Ad-hoc mesh networks.
- Continuous-carrier Power Line Communications Carriers (PLCC)
- Broad Band over Power line
- Ethernet.
- Wireless Local Area Network (IEEE 802.11).
- Wireless Interoperability for Microwave Access (WiMAX) (IEEE 802.16)
- Wireless Metropolitan Area Networks (WirelessMAN or WiMAX, IEEE 802.16d).
- Personal Area Networks

2.5.5 Cyber Security systems

Increasing interconnection may accelerate the exposure of solar energy grid to possible attackers and/or accidental errors. Networks that connect a lot of different networks introduce commonest vulnerabilities which is able to span multiple power networks and increase the probabilities of failures. Such interconnected network may invite extra rejection of service attacks, malicious code, cooperated system and intrusions. As number of entry point increases, these may be utilized by potential adversaries for exploitation. Intensive attacks may possibly broaden the potential for compromise of data and break of secrecy and consumer privacy.

The solar energy grid security may include physical components and management applications, cyber infrastructures required to upkeep necessary operational and market functions, cyber-attacks and its impact on the system, actions and measures to mitigate risks from cyber threats. Risk assessment to realize the potential of undesirable outcome due to internal or external factors, as calculated from the chance of occurrences and additionally the associated consequences is very important to attenuate unacceptable risk levels by applying risk mitigation solutions. This can be performed through the preparation of heaps of durable supporting cyber security facility or applications.

2.6 Software applications for Solar Grid

The performance of the grid connected solar power can be improved with software applications. In grid connected solar photo voltaic energy system deployment of software applications for management, planning, operation, stability and security of the grid is challenging issue as these tasks must be scalable for ever-changing grid environment. In smart grid era, the software application becomes integral part for grid management [13]-[14]. In this section a brief overview of software applications used for solar power system modelling, planning, load flow studies and energy management systems etc. are highlighted in table 2.

Table 2.2: Software applications available and purpose of software

Available software packages	Purpose of software
ETAP, DIgSILENT	Determination of fault level, voltage level and thermal conditions
ETAP, DIgSILENT	For assessments of dynamic behavior of equipment
PSCAD/EMTDC, EMTP	Study of Electromagnetic transients
RTDS, Opal RT	Real time simulation and protection testing
AWS True power, Garrad Hassan-GH Forecaster,Element Energy forecasting tool	For generation and demand forecasting to maintain balance.
PLEXOS,Ventyx PROMOD, AURORAxmp	Electricity Price forecasting and for optimizing generation dispatch
SCADA	It provides information of equipment states, voltage, frequency, Power factor, current in a network [15].
Solarius PV	Used for designing of grid connected PV system integrated with wide range of energy storage system [16].
PV Designer solmetric	This tool is used for designing solar PV system upto 100kWand AC energy output can be calculated using for different scenario [17].

2.7 Power flow model

The power flow model for the proposed solar power grid is shown in Fig.2.5. In this model different solar power producers will submit the bid to the system operator. System operator is responsible for preparation of effective and optimum scheduling and dispatch of electricity. Every solar power producer enters into grid to inject power for fixed period through PPA. Power exchange is proposed at state level which is mainly responsible for price determination of electricity, broadcasting of price and volume of electricity and payment collection and disbursement as per usages. It provides online platform for trading of solar power. All the rules and regulation framed by state level power exchange for trading, price determination and broadcasting of available volumes are approved by state electricity regulatory commission (SERC). Other may be proposed for information of available power at particular per unit cost.

Objectives of the proposed state solar grid are:

- Making available the power at competitive cost to consumers.
- To provide a non-discriminatory platform for green energy trading.
- To Promote Innovation and research in solar energy.
- To make Competitive environment for solar energy business.
- To reduce the pollution level.
- To provision Energy Bank or Virtual power plants for meeting contingencies and sudden requirements.
- To meet the social obligation to feed power to rural area as well.

The power flow or information flow and money flow are important for proper functioning of a grid. Fig. 2.5 is depicting the entire process of power flow from generation end to consumer end via transmission system. All the solar power producers, solar projects and independent power producers can inject power into pool through proper channel of power trading, then selection of appropriate generation block to meet the demand is done on the basis of day ahead demand forecast. Now, in terms of transmission government can increased the existing capacity or opt for the new or private transmission capacity because for state level grid, proper transmission capacity of lines must be maintained to avoid transmission overloading or congestion of lines. Different Discoms and private retailer can direct to distribute power in different locations. Bulk consumers are free to contact directly to solar generator or can receive power through retailer or Discoms. Presence of more Discoms in a market can create healthy competition for proposed market, resulting into drop in electricity cost.

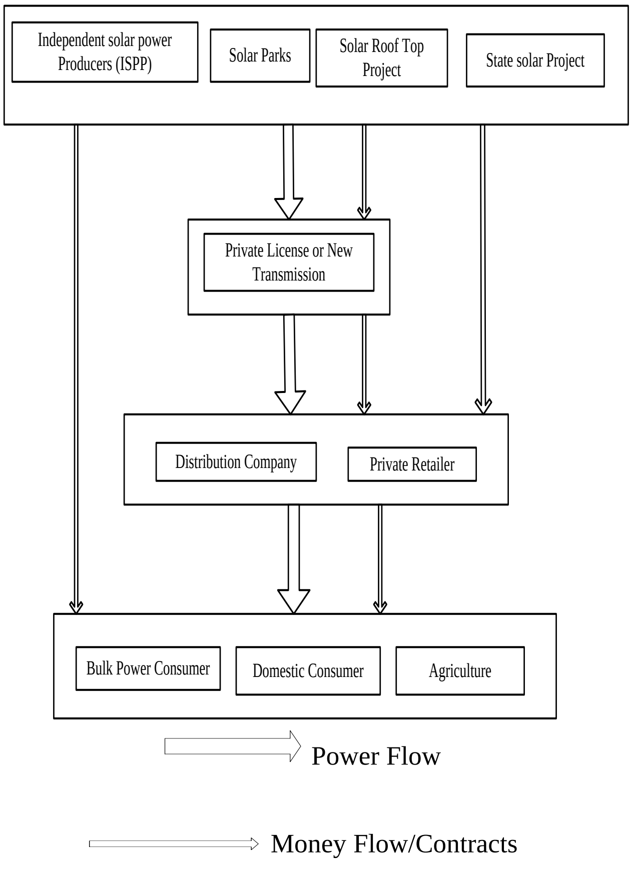

Fig. 2.5: Proposed power flow model for solar grid

2.8 Market structure and operating mechanism

In the proposed market model, the market clearing mechanism may happen in such a way that the reliability of grid is maintained. For this purpose, very short-term forecasting of solar power will be done on regular intervals and forecasted demand will be published every five minutes through website. This comes to be total 12 block of power volume per hour as shown in Fig. 2.7, and 48 blocks for a day. It is proposed that short term (day ahead) or very short term (15 minutes) forecasting may be combined for better assessment of demand. In the day ahead bidding mechanism for the proposed grid, bidding of solar power is done 24 hours in advance for procurement of power form solar power producers to match the demand [31]. The 15 minutes market may be operated to trade the ancillary services in the solar power grid. The bidding horizon diagram for a day ahead (24 hour) market for proposed electricity market is shown in fig. 6 which is self-explanatory.

For solar power trading state level power exchange is proposed a shown in Fig. 7 to provide a platform for solar power trading. It makes possible for new power plant of independent power producers to sell or bid power into state power pool, participation of independent power producers surely ensure innovation and competition among power producers. Another possible solution for making the solar grid reliable could be the use of flexible generation. This can be done by modifying the existing generator ramp rates, by lowering the minimum generation level and by minimizing wear and tear costs. Reserve management practices needs to be modified for solar based grid to accommodate the variability in generation. By proper capping up ramp the variability can be controlled, because reserve level limits are generally set with low probability so, large change in solar output can reduce the reserve limit. In this way, imposing ramping on generators reserve requirement can be significantly reduced.

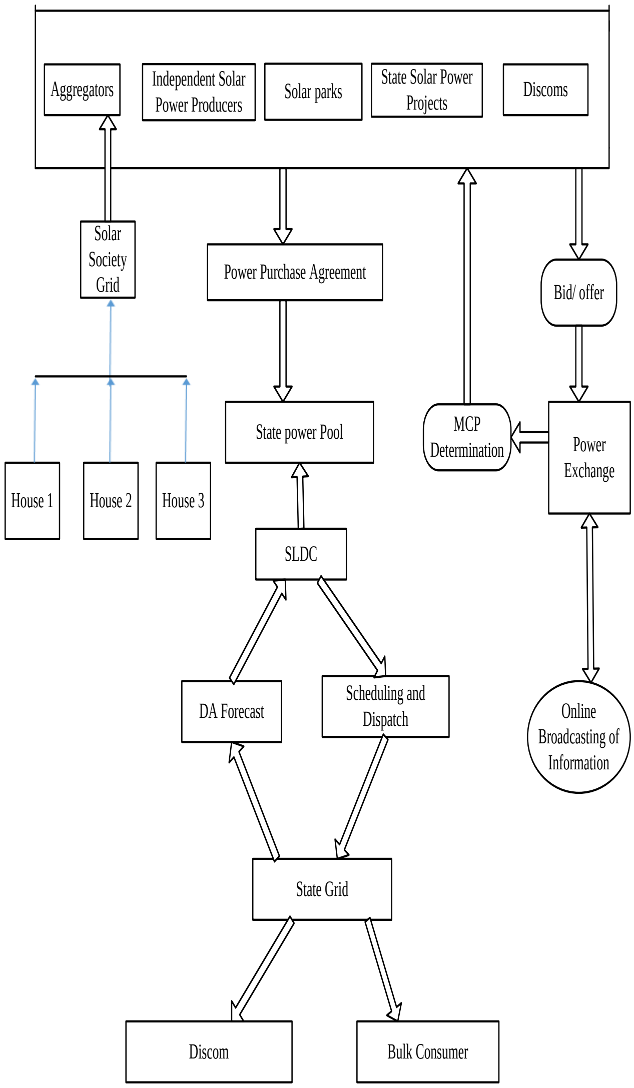

Fig.2.6: Proposed Solar Power market structure

Acronyms used in model

DA: Day ahead

PX: Power Exchange

PPA: Power Purchase Agreement

Bid: Price and Quantity of electricity

MCP: Market Clearing Price

DISCOM: Distribution Company

SLDC: State Load Dispatch Centre

SSG: Solar Society Grid

The components of the proposed solar power market are discussed below.

i. **PPA** – to inject power or sell power to grid, power producers have to sign a contract, which includes all the commercial terms and conditions. Power purchase agreement is a contract between two parties for purchasing power from power producers. Solar power producers have to sign a PPA with the government to supply power under certain terms and condition. Two type of common PPA pricing scheme are fixed price and fixed escalator. In fixed pricing scheme the rate of power being sold is fixed for entire tenure of the PPA.

ii. **SLDC** - It is an entity that is responsible to deliver power to the consumer within state region. SLDC is responsible for efficient operation and control of power. The task of SLDC is to preserve the optimal stability between generation and demand. This job is challenging specifically for solar powered grid due to low predictability. So, forecasting of demand and generated power from solar has to be done accurately. For that purpose, instead of advance15 minutes existing forecasting model can be replaced by 5 minutes interval. In every five minutes interval forecasting of generated power has to be done in co relation with demand. In this manner we can improve the reliability of the system.

iii. **DA Schedule** – Day ahead schedule is important to maintain balance between generation and demand of electric power. For Indian scenario, DA market is suitable as it provides ample time to producers for preparation of their bidding strategy for selling the power.

iv. **DA demand**- Day ahead demand is prepared on the basis of past available data. This is prepared using suitable forecasting model. Forecasting model used by the SLDC to predict the next day demand in advance. In case of solar powered grid, the radiation coming from the sun is not constant throughout the day consequently generator output varies accordingly.

v. **MCP** – MCP is crucial information for power producers. MCP is the price at which market is cleared or determines with the help of aggregated demand and supply curve. The point of intersection of aggregated supply and demand determines the MCP at which all the generators to sell power. MCP determination is done on hourly basis. For this proposed electricity market Special solar Tariff will be proposed so that cost of solar panel will be recovered within the life span of solar panel. As the marginal cost of solar power generation is comparatively low, so in special solar tariff plan will help the power producers to recover the cost of solar panel being used for generation. It helps power producers to timely replace the solar panel without economical loss.

vi. **State Power Exchange (SPX)** – The proposed power exchange for solar energy-based market is a state level electricity market. Power exchange is the important entity in development of grid, as it is responsible for taking important decision for smooth operation of grid and maintenance of stability.

vii. **Solar Power Bidding**- By adopting transparent auction system integrated proper provision of land allocation and transmission system, solar tariff has reduced comparatively to coal based power cost. In India solar power tariff is very competitive compared to Germany, US and china. Energy firm named Finnsurya Energy (FE) won bid quoting the lowest price ever of Rs. 4.34/kWh to established a 70mW Solar plant under NTPC Bhadla solar park situated in Rajasthan [32]. Independent private solar power producers can also participate in bidding process to inject power in power pool. Solar based bidding generates healthy competition among generators and reduce the cost of electricity.

viii. **Aggregators** – the role of aggregator in proposed solar power trading market is significant, as it can contribute additional power to the state power pool. It will also help to make market more competitive. Role of aggregator in power trading is to act as a third party between the end users and solar society. If lots of rooftop solar systems are installed in a society which may connect to grid, where provision to supply surplus energy to grid. These surplus or unused power can feed to Solar Society Grid (SSG). Aggregator may directly communicate for power trading to SSG and further can participate in bidding process to inject power in power pool. This type of unique practice in solar trading must motivate individual solar power users to build a SSG and can participate in solar power trading indirectly. Similar type of programme started in USA called as Solar Community. Uttar Pradesh Electricity Regulatory Commission has also proposed the aggregator model for installation of rooftop solar power through net metering. This model is first hand for group of consumer to generate power of its own and unused power can be fed to the grid.

ix. **Discoms** – Discoms role is not mere restricted to distribute power to the consumers. Now days discoms are participating in bidding process by purchasing power from different sources.

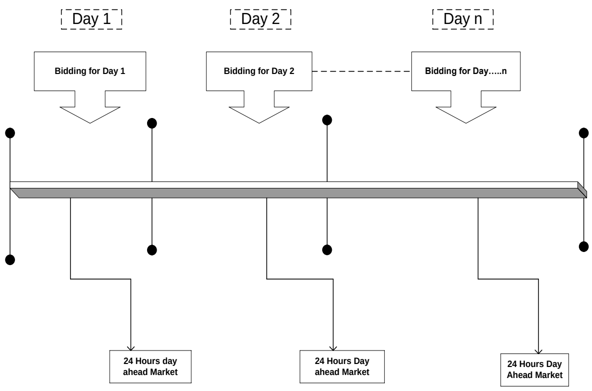

Fig. 2.7: The bidding horizon diagram for a day ahead (24 hour or 48 hour) market for proposed electricity market

2.9 Challenges in the operation of proposed solar power grid

The proposed power grid being new and complex will have many new challenges which need to be addressed. Some of the issues and challenges are listed in Table 2.3.

Table 2.3: Main issues in evolution of solar powered gird and Projects

Challenges	Description
Grid Stability	It is difficult to meet the demand with solar power generation, due to fluctuating weather condition. This problem is critical when plant is sharing major portion of grid to overcome this support of conventional and other renewable generation is necessary to reduce the grid stability [33]- [34].
Cyber Security	In a grid, various number of interconnected systems are present which can increase the private information exposed and Increase the risk when data is aggregated. In the present scenario smart grid changes the way of operation of power from unidirectional to bidirectional, for that purpose different smart devices are used which contain large number of information which has to be transmitted securely to grid [35].
Initial cost	For the development of solar projects high initial cost is one of the concerns for developing country as it requires regular financial support from government [36]

PPA and Land Allocation	Under the category of Generation based incentive (GBI) the signing of PPA and land allocation is a long process [37]-[38].
Lack of technical skilled man power and R&D Project	Skilled manpower is lacking results into lack of innovation and collaborative R&D projects [39]-[40].
Less availability of transmission lines	With increasing capacity addition of solar energy in India the transmission facilities have not grown [41]-[42].

2.10 Summary

This work has proposed the development of independent trading market and its operating mechanism where trading of solar power can be realized. The significant change is in this model form the existing market model, is that the forecasting of solar energy generated has to be done on very short-term basis i.e. five minutes to one-hour interval. The economic feasibility of such markets needs to be explored for bright future of solar energy in India. The development of such a market may involve large capital cost, storage system and additional ancillary services. The improved methods of forecasting, flexible generators, fast dispatch and reserve capacity management can be helpful for operating the proposed solar power trading market.

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Chapter 3

SOLAR POWER TRADING MODELS FOR RESTRUCTURED ELECTRICITY MARKET

3.1 Introduction

Solar power is one of the effective power sources among wind, biomass and others renewable energy sources due to its high availability in India, about 5000 trillion kWh per year incident on the land [1]. By proper harnessing the solar energy, accelerating demand of energy 1137 billion kWh and per capita average of this is 841kWh [2] can be met and energy security can be achieved in a sustainable manner. Different models for electricity trading in restructured market were presented [3] for conventional sources of energy. With the addition of solar PV generation in the grid, distribution system becomes active and it works as an active distribution network (ADN). Due to large addition in the capacity of solar power the system will be benefitted in following ways:

- Power will be locally supplied to consumer and hence the burden on the main grid will be reduced consequently transmission lines also relieved so that transmission losses will be also reduced.
- Transmission and distribution losses will be reduced. In India, average 23% of the total electricity generated is lost in transmission and distribution. In some of the states the loss in transmission and distribution is around 50% [4].
- Feeder capacity will increase and transmission cost will be reduced.

In India, the solar power generation plants are categorized in terms of generation capacity as small solar power plant (up to 99 MW), medium solar power plant (100 MW to 400 MW) and large solar power plant (more than 500MW). Only large solar power plant needs transmission lines to transmit power to grid and in case of small and medium power plants they can directly be connected to the distribution lines for supplying power to the utilities. In the case of medium and small power plants, state distribution unit (SDU) needs to strengthen its capacity of distribution. Special distribution lines need to be installed to accommodate the additional solar power. The availability of large number of distributed generation of solar power may result in better competition and price of electricity may reduce.

However, to be able to use the solar power connected across the grid, a proper market mechanism and trading model for solar power trading required to be put in place. In this paper different solar power trading models and mechanisms are presented for state level solar energy market which can be suitable adopted by different states for incorporation of solar power as regular mode of power supply. The advantages of various models and expected challenges are also outlined.

3.2 Components of solar power electricity market

Different components and flow of power and money of proposed solar power trading is represented through Fig.3.1.

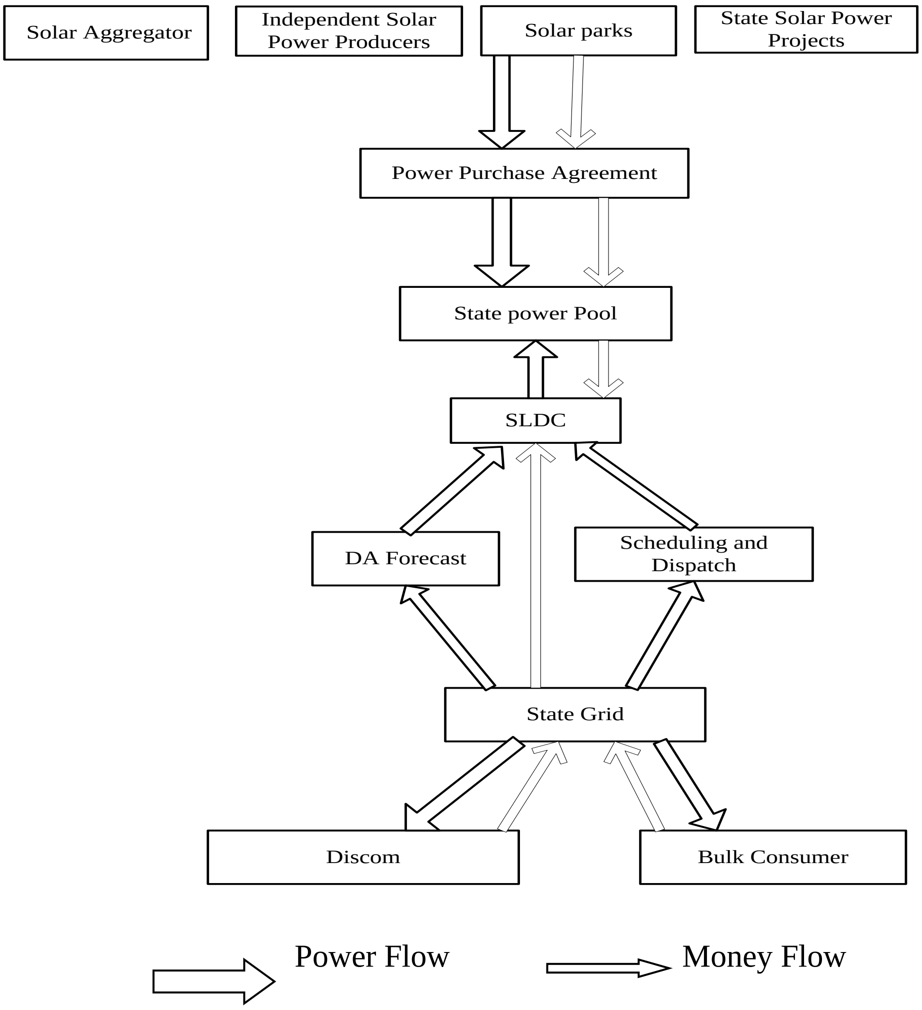

Fig. 3.1: Operating mechanism for solar Power Trading

3.2.1 State Electricity Regulatory Commission (SERC)

It was established under Electricity regulatory commission act in 1998 with the objective of rationalized electricity tariff, transparent trading mechanism and promotion of renewable energy for sustainable development and energy security. There are total 27 SERC established in India [5]. Many SERCs promoting renewable energy for meeting the demand some of them are GERC, MERC, RERC and APERC. These states are giant in renewable power generation and generating large amount of power from solar and wind. With the view of availability of large capacity of solar power producers, individual solar power trading model is proposed working under same SERC.

3.2.2 State Load Dispatch Center (SLDC)

to promote the solar energy at state level a solar state load dispatch center may be proposed for promoting the environment friendly benign energy sources. In this proposed center all solar power producer including government solar projects (Solar parks, solar rooftop, solar society grid) and independent solar power producers are permitted to participate in power trading. an independent body have to set up for proper controlling and investigation of different process involved related to generation trading, transmission of power and distribution. This independent or integrated body is named as solar state load dispatch center (SLDC).

The role and responsibility of this SSLC are as following [6]

i. to supply reliable and quality power to consumer
ii. supply electricity at competitive cost
iii. proper monitoring over dispatch schedule
iv. ensure transmission line maintenance
v. Advanced forecasting of power generation

3.2.3 State Transmission Utilities (STU)

STU is responsible for maintenance of power transmission in state. For proposed solar power load dispatch centre requirement of new transmission capacity lines are required to transmit power in urban, rural or may be longer distance is required, because objective of this SSLDC is to make electricity independent nation for that purpose we may transmit power in electricity deficit area through new tie lines. The purpose can be solved either by opting the private transmission line or by extending the existing transmission line capacity through proper channel.

3.2.4 Power Pool controller (PPC)

PPC is the controlling entity of power pool at state level. This provides a platform for power producers to sell their power capacity through a proper trading mechanism. Each power producers will participate in power pool for selling power through Power Purchase Agreement (PPA) [7]. Government has set up flexible rule for power producers to entering into power pool for selling power.

3.2.5 State Distribution Utilities (SDU)

SDU is responsible for effective power distribution in state. Currently retailers are also come into the play for distribution of power. Retailers can purchase power directly from the power producers and it can distribute power to the bulk consumer or any specific consumer. For solar power distribution in state for proposed models competition among the retailers is primarily required to provide quality power at competitive cost. In this restructured model consumers have choice for their power supply.

3.2.6 Scheduling Coordinator (SC)

SC is responsible for demand and supply balance without the interference of power exchange. It manages the bid and supplier

3.2.7 Power Purchase Agreement

It is possible now setting up power plant without the PPA and it can fed power to the grid. But by signing PPA, can reduce the risk of upfront of electricity price. It also helps to achieve sustainability in volatile energy market.

3.2.8 Storage Unit

Due to intermittent nature of solar radiation. This unit is important to maintain the reliability of the supply system. Without storage unit solar power generation cannot provide all the characteristics of stable grid. The main objectives of this unit are as follow [8]

- Effective connection to gird - solar power output is highly rely on the weather conditions, output is not predictable exactly due weather parameter uncertainty. Electrical Energy Storage Devices (EESD) can be used to mitigate or absorb these fluctuations.
- Standby power supply – it is required to compensate the unplanned outages of transmission lines, congestion management, due to exercise of power market etc.
- Shifting of power – when output power from solar is high and if this power is not utilised at particular time, then this valuable power can be effectively stored in ESSD and cab be traded when the price of power is high, usually it happens when the demand is high.

Proposed solar power models for State load dispatch center

3.3 Solar power trading models

There are four models for trading of electricity globally [7]

- Monopoly model
- Single buyer model
- Open access model
- Power pool or wholesale market model

3.3.1 Solar power trading with aggregator model

In this type of proposed power trading model, different sources of power generation from solar can participate in trading and they can inject their power capacity in state power pool and according to the capacity and they are supplied to serve different purposes. Like power generated from solar parks are generally higher in capacity it can be used to serve peak load demand and accordingly they can bid with respect to power volume. Additionally aggregator model is introduced to strengthen the capacity and competition among solar power producers. Aggregators are important aspect of this model as it collects unutilized power from different houses of the society and individual house. As these individuals' house and houses under society are connected to the main society grid so unutilized power can be fed to the grid and effective power by the end day is substantial for trading. Fig. 3.2. depict the concept of aggregator. The state solar power pool model is presented in Fig. 3.3. The concept of Virtual power plant for market integration Of DGs is presented [8]. The main barrier in implementation of this model is to provide incentive in lieu of unutilized energy supplied to the grid.

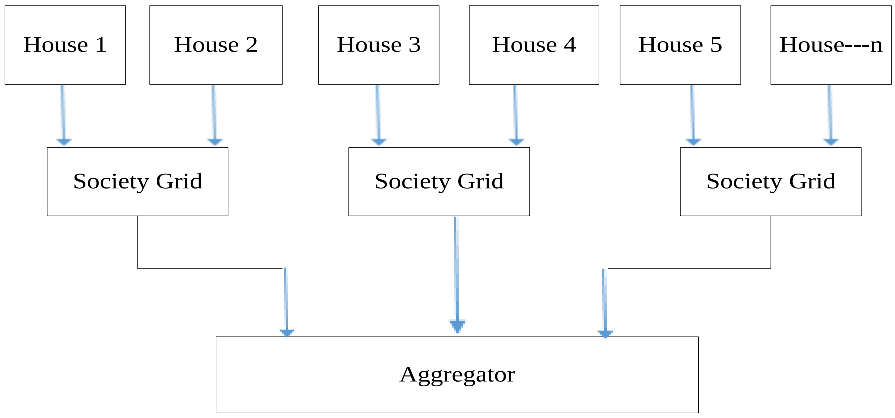

Fig.3.2: Aggregator Model for solar Power Trading

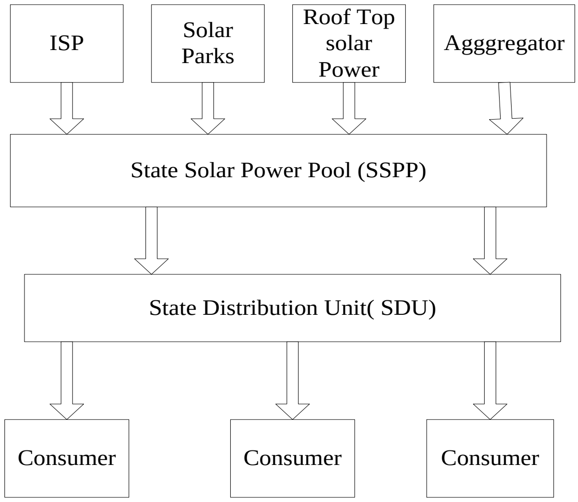

Fig.3.3: State power pool model for solar power trading

3.3.2 Power trading model for rural area supply

This proposed model is based on energy sharing concept dedicated for rural area supply where all solar society grid(SSG) can feed unutilized power to aggregator and aggregator can supply this power capacity to rural area for agriculture and domestic purposes[9] – [10]. In modern day, society houses equipped with grid interconnected solar system which can fed unutilized power to the grid they can get subsidy for that [11]-[12]. House owner is also contributing their surplus power for betterment of rural area and they are also power traders. Establishing proper transmission system for transmitting power to longer distance is one of the major task for the proposed model.

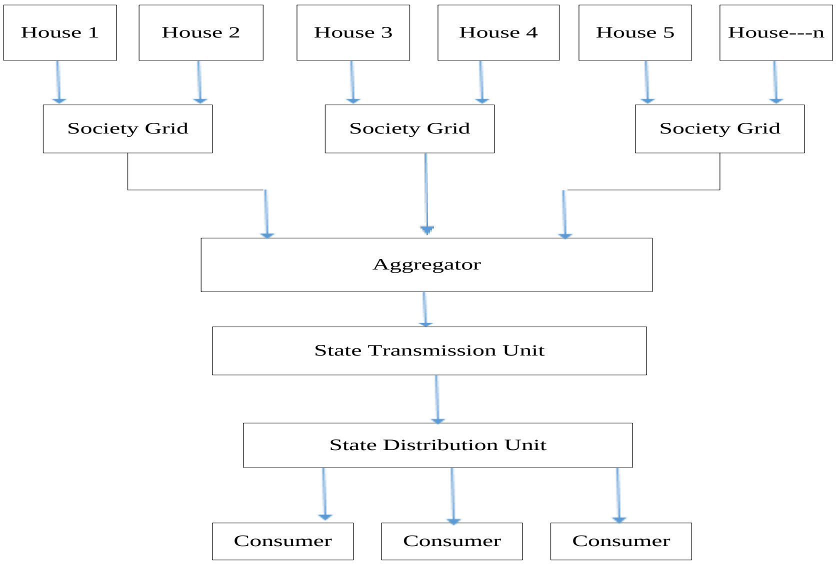

Fig. 3.4: Solar power trading model for rural area

3.3.3 Solar Power Trading model for generation side competition model

Numbers of solar power producers in country are increasing with greater pace and so the competition among generators. Independent solar power producers (ISP) and government solar projects like solar parks, solar roof top power etc. can participate in power pool to sell the power. After selecting the appropriate bid, which match the demand and supply ISO will finalize the deal. After that transmission of power can be allocated to the state transmission unit or if the transmission capacity is not sufficient the state can opt for private or licensed transmission network. This model is restructured version of solar power trading model presented in Fig. 3.5. In proposed model consumers/bulk consumer can buy power directly from solar power producers and negotiate the price directly from seller. As presented in figure 4 due to larger capacity available in solar parks bulk consumer can directly communicate with them for power purchasing. Rooftop solar power less than 5kw capacity can participate in pool for power trading according state solar policy [13]-[14]. Success of this proposed model depends on the number of solar power producers available to participate power pool.

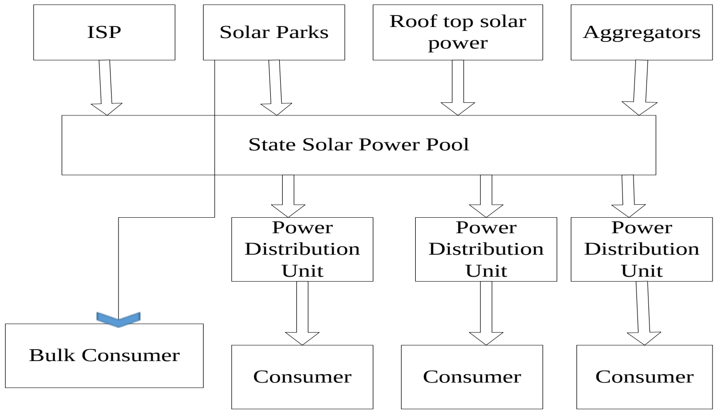

Fig. 3.5: Solar power trading model

3.3.4 Solar Power Trading model for retailer fixed model

In this model power producers are free to sell the power directly to power Distribution Company or retailer for their own profit without entering into pool. This model does not restrict power producers to sell power only to state power pool but the Discom is bound to sell power only to the consumer through power distribution unit of state. In this model power producer have option to negotiate the price with retailer and Discoms or PDU for their own profit. This model helps the solar power generation potentially competitive. Facility of direct power purchase from the available generators is not available in this model as shown in Fig. 3.6.

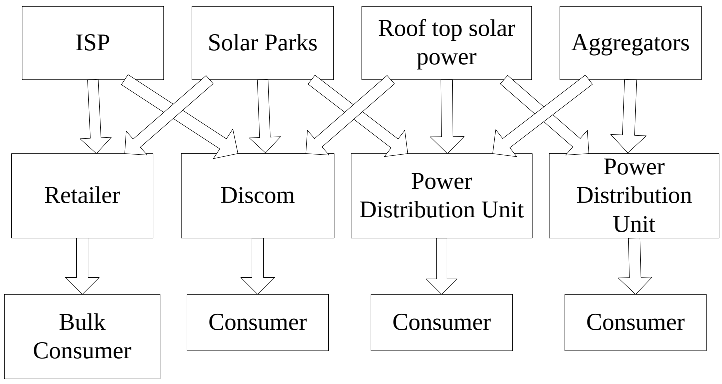

Fig. 3.6: Solar Power trading model for retailer fixed model

3.3.5 Solar power trading for retailer flexible model

It is evident from experience that effect of restructuring is lesser reported in distribution side, as most of the financial resources are aligned towards the generation side whether it is conventional or non-conventional generation. In distribution side the proposed model is to create competition at distribution end so that electricity can be transmitted to consumer at reduced cost. From retailer consumer can buy power instead of SDU or private distributor whichever is supplying quality and reliable power at lower cost. Power trading must be done through proper wire network. Most of the things is common in this model except potential competition at distribution end by introducing local power distributor or private distributor (Fig. 3.7). These distributors can buy power from power pool or directly from power producers through integrated tie line and may participate in distribution.

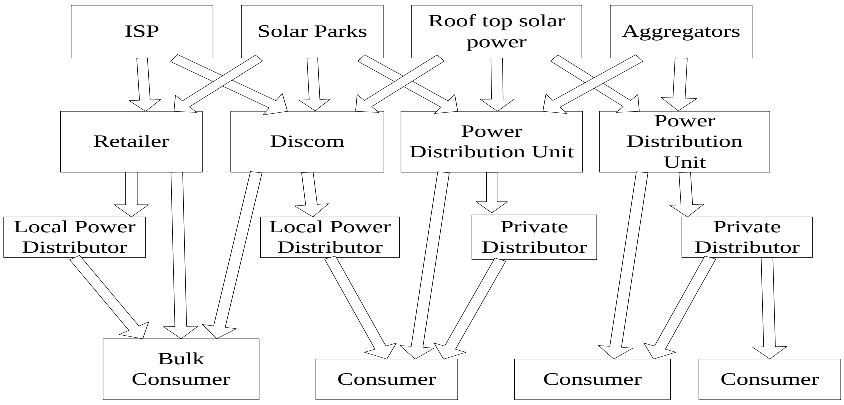

Fig.3.7: Solar power trading for retailer flexible model

3.4 Challenges

The main barrier in implementation of this market model is to lack of additional facility of transmission capacity, additionally distribution sector in India is not ready to take up challenge of variability in supply and demand.

- Renewable energy sources based distributed generation require reactive power and almost 80% of the electrical load are reactive in nature, as load increases demand of reactive power increase. Reactive power imbalance is one of the major issues in such type of system.

- In addition to above problem RES based generation require reactive power, and demand of reactive power increased from both generation and demand side will which reduces the voltage profile of network.
- Solar power is fluctuating in nature, in order to compensate the fluctuating nature compensation devices are required for that purpose D-FACTS devices needs to install which will add extra cost to the solar distribution system. However the cost of D-FACTS is lower as compare to FACTS devices.
- Optimal location of PV sizing according to the demand will be a tough task for the designer.
- Price volatility due to intermittent nature of solar.

3.5 Summary

In this work total five different models were proposed for trading of solar power in Indian market context. Different models are to create healthy competition at generation and distribution side to make solar power available to everyone. These models are similar to conventional electricity market with minor changes in accordance with solar energy characteristics and nature of power such as storage unit is added to maintain reliability in supply system. Aggregator model is introduced to supply power in rural area for agriculture and domestic purpose. In this model surplus power from different houses which are being fed back to the grid and it can be aggregated and it can be transmitted through tie line to the remote location or villages for powering the villages. In this proposed model society or house equipped with solar grid interconnected system can contribute to lighting up the rural area or they are power participating in power trading from home itself. These proposed market models for solar power trading needs to be implemented at small scale at initial stage and then can be extended for state level.

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Chapter 4

ELECTRICITY PRICE FORECASTING

4.1 Introduction

Through the introduction of deregulation, electricity price forecasting (EPF) turn out to be an imperative aspect of power system planning. For electricity price forecasting, with the help of the historical data we can determine the future electricity price so that we can plan the network in better manner for future. In deregulated electricity industry forecasting is the planning tool to manage the power system network with uncertainty. In deregulated environment the electricity price always changes with the time, temperature, weather etc. The governing objective of the deregulation in electric industry is effective utilization of available electricity, consumption of electricity and provide the electricity at lower price. In order to meet these requirements an operative and accurate method of load and price forecasting is required [1]-[2]. The main focus of the deregulated electricity industry is to emphasize on profit maximization for market players and cost minimization of electricity for consumer. Consequences of accurate price forecasting are better power system planning, lesser risk assessment and decision making. Hence accurate price forecasting is necessary for the profit of power producers and benefit to costumers [3]-[5]. High degree of uncertainties is involved in price forecasting problems due to dependency on the factors like weather, demand. Different Artificial intelligence tools are used for price forecasting such as expert systems, fuzzy inference, fuzzy-neural models, ANN, adaptive neural fuzzy interface, regression and expert system. Among the techniques used so far, ANN is most widely used for forecasting of price [6]-[8].

In this chapter a novel methodology of feature selection-based electricity price forecasting using ANN is proposed. In this approach only most, influential parameter i.e. which highly affects the electricity price are considered. In the present case most, influential parameter is load demand among maximum temperature, minimum temperature, global solar exposure, average temperature and rain fall.

4.2 Methodology

For the proposed model of electricity price forecasting as shown in Fig.4.1, the input data, load demand and metrological parameters are collected from the Australian electricity market website. Then these data are prepared for processing. After preparing the data, the forecasting horizon for proposed model is decided as month ahead and week ahead to forecast electricity price. Then the most influential parameter among load and metrological input data is decided. It is observed that load demand is most prioritized input parameter so the load demand and electricity price is considered as input parameter for training and validation of the ANN model. Finally, computation of forecasting accuracy with help of MAPE and RMSE is done and compared.

4.2.1 CORELATION COIFFICIENT OF INPUT VARIABLES

The weather parameter as well as electricity load demand which affect the electricity price are considered for suitability as input parameter. In order to find the suitability, the correlation between these variables and price is obtained using the parson co relation coefficient as given by Eq. 1.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum y^2 - (\sum y)^2][n\sum x^2 - (\sum x)^2}} \quad (1)$$

Where

r = co relation co efficient

n = sample size

x = input variable with respect to calculate the co relation

y = Second input variable

Table 1 shows the correlation coefficient of different input variables with price. It is evident from the table 1 that the electricity price is strongly correlated with load demand as its value is equal to unity. It is also noticed that the electricity price is also dependent on the maximum temperature and it is least dependent on solar exposure. Only the load demand is considered as input in the proposed model of price forecasting in this paper due to highest correlation with price.

4.2.2 ANN FOR PRICE FORECASTING

Artificial neural network is the widely used tool for the purpose of prediction e.g. electricity load, price and weather prediction, because it is can handle large non-linear relationship input data and it can be easily implemented. ANN can capture the non-linearity by collecting the information and detecting the pattern of the system. For real time price forecasting the electricity price of January 2016 to June 2017 period from Australia Electricity Market is used in this chapter. The list of correlation coefficient values for different input parameter is presented in Table 4.1.

Table 4.1: List of co relation co efficient value for proposed model

S.N.	Input Variable	Unit	Correlation co efficient
1.	Load Demand	Megawatt	1.00
2.	Maximum Temperature	Celsius	0.85
3.	Minimum Temperature	Celsius	0.35
4.	Global Solar Exposure	MJ/m^2	0.10
5.	Average Temperature	Celsius	0.17
6.	Rainfall	Millimetre	0.01

In this chapter Multi-Layer Perceptron (MLP) feed forward, neural network (NN) as shown in Fig.4.2 is used. The algorithm used to train the NN model is Levenberg–marquadrat back propagation.

The Multi-Layer Perceptron consist of

1. Input Layer – it includes price and demand of electricity
2. Hidden Layer(s) – four hidden layers are used
3. Output Layer – Electricity price is used as output

The architecture of MLP can be mathematically represented as Eq. 2 [10].

$$o_j = f_i \sum W_{jk} X_k \qquad (2)$$

Where,

o_j Represents for output of neuron

$f_i(.)$ Represents transfer function

W_{jk} Represents adjustable weights

X_k Represents input of neuron

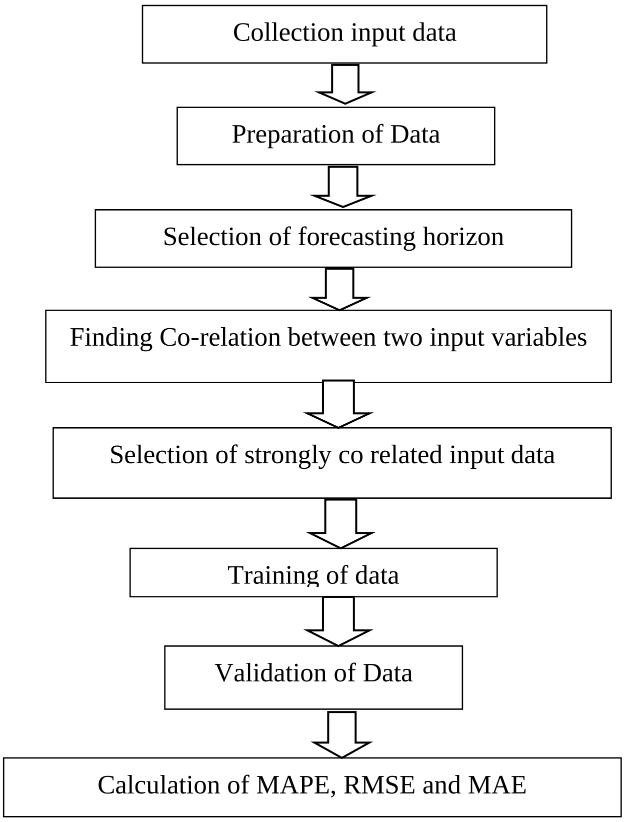


Fig.4.1: Proposed model of electricity price forecasting

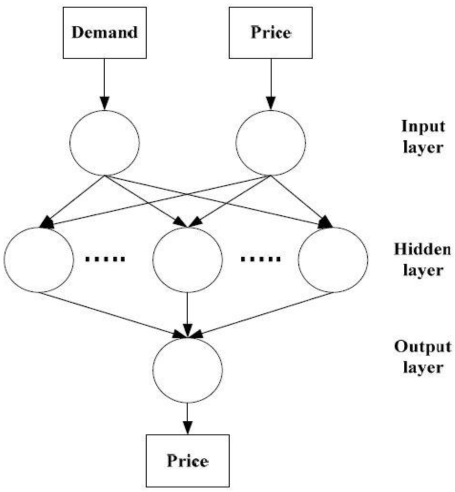


Fig. 4.2: Architecture of Proposed ANN Model

4.3 RESULTS AND DISCUSSION

The ANN model is trained on half hourly data of Electricity price of Australian electricity market from January 2016 to June 2017. Half Hourly electricity demand and electricity price is used as input data and half Electricity Price data is used as target of ANN model. This model is tested on data form January 2017 to June 2017 using ANN toolbox of MATLAB R 2013.

The mean absolute percentage error (MAPE) as given in Eq. 3 is used to check the accuracy of the NN forecasting model.

$$MAPE[\%] = \frac{1}{N}\sum_{1}^{n}\frac{\left[P_A^i - P_F^i\right]}{P_A^i}X100 \qquad (3)$$

where P_A^i and P_F^i are representing the actual and forecasted price. N and i are representing the number of hours and hour index.

For calculation of RMSE Eq. 4 is used.

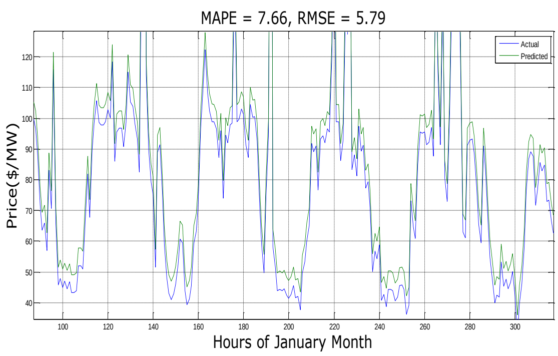
RMSE = mean (sqrt (r. ^2)) (4)

where r is representing the difference between actual and predicted price.

For calculation of MAE Eq. 5 is used.

MAE = mean (abs(r)) (5)

The actual and predicted price of electricity is shown in Fig.4.3 and Fig.4.4 For January 2017 and June 2017 respectively.



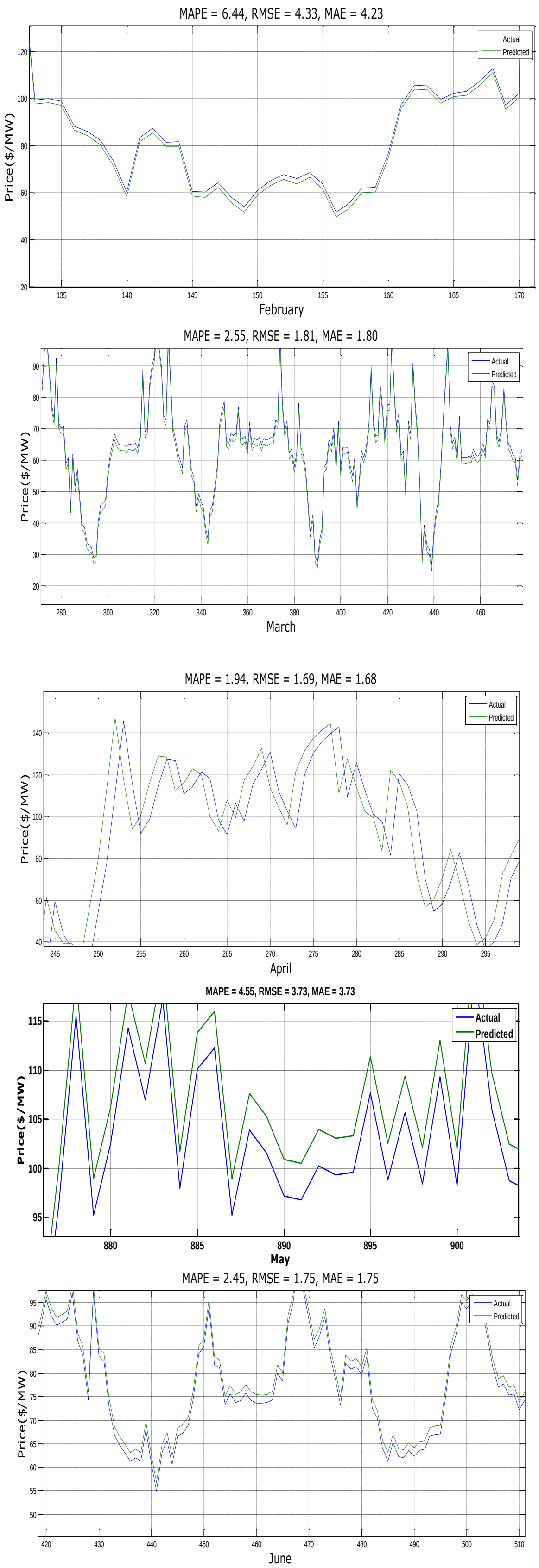
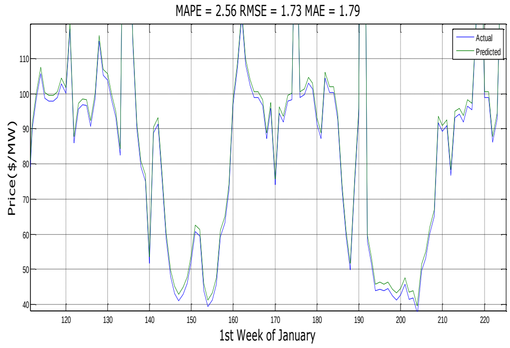
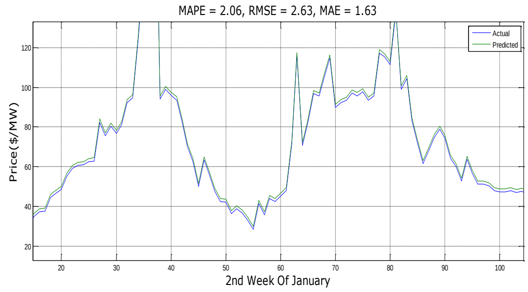
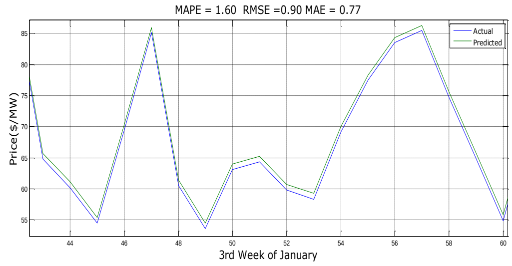
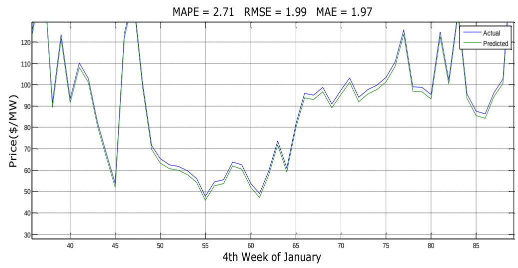


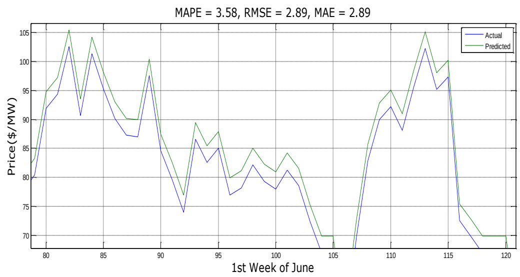
Fig. 4.3: Monthly Price forecast graph from January to June 2017

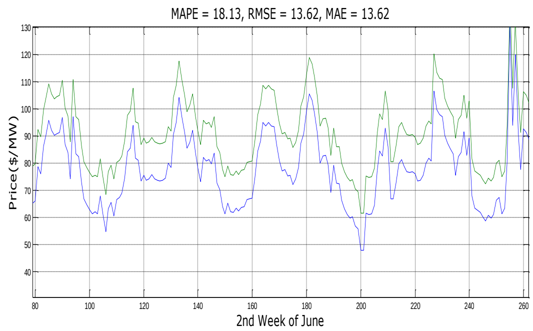

MAPE = 2.56 RMSE = 1.73 MAE = 1.79
Actual
Predicted
Price($/MW)
1st Week of January


MAPE = 2.06, RMSE = 2.63, MAE = 1.63
Actual
Predicted
Price($/MW)
2nd Week Of January


MAPE = 1.60 RMSE =0.90 MAE = 0.77
Actual
Predicted
Price($/MW)
3rd Week of January


MAPE = 2.71 RMSE = 1.99 MAE = 1.97
Actual
Predicted
Price($/MW)
4th Week of January


MAPE = 3.58, RMSE = 2.89, MAE = 2.89
Actual
Predicted
Price($/MW)
1st Week of June


MAPE = 18.13, RMSE = 13.62, MAE = 13.62
Price($/MW)
2nd Week of June

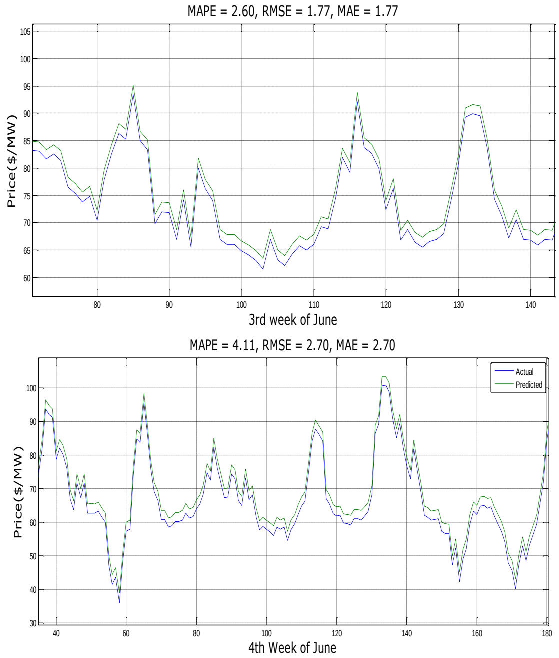


Fig. 4.4: Weekly Price Forecast of January and June 2017 Month

The Table 4.2 presents the MAPE and RMSE values for various months of the year 2017 and Table 4.3 presents the MAPE and RMSE values for various weeks of the January 2017 and June 2017.

Table 4.2: MAPE, MAE and RMSE values for Monthly (January to June) price forecasting.

S. N.	Month	MAPE	RMSE
1.	January 2017	2.56	1.73
2.	February 2017	6.44	4.19
3.	March 2017	2.55	1.81
4.	April 2017	**1.94**	**1.69**
5.	May 2017	4.55	3.73
6.	June 2017	2.45	1.76

Table 4.3: MAPE, MAE and RMSE values for weekly (January and June) price forecasting

S. N.	Week	MAPE	RMSE
1.	Week1 January 2017	14.77	10.30
2.	Week2 January 2017	2.06	2.63
3.	Week3 January 2017	**1.06**	**0.90**
4.	Week4 January 2017	2.71	1.99
5.	Week1 June 2017	3.58	2.89
6.	Week2 June 2017	18.13	13.62
7.	Week3 June 2017	5.04	3.78
8.	Week4 June 2017	4.11	2.70

Table 4.2. shows that the MAPE for different months using proposed ANN ranges from 1.94% to 6.44 % and it is lowest for the month of April 2017. MAE and RMSE is also lowest for the same month.

Table 4.3. shows that the MAPE varies from 1.06% to 18.13% for different weeks and is lowest for week 3 of January 2017. Also the MAE and RMSE are lowest for this week. The error in the first week of January 2017 and 2nd week of June 2017 is highest. The weekly forecast for January 2017 is better than June 2017 whereas monthly forecast for June 2017 is better than January 2017. With certain variations as presented in Table 4.2. and Table 4.3. it is evident that the proposed ANN model is very effective in price forecasting with minimum possible error.

4.4 Summary

This chapter proposes an ANN model to forecast the electricity price using total electricity demand as input to the ANN. The data of the year 2017 of Australian Electricity market was used for forecasting. Correlation coefficient is used to find the highly co related data, and demand is found highly corelated with price. The best result shows the monthly MAPE as 1.94% and weekly MAPE as 1.06% considering only total demand as input to the ANN. Other results also show that for some of the months results of ANN are considerably good. For some weeks error is very high which may be improved using hybrid NN or some new ANN methods.

4.5 References

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Chapter 5

INVESTIGATION ON IMPACT OF SOLAR ENERGY GENERATION ON ELECTRICITY PRICE

5.1 Introduction

Renewable energy resources (wind and solar energy) are used as energy management measures in electricity market [1]. Efficient usage of renewable energy in smart grids results in improvement in the congestion management of power, optimum resource allotment for power market, generation of power at competitive price and competition among generators [2]. Electricity price forecasting is basically prediction of future electricity prices in power system. The forecasting is done using previous data which depends upon meteorological and usage of electricity in previous years. Electricity price forecasting (EPF) helps in liberalizing electricity market in different ways by providing information for market players to bid suitably, improving demand side management and shifting of usage of energy in low price zone. Due to non-stationary and volatile nature of renewable energy, especially for renewable energy integrated grids, the forecasting of price becomes a complicated task for researchers [3]. Market prices of electricity are low in renewable energy integrated grids but due to intermittent nature of solar energy the accurate forecasting of price is important for reliable operation. Forecasting of electricity price is important in renewable energy integrated market so that the consumer can plan the usage of energy accordingly [4]. The utilization of solar energy not only reflects in the reduction of the price but also improves the performance of solar PV, additionally it provides many socio-economic benefits for the users [5].The flexibility and evaluation of grid interconnected solar energy were presented for Nigerian Electricity market and they have reported the increase in spinning reserve and reduction in daily operational revenue of thermal plants by 10 percent and 20percent of solar energy integrated market [6].

Germany is the major country in Europe in terms of renewable energy generation and its integration into the grid. An estimation-based case study has been presented on impact of renewable on electricity price for Germany presented in [7]. A significant increase in the solar powered electricity market has been seen across the globe in past decades, 290GW was reported in the end of 2016. Europe is leading in the solar energy installed capacity with 98.8GW after that Asia with installed capacity of 92.3GW [8] – [9]. Expansion of solar energy and its integration with grid will reach at its peak in near future according to Federal Association Photovoltaic Austria (FAPA), the target of government is to achieve installation of 15GW capacity by year 2030 [10] and that is why the impact of solar energy on electricity price is considered in this paper. The modeling and forecasting of renewable energy with the context of high penetration of non stationary production, balancing of market in uncertainty and flexibility is presented [11]. A market model for variety of trading options of solar energy for Indian electricity market is proposed in [12]. Case study on evaluation of integrating energy electricity market model for Switzerland is discussed in [13] and the market value for futuristic scenario of wind and solar power market for Germany is discussed in [14]

This work has been done on the impact of renewable energy sources fed in the grid, load flow analysis, net transfer capacities, and power transfer distribution factor and demand patterns [15]. LSTM (Long short term memory), a machine learning technique is proven to be one of the accurate models for forecasting the electricity price due to its advantages like retaining previous information for long time, ability to reduce the lag between the output states, Different models recurrent neural network based LSTM were implemented by different researchers in recent years with different levels of accuracy and proven with great level of effectiveness for different electricity markets. [16] – [17]. The deep learning based hybrid algorithm along with LSTM model has been used to forecast price by extracting the optimum nonlinear features of price [18].

In this paper the effect of solar energy generation on electricity price forecasting has been investigated using different machine learning models. The major highlights of the paper are as follows:

(i)Price forecasting of Austria electricity market using LSTM and different state of the art model has been done

(ii) Price forecasting of Austria electricity market under effect of solar energy generation has been investigated

(iii) The comparison has been done for the electricity price forecasting without solar energy and electricity price forecasting under the consideration of solar energy generation.

(iv) Random forest regressor, decision tree, LASSO, Extreme Gradient boost, have been applied for investigating the effect of solar power generation

(v) Proposed LSTM model is implemented and showing better results over Random forest regressor, decision tree, LASSO and XGBOOST on data available for Austria Electricity market.

We have done comparative study of five robust widely adopted machine learning algorithms by the research community. Analysis of LSTM,XGBOOST,DT, RF and LASSO for electricity price forecasting (EPF) under the impact of solar energy generation is done. Price forecasting is an integral aspect for power producer to adopt the optimal bidding strategies. This task is more important in renewable integrated electricity market due to intermittent nature of solar energy. However, most of the existing research in this domain, specifically over the dataset we used, has not taken into the account the impact of solar energy generation. In our research, we have used the actual load data, forecasted load data and actual onshore solar generation data for training models so that each model efficiently captures the impact of these influential features.

b) We have experimented with different kernel combinations, loss functions, and model setups for each of the five models given in the article and reported the best performing algorithmic setting for each model.

c) We also conduct extensive hyper-parameter tuning of the models for obtaining optimum results. We have shared the best hyper-parametric configuration of the best performing model.

5.2 Data analysis

For investigating the effect of solar energy generation on electricity price, the data of Austria electricity market is considered. The raw data of Austria market consists of actual day ahead load, forecasted day ahead load, actual day ahead price and actual solar generation. Day ahead data of electricity prices and actual solar energy generation of 15 minutes interval are obtained from 31/12/2017 to 30/04/2019 [19]. Considering the uncertainty in solar energy output, 15 minutes interval data is considered for better accuracy and reliability of forecasted price. The scatter plot of electricity price vs. solar energy penetration into grid is shown in the Fig. 5.1.

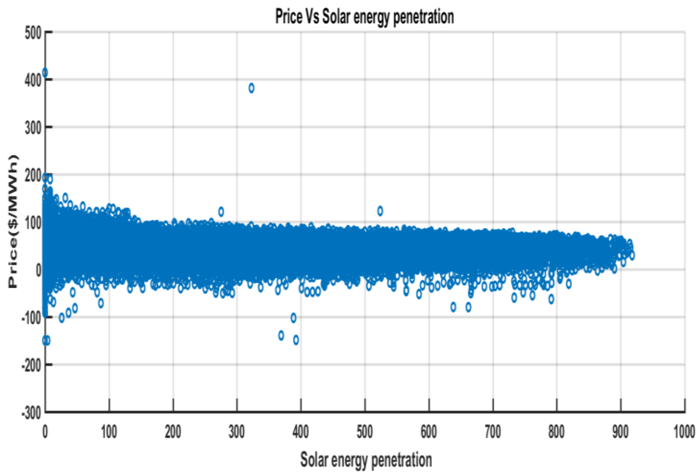
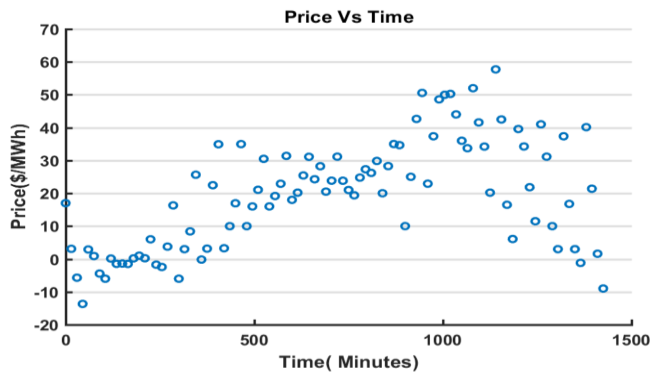


Fig.5.1: Scatter plot of day ahead price vs solar energy penetration

It evident from the figure that for peak periods the electricity prices are at higher side and in off peak periods the price of electricity is low. For lower penetration of solar energy, the price is high as it can be observed, for initial periods in the graph. there is also negative price shown in this graph which represents the surplus power availability for particular time and for that particular period demand is low. Negative price occurrence happens in renewable energy integrated market due to intermittent nature of renewable energy. However, the intermittency is low in case of solar energy consequently the possibility of negative price for solar energy integrated market is comparatively low as compared to wind energy. The scatter plot for solar generation is shown in Fig. 5.2. for same periods. From Fig. 2. inferring about the spike in the generation for some periods, lower spikes can be noticed for morning periods and almost zero output power during cloudy days and night. In the available dataset 75% and 25 % of the dataset are used for training and testing of the model. The data used in this study is flat type data, analysis of this dataset provides crucial information for optimal resource allocation and demand side management. Also, flat rate tariff is widely used in the energy sector as it offers uniform pricing over the fixed period, consequently consumers are not affected by dynamics of variable demand and price. The dynamic pricing is also popular in different regions, a review and analysis is presented in [20]. Some of the highlights for the data of Austria Electricity markets are

(i)For the peak load hours the electricity prices are higher and solar energy output is high for sunny days

(ii) Self correlated and strongly regulated for fixed interval



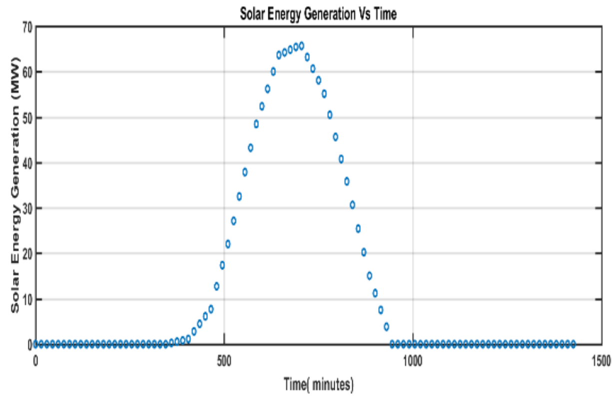


Fig.5.2: Scatter plot of price vs Time and same day solar energy generation

Fig.5.2 Scatter Plot of Day Ahead price and same day solar generation with respect to time

Fig. 5.2 is the representation of price and solar energy generation variation for one day of January month. It could be inferred from the plot that the price spikes can be seen for the peak period and for the same period solar energy output is at its peak. Penetration of intermittent solar energy into grid can reduce the price by significant amount and hence it becomes an important task to forecast the electricity price in renewable energy integrated systems. It helps system planner to schedule generation with demand accurately when accurately solar energy is available and also helpful for consumer to shift their energy usage in low price periods. Also, bidder demands higher price for peak periods but due to solar energy penetration demand can be easily managed and price spike can be overcome. Hence analysis of solar energy effect on price is an important task.

5.3 Methodology

The methodology of this paper for investigation of impact of solar energy on forecasting is represented with the help of Fig. 3. The descriptions of different models used are as follow

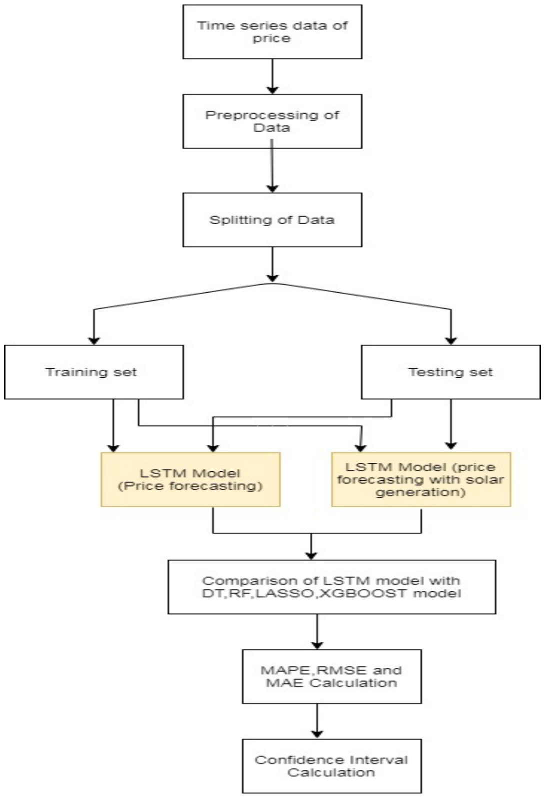


Fig. 5.3: Forecasting steps and evaluation

5.3.1 LSTM Model

Long short-term memory (LSTM) is a superior version of the recurrent neural network (RNN) architecture, were proposed by Hochreiter and Schmidhuber in 1997 [21]. LSTM model were specially intended to overcome the issue of vanishing gradient, while dealing the long-term dependency of the time series data. In the basic structure of the LSTM, memory cell and gate are present. Further in LSTM cell consists of following

i. Forget gates (f_t)

ii. Input gates (i_t) and

iii. Output gates (O_t)

The forget gate in the structure shown in Fig. 5.4. represented by first sigmoid activation function perform the task of information forgetting available from previous memory.

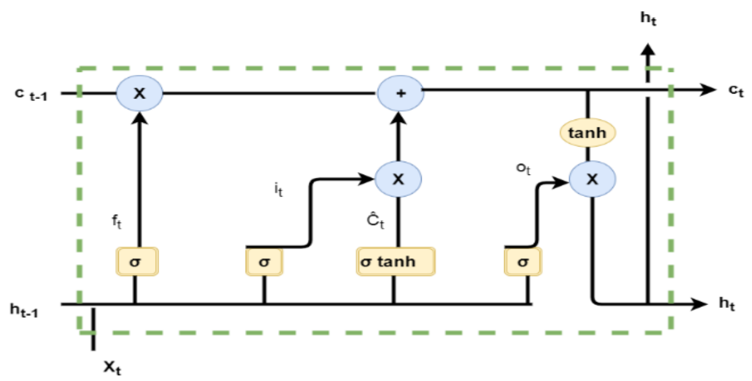


Fig. 5.4: the internal structure of LSTM cell [22]

State, c_{t-1} the extent of information forgetting is also decided by this unit. The function of the input gate is related to the extent of input to be carried out for written in the cell for processing, it is represented by second sigmoid and first tan*h* activation function. Output gate filters the output from cell activation and feed it to the next successive stage. Apart from these three main units cell state acts as transmission agent which carries all information present in the memory. The equations describing the gate function are represented as follows

$$X = \left[X_1, X_2, X_3, \ldots\ldots\ldots\ldots X_t \right] \qquad (1)$$

$$Y = \left[Y_1, Y_2, Y_3, \ldots\ldots\ldots\ldots Y_t \right] \qquad (2)$$

$$h = \left[h_1, h_2, h_3, \ldots\ldots\ldots\ldots h_t \right] \qquad (3)$$

Eq. (1). is for input vector, equation is hidden output layer, Eq. (3). is for output vector. The forget as shown in Fig. 5.4 is represented by Eq. (4). and Eq. (5). is the expression for input gate, it provides modulation to the new memory added to the memory cell. Memory content is provided by the hyperbolic tangent function in Eq. (6). The memory cell is C_t is represented in Eq. (7). The other sigmoid function is used in Eq. (8). to represent the output gate O_t. b_i, b_f, b_g, and b_o are used for denoting the bias weight to the input signal [X] and hidden layer output [Y].

O_f , O_i, O_t and O_g are offset vectors . Table 1 describes the details of parameter used for training and testing the LSTM model.

Table 5.1: Details of parameter used for LSTM model

Objective for Learning Task	LSTM Model
Layers Of LSTM	2
No. of Neurons in layer 1	10
No. of Neurons in layer 2	50
Optimizer	adam
Loss Function	mse
Epoch	180

Step wise implementation of LSTM model.

Step I. Decision on retraining the old information. The output is obtained from Eq. (4). for each number in the cell state and will varies from 0 and 1

$$f_t = \sigma\left(x_t O_f + h_{t-1} b_f\right) \qquad (4)$$

Step II. Storage of new information in the cell state. It has two parts; first one is a sigmoid layer that decides the values to be updated. The output is presented with Eq. (5). The tan*h* layer computes a vector of new values, given by Eq. (6).

$$i_t = \sigma\left(x_t O_i + h_{t-1} b_i\right) \qquad (5)$$

$$\tilde{C} = \tanh\left(X_t O_g + h_{t-1} b_g\right) \qquad (6)$$

Step III. Combining the output of Eq. (5). and Eq. (6).

Step IV. The new cell C_t is computed by updating the old cell state C_{t-1}, given by Eq. (7).

$$C_t = \sigma\left(f_t * C_{t-1} + i_t * \tilde{C}\right) \qquad (7)$$

Step V. Finally the output is obtained using Eq. (8). and Eq. (9).

$$O_t = \sigma\left(X_t O_o + h_{t-1} b_o\right) \qquad (8)$$

$$h_t = \tanh\left(C_t\right) * O_t \qquad (9)$$

5.3.2 Xtreme Gradient Boost Method

Tianqi Chen initially introduced itin 2014 via a research project at the Distributed Machine Learning Community (DMLC), University of Washington [23]. The problem with Gradient boost machine is that no provision for handling of over fitting of data is there, XGBoost incorporates the regularization to prevent this which also acts as additional advantage for tree based and linear models. XG boost model uses the principle of gradient boosting with added features of highly regularized model which results in improved accuracy compared to GBM. The better accuracy is achieved in XGBoost due to minimization of both training loss and the regularization loss. In GBM the pruning is stopped when negative loss is reported, but the case is different in the XG Boost it performs cross validation for handling the missing values internally and it develops tree upto the value specified for parameter called max depth and prunes regularly until the stability in loss function is not within a threshold level. The feature of the Gb tree is that it can provide effective mapping of linear and non-linear data. XGBoost is also robust and computationally inexpensive method used for time series problem.

$$\alpha_m = \arg_m \min \sum_{i=1}^{n} L(X_i, G_{m-1}(y_i) + \alpha F_m(X_i)) \quad (10)$$

x_i, and y_i represents the input and output variable for ith case. and $G_m(Y_i)$ is representing put variable for ith instance at m iterations. L is the measure of differentiable loss convex function, which measures the difference between prediction and target values. α is used here as regression tree function, the significance of this term in this equation is to penalize the complexity of the model. is the multiplier for pseudo residual. $F_m(X_i)$ is denoting the function of weak learner for pseudo residual in Eq. (10) [23]. In order to find the optimal hyper-parameter values, cross-validation approach was used, and kept on tuning the hyper-parameter values via a series of comparisons using RMSE scores. The best performance was achieved by using an XGBoost regressor having the parametric configuration listed in Table 2.

Table 5.2: Details of parameter used for XGBoost model

Objective for Learning Task	Linear Regressio
Booster Parameter	gb-tree
Number of Trees	100
Size of tree (depth)	6
Learning Rate for Tree Booster	0.3
Column Sub sampling	1
Alpha regularization parameter	0
Lambda regularization parameter	1

5.3.3 Decision Tree

In linear regression, single predictive formula is present to handle the entire dataset which makes it very complicated for the dataset having many features to interact with non- linear variables. The decision tree is a popular supervised learning method widely applied for solving time series and classification problems. The decision tree uses the concept of recursive partitioning, in this method the entire dataset is sub divided into smaller space for manageable interactions. The recursive partitioning starts with the root node of the tree and by asking a series of question about the features present in the dataset [24]. The interior nodes are labeled with question and associated branches between them are labeled with answers. After fixing of tree according to the features availability from the dataset, the next important point is how to decide where we have to stop the growing of tree. It is typically decided on the basis of information provided by the particular node. The performance of the model can be improved by minimizing the value of sum of squared errors (S) between the node and its child node, represented by Eq. (11).

$$S = \sum_{i=1}^{n} (Y_i - C)^2 \qquad (11)$$

n is representing the number of cases present at that node, C is representing the average outcome considering all cases at that node and y_i is the predicted value for i^{th} case. Cross validation technique used to prune the growing tree, alternate grow and prune technique is used. The details of parameter used in training and testing of dataset using decision tree model are given in Table 3.

Table 5.3: Details of parameter used for Decision Tree model

Objective for Learnin Task	Regression model
Tuning linear model	Regression tree
No. of tree	100
Maximum depth of tree	6
Minimum sample at leaf node	4
Parameter tuning	Grid search with 5 Fold CV

5.3.4 Random Forest

The problems associated with decision tree are over fitting of data and the computation time for training the data is large. These problems are minimized in random forest model. It is an ensemble learning technique based on meta estimator. In this process the multiple parallel trees are working independently. The results of each tree are aggregated and the final result is again processed for improving the accuracy of the model. The feature bagging concept is used in random forest, which includes random selection of subset, containing features from each tree during training. Now models for resampled data will be developed, consequently it helps to reduce the variance which in turn increases the generalization capability of model. Generalization capability improves in finding the uniform correlation among available variables which governs the target variable. [25]. The parametric configuration of Random forest model is presented in Table 5.4.

Table 5.4: Details of parameter used for Random Forest model

Objective for Learnin Task	Regression model
Tuning linear model	Random forest regressor
No. of tree	100
Maximum depth of tree	10
Minimum sample at leaf node	8
Parameter tuning	Grid search with 5 Fold CV

5.3.5 LASSO

Least absolute shrinkage and selector operator (LASSO) is a regression method with minimized equation which consists of two component one component is known as Residual sum of squares (RSS) and other is L1 regularization. This technique uses both variable selection and regularization simultaneously. L1 regularization uses only absolute values of coefficient and sum up this factor in optimization objective function as represented in Eq. (12). This method is suitable for time series problem with large number of features. This method minimizes the sum of RSS and product of penalty factor and slope of the regression plot. this model uses shrinkage of value of coefficient which makes it computationally inexpensive [26].

$$£(\beta; \lambda) = \min \sum_{i=1}^{n} (Y_i - X_i\beta)^2 + \lambda_1 \sum_{i=1}^{n} |\beta_k| \qquad (12)$$

is representing the outcome of the predicted variable for i[th] case. $X_i\beta$ is the mapped vector of prediction, in which X_i is representing the feature of ith variable. and β is representing the bias weight. $\beta_k \beta_k$is representing the absolute value of coefficient whereas λ_1 is representing the penalty factor. The details of parameters selected for training and testing the model are presented in Table 5.5.

Table 5.5: Details of parameter used for LASSO model

Objective for Learning Task	LASSO L1 regularize for linear model
Tuning linear mode	Lasso Regression
Fit_intercept	True
Copy_X	True
Alpha regularizatio parameter	1e – 15
Normalize	True

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(Y_{A,j} - Y_{P,j}\right)^2} \qquad (13)$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|Y_{A,j} - Y_{P,j}\right| \qquad (14)$$

5.4 Results and Discussion

All models implemented and mentioned above were trained and tested on a machine having 8GB of 16MHz DDR3 RAM and a 1.6 GHz Intel Core i5 processor, running a jupyter-notebook development environment. The metric used for evaluation of the models' performance is the Root-Mean-Square-Error (RMSE), Mean-Absolute-Error (MAE) and Mean Absolute Percentage Error (MAPE) represented in Eq. (13), (14) and (15). n is representing the number of samples, $y_{A,j}$ and $y_{P,j}$ are actual and forecasted price for j^{th} instance respectively in Eq. (13), (14) and (15) . In Table I, Table II and Table III comparison of different forecasting metrics has been presented and graphical presentation of evaluation metrics is shown in Fig. 5.14.

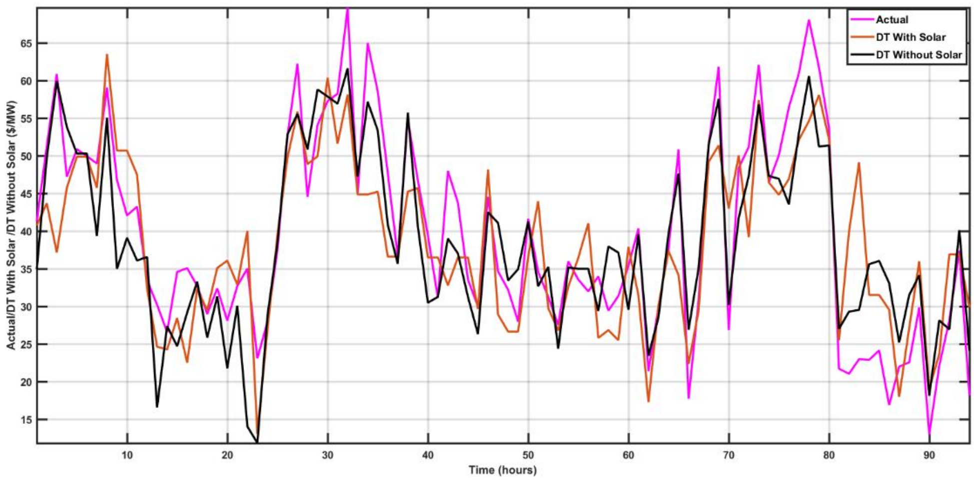


Fig. 5.5: Comparison of forecasting result for DT Models of electricity price with and without solar energy

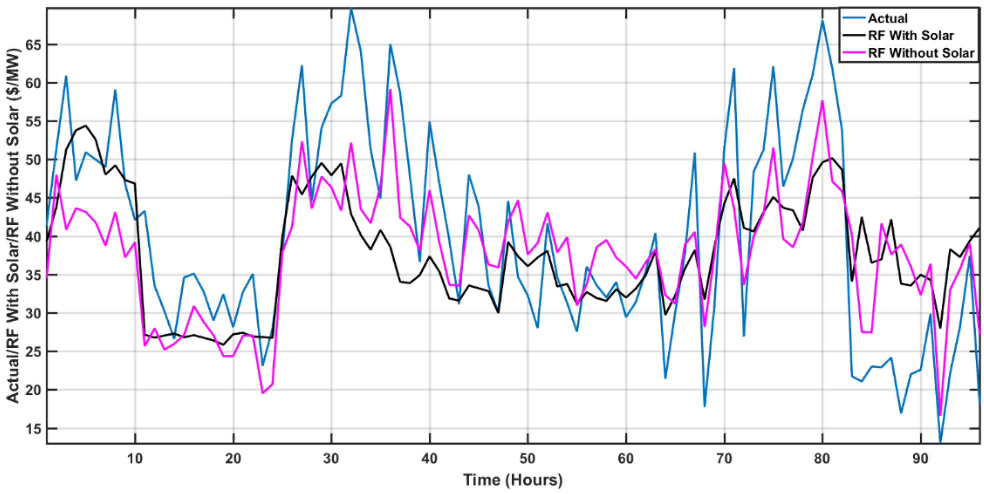


Fig. 5.6: Comparison of forecasting result for RF Models of electricity price with and without solar energy

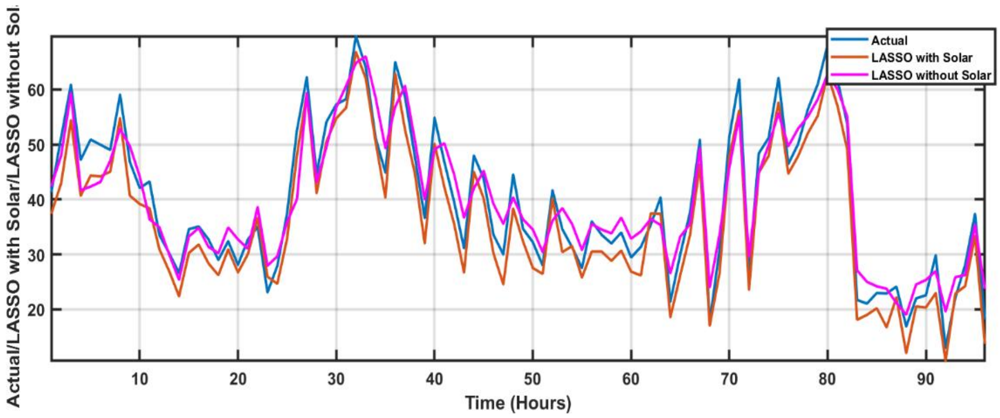


Fig. 5.7: Comparison of forecasting result for LASSO Models of electricity price with and without solar energy

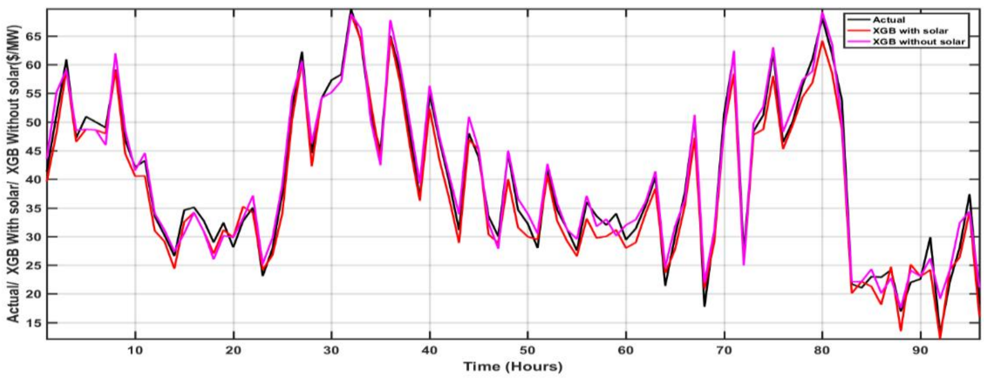


Fig. 5.8: Comparison of forecasting result for XGB Models of electricity price with and without solar energy

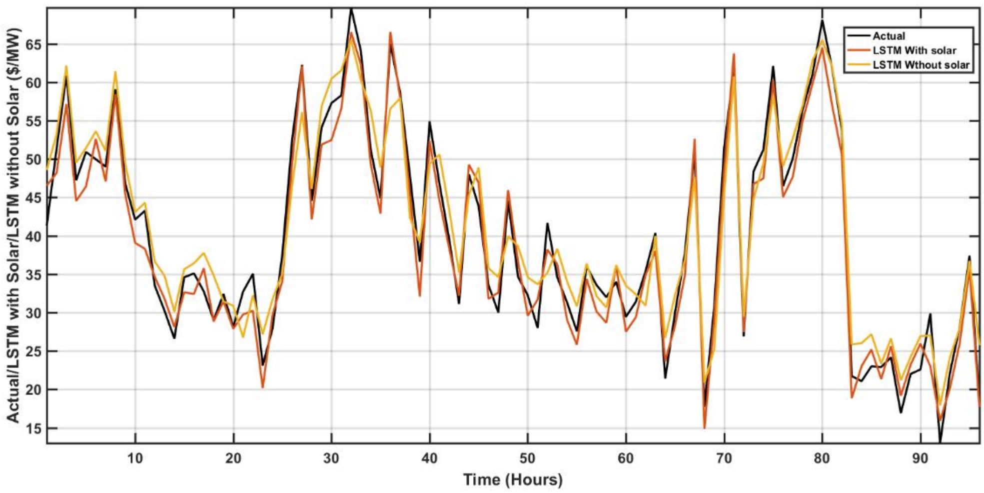


Fig. 5.9: Comparison of forecasting result for LSTM Models of electricity price with and without solar energy

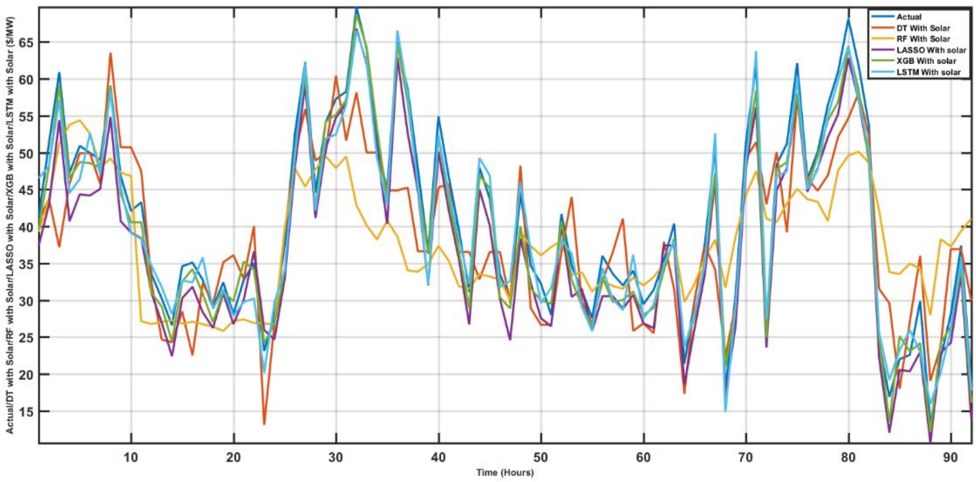


Fig. 5.10: Comparison of forecasting result for different Models of electricity price without solar energy

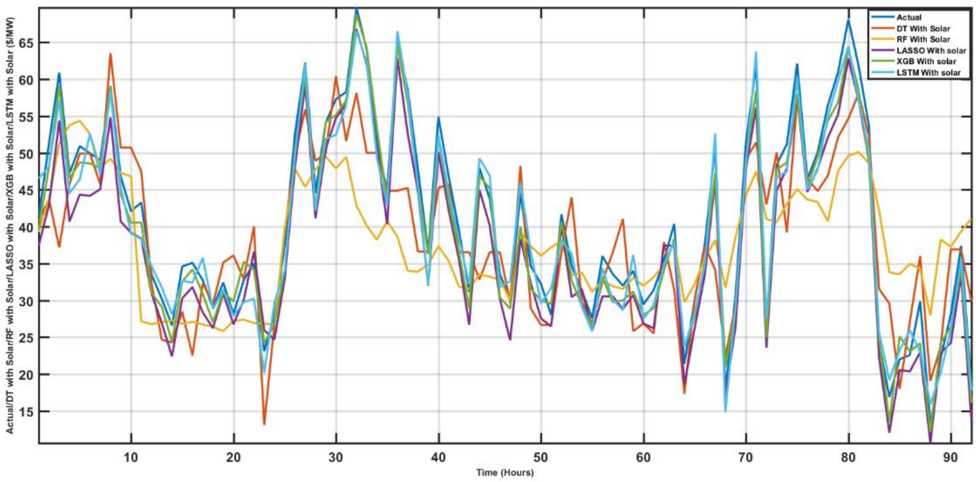


Fig. 5.11: Comparison of forecasting result for different Models of electricity price without solar energy

Fig.5.5, Fig.5.6., Fig.5.7.,.and Fig. 5.8. are representing the forecasting result for electricity price with and without solar energy penetration for DT, RF LASSO and XGBOOST model respectively. In Fig. 5.10. the comparative graph for Decision Tree (DT), Random Forest (RF), LASSO, XGBoost and LSTM were presented to observe the error between actual and forecasted price without solar energy inclusion as input variable. In Fig.5.11. the comparative graph for forecasted price with solar energy input variable were presented. LSTM model performed slightly better over DT, RF and LASSO and XGBoost because it captures the stochastic changes of price and uses regularization for pruning as well as for tuning the parameters. Due to over fitting of the data in decision tree, complexity and longer training period involved in random forest regression and lesser feature available in dataset, LASSO not performed very well for the available data set. The performance of the various models used in this paper is also evaluated for the training dataset. Fig. 5.12. and Fig. 5.13. are representing the actual vs. forecasted price for training subset for DT, RF, LASSO, XGB and LSTM without and with solar data respectively. In Fig. 5.12. y1 plot is for actual day ahead price data used for training and similarly y2, y3, y4, y5 and y6 are representing the actual (grey colored) and forecasted (blue colored) training data subset for DT, RF, XGBOOST, LASSO and LSTM models respectively without consideration of solar energy input variable. In Fig.5.13. the actual and forecasted plots for training subset used in forecasting of price by taking solar energy impact using DT, RF, LASSO, XGBOOST and LSTM models has been presented. The forecasted price with LSTM model is lower as compared to DT, RF, LASSO and XGBOOST is relatively lower also the price spikes is observed higher in case other above-mentioned models.

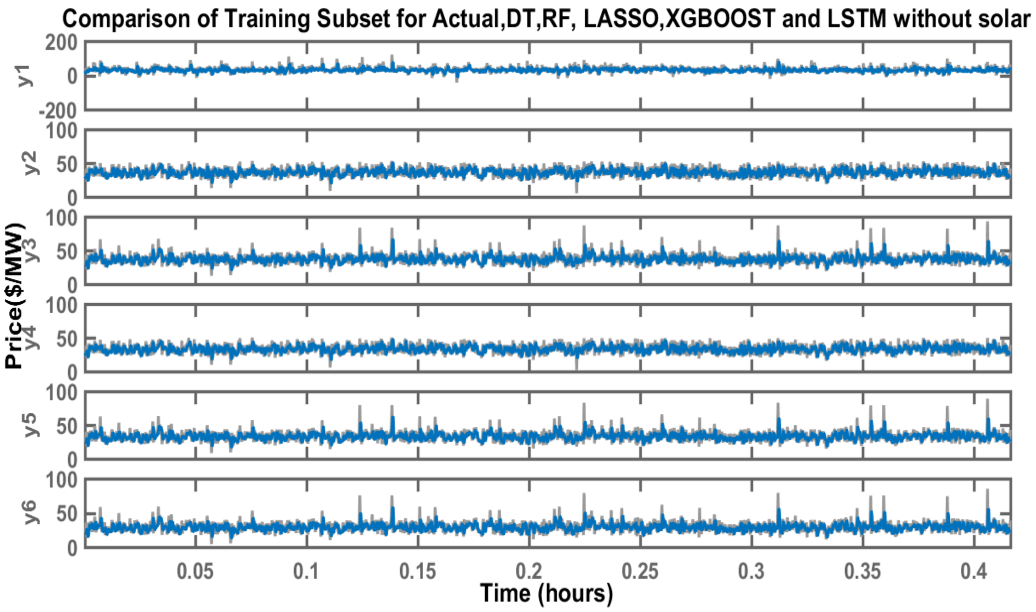


Fig.5.12: Comparison of different models for price forecasting of training subset without solar energy

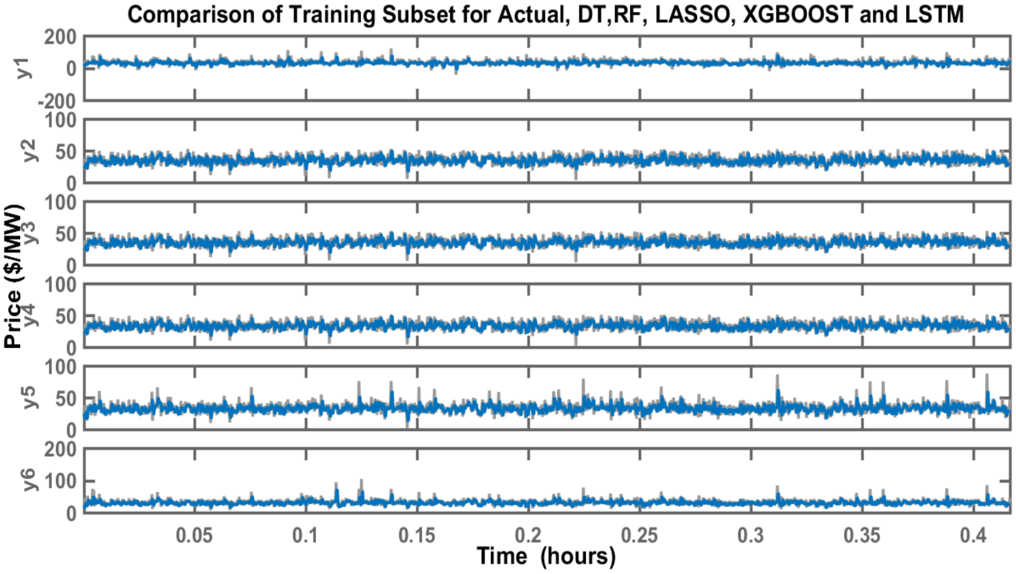


Fig. 5.13: Comparison of different models for price forecasting of training subset with solar energy

TABLE 5.6: EVALUATION OF DIFFERENT MODELS IN TERMS OF MAE AND RMSE VALUES

Models	MAE without solar	MAE with solar	RMSE without solar	RMSE with solar
Decision Tree	5.17	5.97	4.55	5.88
Random Forest	7.77	8.21	6.69	8.02
LASSO	4.94	4.63	4.11	3.93
XG Boost	4.78	4.06	3.56	3.79
LSTM	3.16	2.36	2.45	2.40

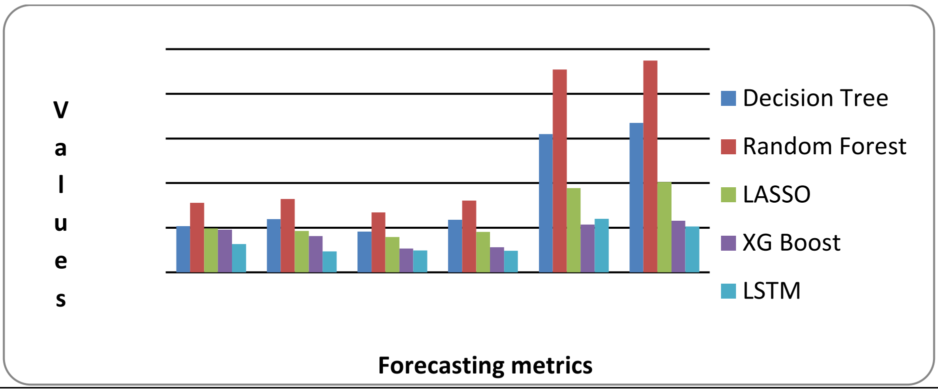


Fig. 5.14: Graphical Representation of performance metrics used for different models

5.5. Confidence Interval (CI)

Confidence Interval (CI) is calculated for evaluating the reliability of the forecasted price. The CI analysis is important from the econometric aspect of the electricity price. It felicitates the possible change of variation in the electricity price under uncertainty involves with solar generation. This analysis holds importance in price forecasting in renewable integrated market where the uncertainty involves with wind and solar is at risk. The steps adopted for the calculation of CI of MAPE values [27] are illustrated as

Step I. Calculation of standard Error (SE) by using Eq. (16).

$$SE = \frac{\sigma}{\sqrt{n}} \qquad (16)$$

σ is representing the standard deviation (SD) of available sample, X and n is the number of samples.

Step II. Calculation of T –Score. The value of T –score depends on the level of CI required. Formula for calculating T-score given by Eq. (17).

$$ME = t * SE \qquad (17)$$

Where t = 1.98 for 95% CI for MAPE

Step III Calculation of CI by using Eq. (18).

$$CI = mean(X) + T \qquad (18)$$

Where $mean(X)$ is the mean of vector X

TABLE 5.7: EVALUATION OF CONFIDENCE INTERVAL (CI) FOR WITHOUT SOLAR OF MAPE VALUES FOR DIFFERENT MODELS

Models	MAPE	MIN –MAX Range	CI
Decision Tree	15.47	[12.14, 18.53]	3.19
Random Forest	22.730	[17.74, 25.59]	3.92
LASSO	10.12	[8.55, 10.95]	1.55
XG Boost	5.359	[4.32,6.67]	1.17
LSTM	9.143	[7.89, 10.90]	1.50

TABLE 5.8: EVALUATION OF CONFIDENCE INTERVAL (CI) FOR WITH SOLAR OF MAPE VALUES FOR DIFFERENT MODELS

Models	MAPE	MIN –MAX Range	Confidence Interval (CI)
Decision Tree	16.73	[13.22, 20.22]	3.85
Random Forest	23.73	[18.70, 22.94]	5.11
LASSO	9.43	[8.11, 10.56]	1.22
XG Boost	5.786	[5.06, 6.67]	0.84
LSTM	6.00	[5.695, 7.37]	0.80

5.5 Summary

In this chapter a novel method has been proposed and implemented for investigation of effect of solar energy output on electricity pricing in renewable integrated grid system. In renewable integrated grid the solar and wind capacities are penetrated strategically into grid according to their availability to meet the increasing demand. As the penetration of renewable energy capacities are more, consequently the marginal cost will drop and thus price of electricity will drop. The major problem associated with the renewable energies is their intermittent nature, so price forecasting in grid connected environment is important. The forecasted price will provide the crucial information to the bidder and renewable energy producers to quote bid. Following conclusions were drawn from the work

1. Price drop due to penetration of solar energy even in peak hours, when demand is high.
2. Improvement In the forecasting accuracy of electricity price due to inclusion of solar energy as input variable.
3. Reliability of forecasted price by calculating CI values, which is considerably good in capturing the seasonality and variability in the output.

However, LSTM Model performs well for the dataset used in this study, but some issues like large training period, data overfitting and large memory requirements are reported. So, the forecasting accuracy may be improved by using appropriate data processing methods with hybrid machine learning techniques. However Comparative investigation among various machine learning models is performed to make this research extensive and exhaustive. In future, more input parameters can be included and effect of wind power penetration on electricity price can also be investigated for RES integrated market.

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Chapter 6

STUDY OF POTENTIAL IMPACT OF WIND EENRGY ON ELECTRICITY PRICE

6.1 Introduction

The growing demand of electricity across the globe and so the expansion of renewable energy generation, grid integration is one of the concurrent aspects of power system. The speedy development in the expansion of renewable energy (wind and solar) across the world provides energy security and sustainability. The integration of RES into grid felicitates lower price to consumer when power is in surplus and price is higher in under supply conditions [1] the optimal allocation and generation of power in RES integrated environment is tough task due to intermittent nature of wind and solar. The wind energy installed both onshore and offshore worldwide is reached to 564 GW [2] in 2018 and it is expected to add more 2000 GW [3] to 2030. Large scale generation of wind and its integration into grid the impact analysis on price is important task. The literature survey is proven to be dropping in the electricity price due to wind energy penetration [4]- [7].

The variety in the study of impact analysis on price were presented covering different aspects of wind energy and price forecasting. The analysis of effect of renewable energy on wholesale electricity price is investigated and reported a significant change for Italy and Sicily market [8]. The econometric analysis has been done for small scale wind farms [9]. The large-scale wind generation and its impacts analysis by evaluating different aspects of wind have been discussed [10]. The statistical model has been presented for analysis of the impact and was simulated on real time data [11]. The economic analysis on price forecasting error in wind integrated market has been presented.

From the literature survey it was observed that the, the machine learning algorithm models were not completely explored in the study of impact analysis of wind energy on price compared to price forecasting for conventional based generation market. In the literature regression methods are widely applied on price forecasting with different level of accuracy for different electricity market data as they are simple and easy to implement [12]-[13], but ANN based methods performance are proven to be more reliable and felicitate more accuracy due to capability of handling the nonlinear and stochastic nature of price. This task is more complex in renewable energy integrated market due to intermittent nature of wind.

Most of the researchers have attempted to explore the price forecasting using different models of machine learning with different level of success in terms of accuracy for fuel-based electricity market. In current scenario, in the light of renewable energy penetration the grid operation and their scheduling and their dynamics is changing, price forecasting in such grid interactive scenario is crucial task due to variability in the wind and solar energy output. Though, accurate price forecasting is tough task due to non-stationary and stochastic nature. This task is even more complex and important at the same time in renewable energy interactive environment. Due to elevating expansion in the capacities and growth of renewable energy across the globe, price forecasting becomes the hot topic among researchers. In this paper an attempt has been made to bridge the gap between the price forecasting of fuel-based plant and Distributed Energy (DE) based plant.

This chapter attempts to explore the information available in time series data with regression models, namely DT, RF, LR and LASSO model to explore the impact of wind energy generation on price. DT model is used to forecast the price in wind energy integrated market. DT utilized due to its capability to capture the linear and nonlinear relationship of price, additionally it captures the stochastic nature of price and able to operate large number of input and output variables. Additionally, extensive hyper parameter tuning and experimentation with different kernel function and loss function has been done and best parameter details shared in this study. This study helps wind power producers in scheduling their demand and optimizes their resources.

6.2 Data Preparation and statistics analysis

The dataset of Austria electricity market has been used in this work for examining the impact of wind energy penetration into the grid on price. The raw data of day ahead price, load, forecasted load and wind energy has been collected, due to intermittent nature of wind the wind generation data is not fully regularized over time span. In order to improve the data set redundancy, the pre-processing and normalization has been done using min max method. The statistical analysis has been also represented in table for both price data and wind generation data to observe the stochastic and non-linearity involve with price and intermittency with wind data. Due to missing values 10 months data set of year 2018 has been used to train the model [14]. The data splitting for training and testing the model is used as 70% for training the model rest is for testing purpose. The scatter plot of wind energy generation over 15 minutes interval data has been represented in the Fig. 6.1. The statistical analysis of the data set is shown in Table 7.1.

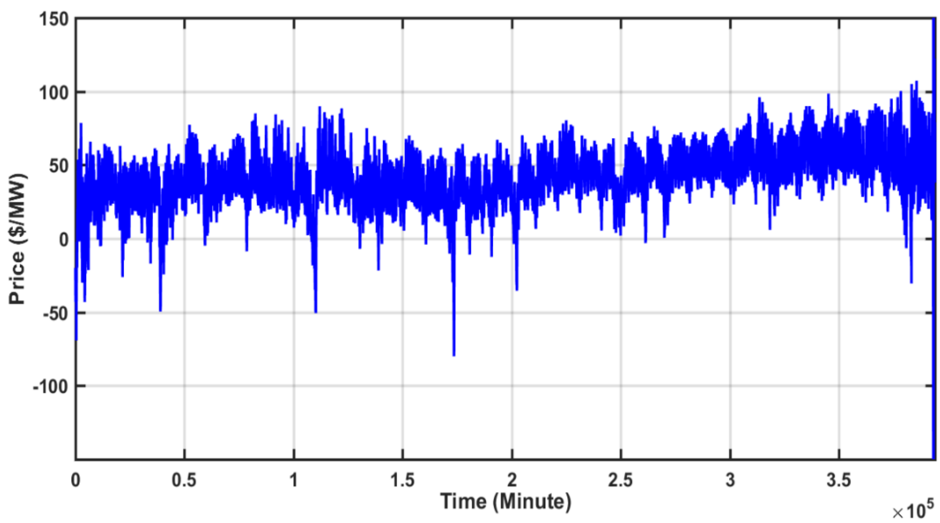


Fig.6.1: Scatter plot of price with time

Fig. 6.1. is the representation of price data, dotted line represents the linear day ahead price the variation in the price is according to the demand is observed at the same time negative price

for specific period also exist. Negative price indicates the surplus power availability and reduced demand in the market. To tackle the price variation and stochascity under the effect intermittent nature of wind energy is a typical task for researchers to forecast the price accurately. To forecast the price, by considering wind generation as one of the constraints two different regression methodologies were modelled and compared.

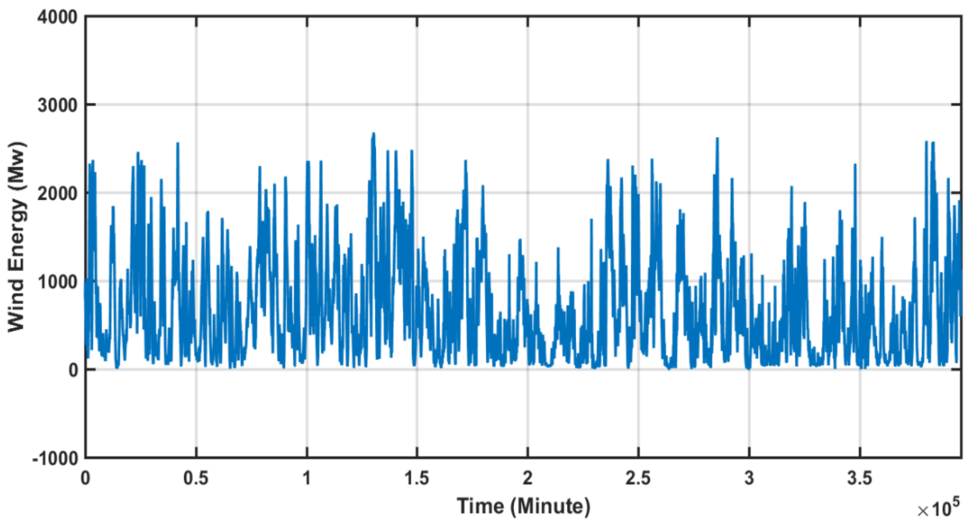


Fig.6.2: Variation of wind energy output with time

Table 6.1. provides the statistical analysis of the data set used to train the models. The statistical analysis of dataset is important before finalizing the models to forecast price so that we can distinctly observe the different features like symmetry of data and finally based on observation of data set features we can suitably choose the model to train for accurate forecasting.

Table 6.1: Data Statistical Summary

Parameters	Price data	Wind data
Total samples	26393	26393
Data Interval	15Minutes	15 Minutes
Missing values	0	0
Mean	41.84024	658.2215
Standard Deviation	19.13648	583.0336
Min	-149.99	0
Max	977.74	2678.95
Skewness	4.115554	1.052051
Kurtosis	225.2523	0.389033

6.3 Methodology

6.3.1 Decision Tree

DT is a well-established supervised learning machine learning technique used for finding solution for classification and regression problems, it receives a set of features and based on these it gives a Boolean decision as outcome [15] - [16]. DT works based on the classification or regression models in the arrangement of tree like structure, then it divides the task into minor subsets and simultaneously develop an incremental decision tree. The final outcome will be a tree with decision node and leaf node, each decision node will represent a value for the features tested and leaf node will represent a decision on target value. The uppermost decision node in a tree which belongs to the finest predictor called root node. The algorithm used for building decision tree model is ID3 with standard deviation reduction. Standard deviation is used for calculation of presence of homogeneity in the dataset, the value of standard deviation will be zero for homogeneous data. The reduction in the standard deviation after dataset is splitting on attributes done for getting the maximum number attributes providing maximum standard deviation. Details of hyper tuned parameters for training and testing of DT model is given in Table 6.2.

Table 6.2: Details of hyper tuned parameters for Decision Tree model

Objective for Learning Task	Regression model
Tuning linear model	Regression tree
No. of tree	100
Maximum depth of tree	6
Minimum sample at leaf node	4
Parameter tuning	Grid search with 5-Fold CV

The improvement in the model performance can be performed by minimization of sum of squared error (S) between the node and its respective child node. In equation (1) formula for calculation of S is give.

$$S = \sum_{i=1}^{n} (Y_i - C)^2 \qquad (1)$$

In Eq. (1) S is Sum of Squared Errors, n is representing the number of cases present at that node, C is representing the average outcome considering all cases at that node and $y_i$is the predicted value for ith case.

6.3.2 Random Forest

RF is an ensemble learning technique which works on meta estimator. The final results will be improved by taking average of all the trees and further processed for improving the accuracy. The main feature of random forest is bagging, in bagging concept selection of random subset, containing features from each tree during training. In this method a model is developed for resampled and which helps in reduction the variance, consequently improves the generalization capability. The advantages of random forest are they do not suffer from over fitting even if the dataset is too large and the selection of random samples makes it better predictor model. Details of hyper tuned parameters for training and testing of RF model is given in Table 6.3.

Table 6.3: Details of hyper tuned parameters for Random Forest model

Objective for Learning Task	Regression model
Tuning linear model	Random forest regressor
Maximum depth of tree	10
Minimum sample at leaf node	8
Parameter tuning	Grid search with 5-Fold CV

From the original dataset n bootstrap samples drawn and for each sample unpruned tree is grown. Instead of choosing the best sample among all predictors random selection of samples from predictors at each node and from those selections of best split is done. New data values are predicted by taking average of all n trees from samples for regression problems (majority votes considered in for classification). Based on training data calculate the error [17].

6.3.3 Linear Regression

LR is statistical approach, widely used for time series forecasting. Regression is data mining task used for prediction of future values of any target values by creating a model based on the variables.

$$Y = X * \beta + \mathrm{r} \qquad (2)$$

Y is outcome variable, X is predictor matrix, β is relationship vector and r are a residual vector in Eq. (2). LR method follows least square approach in which the sum of squared error between predicted and actual values is minimized [18]-[20]. The mathematical form of LR method is given in Eq. (3). Details of hyper tuned parameters for training and testing of LR model is given in Table 6.4.

$$\min_{\beta} \lVert X.\beta - Y \rVert^2 \qquad (3)$$

Table 6.4: Details of hyper tuned parameters for Linear Regression model

Objective for Learnin Task	Regression model
Tuning linear model	Linear Regression
Fit_intercept	true
Copy_X	true
normalize	false

6.3.4 LASSO

Least absolute shrinkage and selector operator (LASSO), is widely used for the time series problem. It uses reduced Eq. (4), it consists of two components one is known as sum of squared error and second one is L1 regularization parameter. It works on principal of regularization and gives accurate results for the complex system and data with large features. The feature of the LASSO model is it assign penalty to the magnitude of coefficient [21]. The necessity of penalty factor in LASSO model is, by increasing the magnitude of the coefficient the model become complex and availability of features is also large. The level of importance of the features for forecasting is decided by the magnitude of the coefficient [22].

$$£\left(\beta;\lambda\right) = \min \sum_{i=1}^{n} (Y_i - X_i\beta)^2 + \lambda_1 \sum_{i=1}^{n} \left|\beta_k\right| \quad (4)$$

in Eq. (4) Y_i is representing the outcome of the predicted variable for ith case. $x_i\beta$ is the mapped vector of prediction, in which x_i is representing the feature of ith variable and β is representing the bias weight. β_k is representing the absolute value of coefficient whereas λ_1 is representing the penalty factor. The accuracy of the LASSO model for the available dataset is comparatively not good due to fewer available features in the dataset and over fitting problem due to higher importance given to some specific features. Details of hyper tuned parameters for training and testing the LASSO model is given in Table 6.5.

Table 6.5: Details of hyper tuned parameters for LASSO model

Objective for Learning Task	LASSO L1 regularize for linear model
Tuning linear mode	Lasso Regression
Fit_intercept	True
Copy_X	True
Alpha regularizatio parameter	1e – 15
Normalize	True

6.3.5 Support vector machine

SVM is a supervised ML technique widely used for classification-based problems and also finds application in regression problems [22]. The feature of the SVR is that it felicitates the flexibility in error range and accordingly finds optimal hyperplane to fit the data. SVM is proven to provide good accuracy for the lower span dataset as it takes long computation time for a large set of data set. The polynomial kernel function was used in support vector regression for accurate calculation is represented in Eq. (1).

$$y = (w.x + b)^3 \qquad (1)$$

$$f = \min \frac{1}{2} \left\| w^2 \right\| + c \sum_{i=1}^{i=n} \left(\xi_i + \xi_i^* \right) \qquad (2)$$

In Eq. (1), y is denoting the input space, w.x is representing the vector product, where w is bias weight and x is the feature of input data and b is a constant term. In equation (2), c is a pre-specified value. ξ_i and ξ_i^* represent the lower and upper bound constraints of the slack variable on the output of the system [23]. The details of parameters used for training the SVM model is given in Table 6.6.

Table 6.6: Details for parameters used for the SVR model

Parameters of SVR models	
kernel	polynomial
tolerance	0.00001
Regularization parameter (C)	100
Gamma( )	1
Epsilon	0.001
Shrinking	true
Cache size	200
verbose	false

6.3.6 Deep Neural Network (DNN)

DNN is a special type of neural network used in classification and regression problems. In DNN several layers are stacked together to perform the task. The basic difference between ANN a DNN is the number of hidden layers performing input and output operations. Additionally, DNN able to adapt complex mapping of input and output and it is also capable of handling multiple inputs and outputs simultaneously. The accuracy of the model is not only dependent on the type of dataset, as it provides good accuracy for missing values data unlike ARIMA and naive model [24]. Additionally, the temporal dependency of datasets like trends and seasonality is also one of the major advantages of DNN model [25] – [26]. The details of parameters used for training the DNN model is given in table 6.7.

Table 6.7: Details for parameters used for the DNN model

Parameters of DNN models	
Model	Sequential
Activation Function	Rectified Linear Unit(ReLu)
Dense Layer	12 for input 8 for output
Regularization parameter (C)	100
Gamma( )	1
Epsilon	0.001
Shrinking	true
Cache size	200
verbose	2

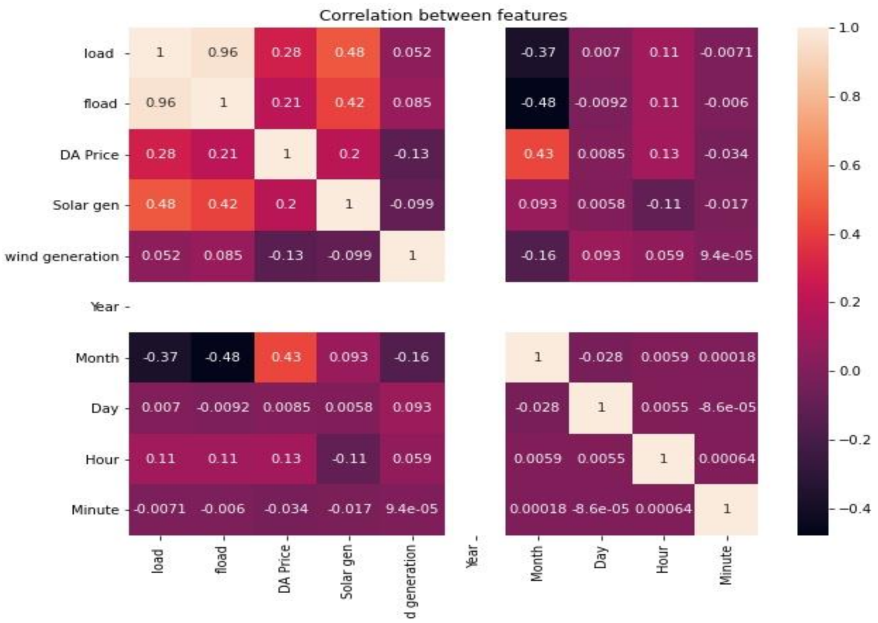


Fig 6.3: Correlation plot for the dataset used

In Fig.6.3 Correlation plot for dataset used is shown. The correlation plot felicitates the information related to dependency of the input variable on the target. From Fig. 6.3. it can be clearly deducing that electricity price is highly correlated to load and least correlated to day of the month. Additionally, electricity price is related to wind generation as well, however the value of correlation coefficient is not significant but for wind energy integrated market electricity price depends upon wind energy. So, this is imperative to investigate the impact of wind energy penetration on electricity price.

6.4 Results and discussion

The models namely DT, RF, LR and LASSO used for forecasting the electricity price implemented were trained and tested on a machine having 8GB of 16MHz DDR3 RAM and a 1.6 GHz Intel Core i5 processor, running a jupyter-notebook development environment. The metric used for assessment of the models' performance is the Root-Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) represented in Eq. (5), (6) and (7). n is representing the number of samples, $y_{A,j}$ and $y_{P,j}$ are actual and forecasted price for j[th] instance respectively in Eq. (5), (6) and (7). In Table 6.8. comparison of different forecasting metrics has been presented.

$$MAE = \frac{1}{n} \sum_{j=1}^{n} \left| Y_{A,j} - Y_{P,j} \right| \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^{n} \left(Y_{A,j} - Y_{P,j} \right)^2} \quad (6)$$

$$MAPE = \frac{100}{n} \sum_{j=1}^{n} \left| \frac{Y_{A,j} - Y_{P,j}}{Y_{A,j}} \right| \quad (7)$$

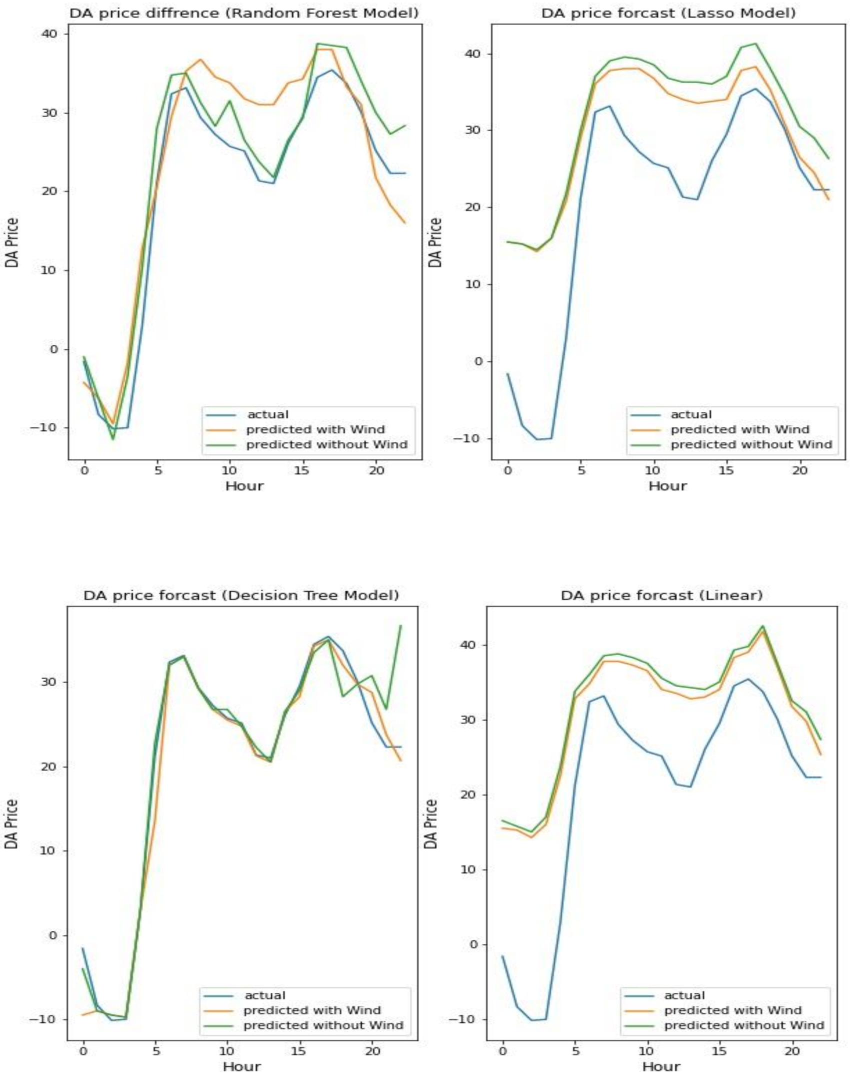


Fig.6.4: Forecasted and actual price with and without consideration of wind energy using DT, RF, LR and LASSO Model

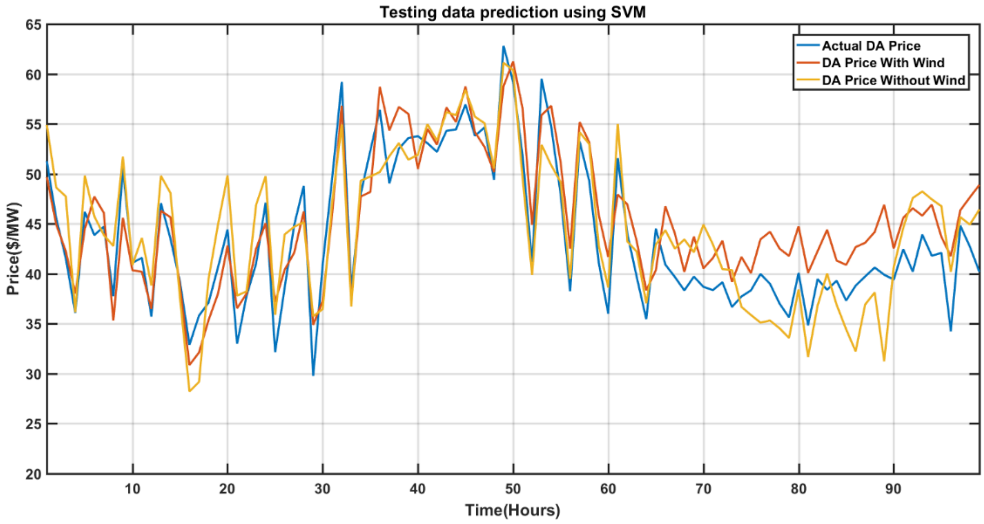


Fig. 6.5: Forecasted and actual price with and without consideration of wind energy using SVM Model

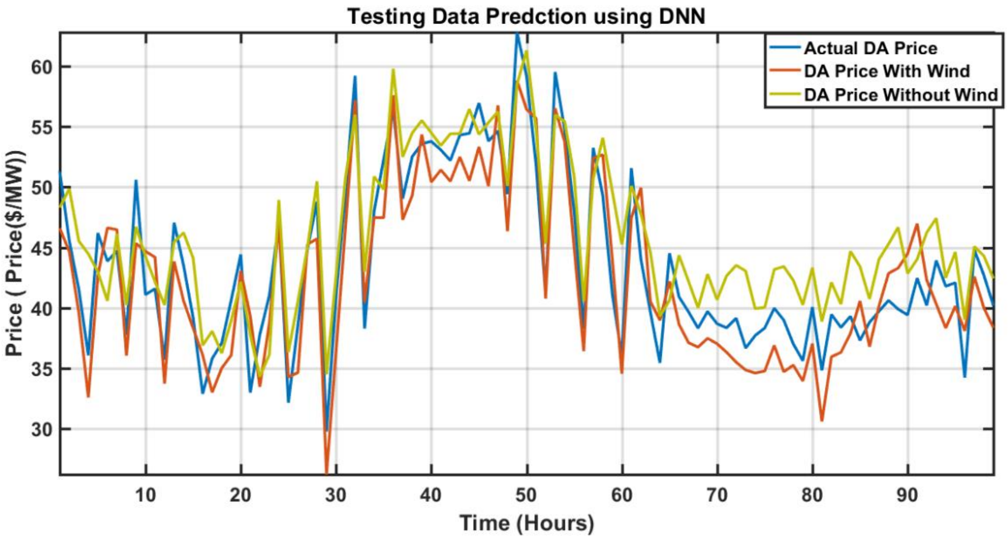


Fig 6.6: Forecasted and actual price with and without consideration of wind energy using DNN Model

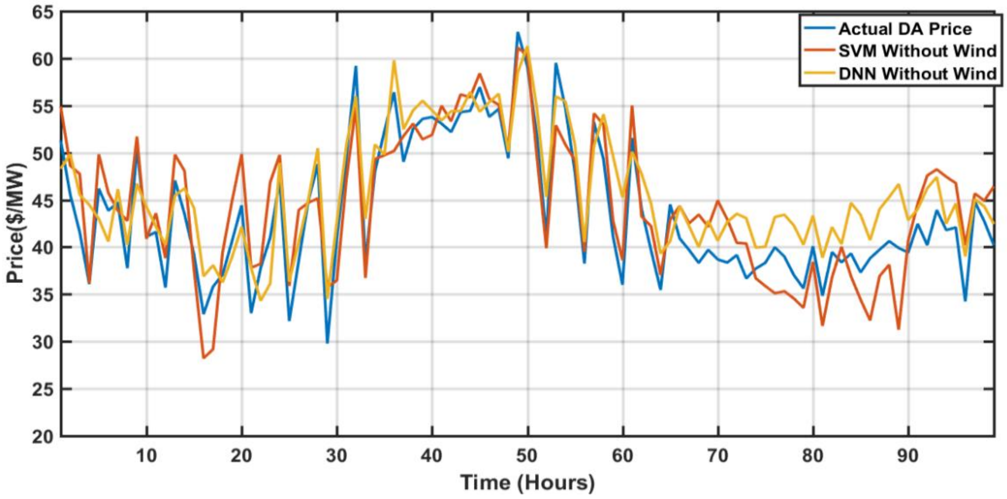


Fig. 6.7: Comparison of DA price forecasting for SVM and DNN Model using without wind generation

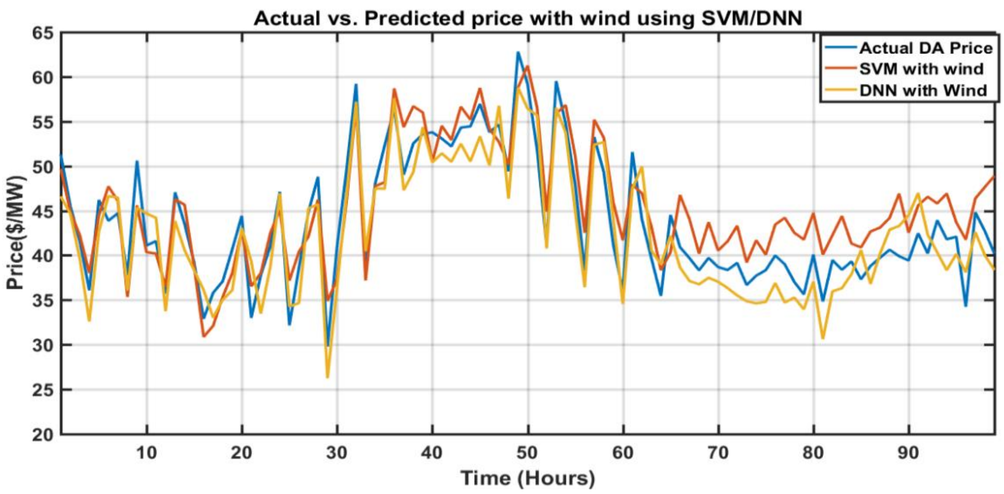
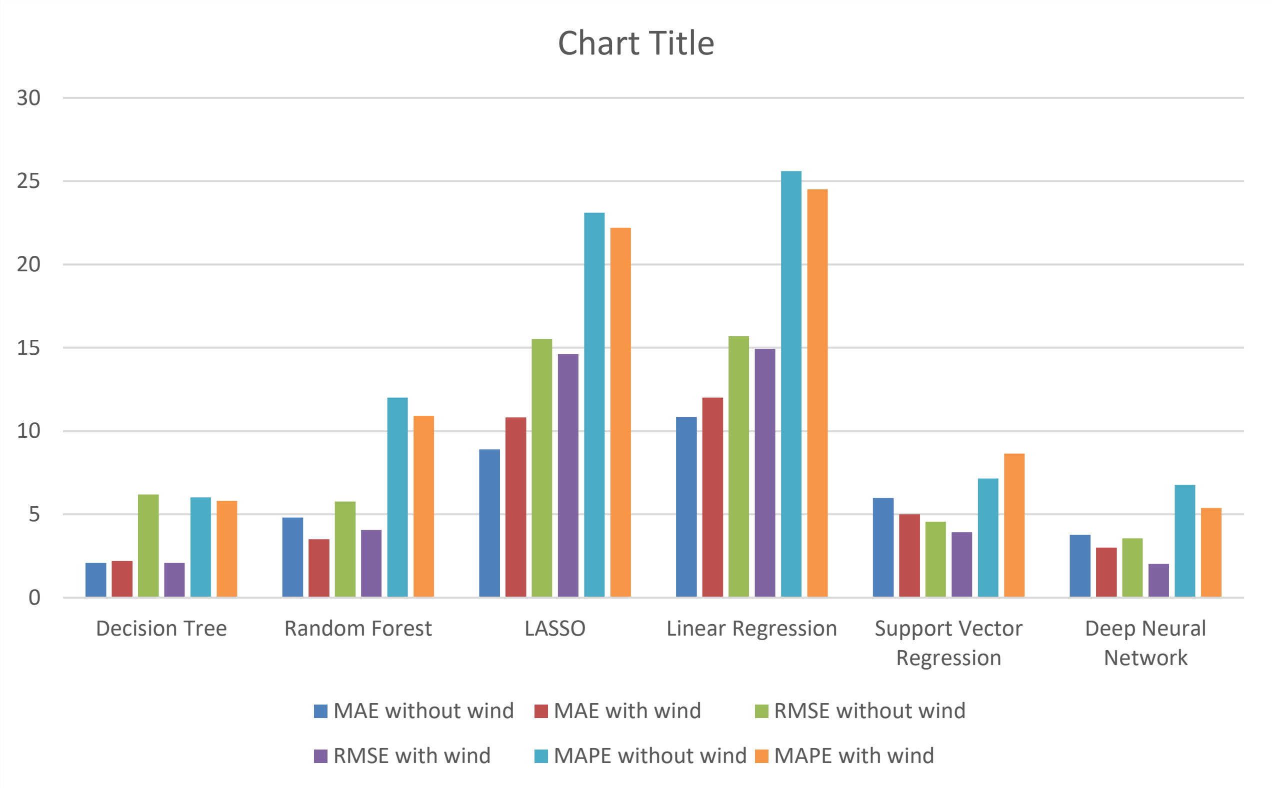


Fig. 6.8: Comparison of DA price forecasting for SVM and DNN Model using with wind generation

In fig.4. the results of forecasted price for RF, LASSO, DT and LR model are presented. The results in each graph represented with three lines of different colour (green, blue and pink). Blue line is for actual price, green line is forecasted price without wind energy consideration and pink line is representing the forecasted price taking wind energy into consideration. From the results it is evident that the forecasted DA price for DT model is closely following the actual price curve as compared to LR, RF and LASSO models. It can be deduced from the above graph that DT model outperform all other models and the impact of wind energy on electricity price is evaluated using MAE, RMSE and MAPE. The MAPE value for DT model with wind generation is minimum (= 5.802) and without wind energy generation is also minimum (= 6.018). The values of evaluation metric for DT model is marginally good over other regression models for Austria Electricity market dataset. Only evaluation of wind impact has been investigated from the dataset of the Austria electricity market. In Table 6.8 comparison of evaluation metric for different regression models used for investigation of impact of wind energy on electricity price has been shown.

Table 6.8: Evaluation of different models in terms of MAE, RMSE and MAPE

Models	MAE without wind	MAE with wind	RMSE without wind	RMSE with wind	MAPE without wind	MAPE with wind
Decision Tree	2.084	2.204	6.195	2.084	6.018	5.802
Random Forest	4.816	3.505	5.760	4.061	12.012	10.912
LASSO	8.890	10.820	15.518	14.622	23.102	22.204
Linear Regression	10.828	12.015	15.697	14.937	25.602	24.502
Support Vector Regression	5.973	5.009	4.556	3.918	7.150	8.640
Deep Neural Network	3.773	3.008	3.558	2.028	6.773	5.384



6.5 Summary

In this chapter the potential impact of wind energy on electricity price is investigated. the models used in this study for evaluation of impact on price are DT, LASSO, RF, LR, SVR and DNN. DT show superiority over RF, LR, SVR, DNN and LASSO due to its capability of complex mapping of input and output and capturing of variability and non-linearity in effective manner. The main findings of this study are reduction in electricity price due to wind energy penetration, it felicitates flexibility to consumer for the usage of energy at competitive price even in peak periods. The secondly the variability in the price due wind energy intermittency. This will increase the uncertainty in price signal for coal-based power producers. Advanced forecasting is suitable for the mass wind energy penetration into grid for reliable and effective power supply to the grid will be necessary. The accurate forecasting of price in renewable integrated market is key concern due variability in the generation. Hybrid techniques may improve the forecasting accuracy and this is helpful for the operator to plan the resources effectively and harness the capacity of RE to its maximum capacity.

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Chapter 7

DESIGN OF BIDDING STRATEGY FOR SOLAR PV PRODUCER

7.1 Introduction

The elevating demand of electricity across the globe can be repaired by injecting more RE sources into the grid. The major challenges market needs to cope up with are variability, seasonality and power quality issues, apart from the technical challenges pose by nature of the solar. The electricity price in such type of system is varied according to the volumes injected into the gird. The deigning of optimal bidding strategy for solar power producers is important due to stochastic nature of solar energy. In such type grid interactive scenario, the power producers are remunerated according to the committed load to the grid. The optimal bidding strategy is important for the renewable energy market due to risk of availability of the dispatchable power to the grid.

The stochastic optimization proposed for optimal bidding of wind power producers to maximize their profit considering market and wind speed uncertainties. Point estimate method explored to deal with uncertainties and correlation between wind power and electricity price [1]. Bi-level stochastic optimization is extensively used to design the optimal bidding strategy for fuel-based power [2] and wind power producers [3] – [4]. Power to gas (P2G) technology is used to store the electrical energy for long time and it can be used in higher demand in RE integrated grid, to enhance the reliability [5]. Cooperative game approach proposed for design of coordinated bidding strategy for wind power and P2G system, wind power producer and P2G system can maximize their profit [6]

The bidding strategy for virtual power plant (VPP) with storage for wind and PV system is presented using real time data for day ahead energy market [7]. Energy storage system (ESS) is preferred for energy management in grid, the gradient decent method formulated to obtain the integrated optimal bid for wind farms and ESS [8]. Improved Artificial bee colony optimization implemented for electric vehicle integrated VPP to optimal design of bidding strategy for profit maximization [9]. Handling the uncertainties of wind energy and maximization of profit for producers is the challenging task, by purchasing reserve and optimal bidding power producer can maximize the profit [10]. Mixed integer linear programming formulated for solving the bidding problem for electric vehicle integrated with variable energy resources, the simulation has been done and tested on IEEE bus for practical feasibility [11].

The HPSO – GSA algorithm is employed to design optimal bidding strategy for solar power producers. In HPSO-GSA algorithm combine the features of PSO and GSA for better result. Features of the agents that describe the goodness of result are designed by GSA. GSA describes the mass, force and acceleration of the agents. With these features, the algorithm is able to achieve improved solutions, however, the velocities and the position of each agent, updated in each iteration, are tracked by the process of PSO. With this ability, the algorithm determines for the global optimal solution.

HPSO – GSA finds wide application in the field of engineering. It gives better results in optimization problem in electrical and electronics engineering. The literature survey of HPSO –GSA is rich and some of the applications discussed in this section to motivate the researchers. HPSO – GSA have not been implemented for designing of bidding strategy for conventional power and renewable power producers. However, HPSO – GSA have implemented in the field of economic emission load dispatch problem [12] for optimum design of RC frame [13], for non-convex economic load dispatch [14], in design of infinite impulse response filter (IIR) filter [15]. HPSO – GSA applied for designing the parameters of controller for power system stability analysis [16].

The key concern in the renewable energy generation is the variability and intermittent power. In spite of this, due to the environmental aspects and increasing in power demand of energy renewable energy penetration is the only possible solution. Among available renewable energy resources, solar PV is the preferable option for grid integration across the globe due to its better predictability over other resources. The capacity addition and flexible government policies for generation and its trading motivate the planner to invest more in solar energy and generate revenues. There are few optimal bidding strategies available for solar and wind power producers. Moreover, the variability the variability of solar energy is not considered in the designing of bidding strategy for solar power producers. The optimization-based AI techniques are not fully explored for designing bidding strategy for power producers, since there is scope for the researchers in this field to investigate. In the Indian electricity market context, there are very few solar power producers and the market is not fully competitive. So, in such a scenario bidding of solar power in electricity market is difficult task for power system planner.

7.2 Problem Formulation

The designing of bidding strategies for solar power producer is a challenging task due to the uncertainties associated with solar generation and with the rise in electricity demand time demand. The power producers must bid optimally to maximize the profit. The power producers must quote bid in such a way so that profit per bid block should be maximised with optimized operation cost. If the power producers fail to address these constraints, it may lead to incur them loss in the market due to penalties posed by authority and price imbalances. Considering variability and uncertainties and price imbalance, objective function is designed to maximize the profit [17]. Imbalance in price is an important aspect in RE integrated market. Imbalance occurs in a system when energy demand is higher than the energy supplied by the producers or energy offered by producers is higher than the demand, the first case is treated as energy deficit and second case is energy surplus case. In both the cases imbalance in electricity price will happen in the market. The negative and positive imbalance price represented mathematically in Eq. (1) to Eq. (4)

$$\lambda_t^- = \lambda_t \qquad (1)$$

$$\lambda_t^+ = \min(\lambda_t, \lambda_t^{SUR}) \qquad (2)$$

For Negative imbalance price

$$\lambda_t^+ = \lambda_t \qquad (3)$$

$$\lambda_t^- = \max(\lambda_t, \lambda_t^{DEF}) \qquad (4)$$

In Eq. (1) to Eq. (4) λ_t is the DA market clearing price for period t. λ_t^+ and λ_t^- are the positive and negative imbalance price. λ_t^{SUR} and λ_t^{DEF} are the price for excess and deficit of energy resulting of balancing in market for time t.

Profit calculation of producers, p(t) for offered bid for certain amount of energy for specific hour t is given in Eq. (5) I_{mt} is the profit generated from imbalance in the market and c is the marginal cost of the system.

$$p(t) = \lambda_t P_t + I_{mt} - cP_t \qquad (5)$$

$$\sum_{w=1}^{\Omega}\sum_{t=1}^{T}\Pi_w\left(\lambda_{tw}P_t^{PV} + \lambda_{tw}r_{tw}^{+}\Delta_{tw}^{PV+} - \lambda_{tw}r_{tw}^{-}\Delta_{tw}^{PV-} - C^{PV}P_{tw}^{PV}\right) \quad (6)$$

Subject to:

$$0 \le P_t^{pv} \le P^{pv\max}, \forall t$$

$$\Delta_{tw}^{pv} = P_{tw}^{pv} - P_t^{pv}, \forall t, \forall \omega$$

$$\Delta_{tw}^{pv} = P_{tw}^{pv+} - P_{tw}^{pv-}, \forall t, \forall \omega$$

$$0 \le \Delta_{tw}^{pv+} \le \Delta_{tw}^{pv}, \forall t, \forall \omega$$

$$0 \le \Delta_{tw}^{pv-} \le P^{pv\max}, \forall t, \forall \omega$$

In Eq. (1) solar power bidding is represented as stochastic process, here Ω and ω represents the set and index of scenario for different hour. λ_{tw} is the day ahead market clearing price for w scenario. P_t^{pv} is the energy traded of the PV system in time t. R_{tw}^+ and R_{tw}^- is the ration between positive and negative imbalance price and day ahead market price for period t respectively. Δ_{tw}^{pv+} and Δ_{tw}^{pv-} is positive and negative energy deviation of PV system in period t and scenario w respectively. C^{pv} is PV marginal cost. P_{tw}^{pv} PV generation in time t and scenario ω. The above objective function is used to maximize the profit of power producer for the energy dispatched over a specific time period.

7.3 Case Study

In India the solar power bidding is monitored by two power companies namely, Vidyut Vyapar Nigam Limited (NVVNL) and Solar Energy Corporation of India (SECI). The data for designing the optimal bidding strategies for solar power producer is considered from Jawahar lal Nehru National Solar Mission (JNNSM), phase 2 batch2 and phase 3 batch3 respectively for calculation of profit [18]. In the data used, the minimum size of the bid is 50 MW and Viability Gap Funding (VGF) based tariff has been used. From the past data of winning bids, rival power producers data has been estimated and it is assumed constant for the proposed work [19].

JNNSM Phase 2 Batch 2

The capacity of solar power producer (S_1) for which optimal bidding strategy has to be design is maximum 500 MW. Total ten blocks have considered in the difference of 50 MW intervals. The range of the bid is 5.19(rs)/unit – 4.80 (rs)/unit, the range is defined for domestic content requirement.

JNNSM Phase 2 Batch 3

The capacity of solar power producer (S_2) for which optimal bidding strategy has to be design is maximum 350 MW. Total 5 blocks have considered in the difference of 50 MW intervals. The range of the bid is 13 million/MW – 6.5 million/MW, the range is defined for domestic content requirement.

7.4 Implemented methods

7.4.1 Real-Code Genetic Algorithm

GA is meta-heuristic optimization approach based on biological evolution process. RCGA is a modified form of GA. RCGA is effective in solving the problems based on approximations. In

RCGA the possible solution is represented in exact real values for avoiding its internal encoding and decoding process. With the help of real values, significant improvement in the results can be achieved in terms of efficiency, speed of operation, and correctness as compared to real code Genetic algorithm [20],[25].

The three major process involved in the implementation of RCGA in search of the optimal biding strategy to maximize the profit of solar power producers are:

Initialization: Random generation of initial population of chromosome and with the help of selection of operator optimum individual chromosome is selected.

Crossover: the purpose of crossover is to search for better fitness value. This is done by flipping the genes of one parent to other for maintaining the diversity.

Mutation: this process helps to prevent from local minima through varying one or additional genes from their initial values. The employment steps for RCGA are adopted from [25] for designing of optimal biding strategy.

7.4.2 Particle Swarm Optimization

PSO is initially presented by Kennedy and Eberhart in 1949 [21]. PSO is a self-educating optimization method widely used to solve the non-linear optimization problem. In PSO the particles are called potential solution which flies throughout the space available for finding the best fitness of the particle. Each particle has its position and speed, on that basis their characterized for best solution. The key finding of the particle is the required solution and velocity of the particle decides its speed. The fitness value is determining criteria for each particle for every iteration. The position and speed of the particle is updated for each particle for every iteration [22].

$$v_r^{k+1} = w^k v_r^k + a_1 rand_1 * (p_{bestr}^k - X_r^k) + a_2 rand_2 * (G_{best}^k - X_r^k) \quad (7)$$

$$X_r^{k+1} = X_r^k + v_r^{k+1} \quad (8)$$

New Velocity of each particle r is calculated using Eq. (7), v_r^k is the previous velocity, $p_{best\ r}$ is the location at which particle's achieved their best fitness value and G_{best} is best particle amongst all the particles present in the neighbors at which best fitness has been achieved. a_1 and a_2 are known as acceleration constant that alter the values of particle velocity towards p_{best} and G_{best}. $Rand_1$ and $rand_2$ represents the uniformly distributed numbers in between 0 and 1. The location of the particle is updated using Eq. (8) in solution hyperspace. The execution steps of PSO are taken from [21] for the designing of optimal biding strategy.

7.4.3 Gravitational Search Algorithm

GSA is the heuristic optimization method used for solving non-linear functions. GSA is based on the Newton's law of gravity and law of motion [23]. In GSA algorithm, the particle (agents) is possible solution and their effectiveness is decided through their respective masses. All these objects attract toward each other and gravitational force is experienced by agents, due to this force agents attracted towards heavier masses which corresponds to optimally good solution.

The mathematical formulation of GSA involves considering a system having N agents and the position of ith agent is represented by α_i

$\alpha_i = x_i^1 \ldots\ldots\ldots x_i^d, \ldots\ldots\ldots x_i^n$, (i = 1, 2,.....k), where x_i^d is the location of the ith agent in the dth dimension and n is the dimension for objective function. For calculating effectiveness of method mass of each agent is evaluated afterward evaluation of fitness function of the recent population

$$m_i^t = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{9}$$

$$M_i^t = \frac{m_i(t)}{\sum_{j=1}^{k} m_j^t} \tag{10}$$

M_i^t is the normalization of calculated masses, $fit_i(t)$ denotes the fitness value of the i th agent at *t* th iteration. The value of $worst(t)$ and $best(t)$ for the algorithm is defined using Eq. (5) and Eq. (6) for minimization problem

$$best(t) = \min_{j \in \{1......N\}} fit_j(t) \qquad (11)$$

$$worst(t) = \max_{j \in \{1......N\}} fit_j(t) \qquad (12)$$

For maximization problem above equation (equation (11) and (12)) changes to equation (13) and (14) given as

$$best(t) = \max_{j \in \{1......N\}} fit_j(t) \qquad (13)$$

$$worst(t) = \min_{j \in \{1......N\}} fit_j(t) \qquad (14)$$

In Eq. (15) is for computation of gravitational force for agent j and ith iteration at time t for dimension d. In Eq. (9) R_{ij}^t is the distance between agents i and j. $\in$ is the constant value and the first k agents having best fitness values is represented by kbest. It has biggest mass among particles. The initial value of K starts with k_0 and its decreases with increase in time. $rand_j$ is unvaryingly distributed number lies between 0 and 1. The value of gravitational constant G^t is given in Eq. (16).

$$F_i^d(t) = \sum_{j \in kbestj \neq i} rand_j G^t \frac{M_j^t M_i^t}{R_{ij}^t + \in} \left(x_j^d(t) - x_i^d(t) \right) \quad (15)$$

$$G^t = G_0 \times (-g \times \frac{t}{t_{\max}}) \qquad (16)$$

In Eq. (10) G_0 is the initial value of gravitational constant and t is the recent iteration and $t_{\max}$ is for maximum iteration. g is the plunging coefficient with time. The acceleration of the agent $a_i^d(t)$ is evaluated using Eq. (17). The position of the agent is evaluated using velocity which in turn calculated using Eq. (17).

$$a_i^d(t) = \frac{F_i^d(t)}{M_i^t} \qquad (17)$$

The velocity and position of the agent *i* is rationalized by using Eq. (18) and (19) for every iteration and when maximum iteration is reached algorithm stops. In Eq. (18) $rand_i$ is the uniformly distributed numbers in the interval of 0 and 1.

$$v_i^d(t+1) = (rand_i \times v_i^d(t)) \times a_i^d(t) \quad (18)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \qquad (19)$$

The position of the agent finally updated at the last iteration is the optimal solution for the biding strategy.

7.4.4 Hybrid Particle Swarm Optimization and Gravitational Search Algorithm

HPSO-GSA is the stochastic optimization technique having the attributes of both PSO and GSA. It incorporates societal accomplishment of PSO and motion appliance from GSA to find optimal solution. For finding the best solution of a problem it searches and updates the particle position based on co evolutionary scheme using PSO velocity and GSA acceleration [24].

The HPSO-GSA algorithm start with initialization of all the agents randomly, considering each agent as potential solution after that it calculates the gravitational constant, masses effective force and acceleration for each agent using Eq. (20) – (21). The best solution for every iteration is updated by altering the position (X_i) and velocities (V_i) of the agent i using Eq. (20) and (21)

$$V_i(t+1) = w \times v_i(t) + c_1 \times rand \times a_i(t) + c_2 rand \times [gbest(t) - X_i(t)] \qquad (20)$$

$$X_i(t+1) = X_i(t) + V_i(t) \qquad (21)$$

In Eq. (20), $V_i(t+1)$ is the velocity of the ith agent for the next iteration, t+1. *W* is the weighing function and c_1 and c_2 are the social cognitive behavior parameters, *r* is the random number ranging between 0 and 1. a_i is the acceleration of the agent for ith iteration and $gbest(t)$ is the global optimal solution for the current iteration. the implementation steps of the algorithm for designing of optimal bidding strategies explain in section 4.4.1 and flow chart for the same is shown in the Fig 1.

7.5 Implementation steps of HPSO-GSA Algorithm for bidding problem

The HPSO-GSA steps are described as follows for the design of optimal bidding strategy for maximizing the profit for solar power generators. The constant values and initial variables used are chosen for best result after performing number of simulations with accidental values.

Step1: Generate the initial population of agents (solutions), $X(i) = x(i)^1,\ldots,x(i)^d,\ldots,x(i)^n$, $(i=1,2,\ldots,N_h)$, with N_h is the population size. Initialize the maximum iteration cycle with N. Further, initialize the search space limit, G_0, g, c_1,c_2, v_{min}, v_{max} and w.

{Step2:} Compute the fitness values for the initially generated population, N_h using Eq. (6). Calculate the variables, G and gb using all the fitness values for the current iteration.

{Step3:} Calculate the masses, M_i, forces, F_i and acceleration, a_i for the population using Eq. (10), (15) and (17), respectively.

{Step4:} Update the position of all the agents using Eq. (21). The velocity of each agent is updated for the next iteration according to the Eq. (20), with which the global optimal solution is searched.

{Step5:} With every new solution obtained in each iteration, the condition of maximum iteration is checked. Go to Step 2, if the stopping criteria is not met.

{Step6:} The algorithm cycle is stopped if maximum number of iterations are elapsed. The global best solution, gb gives the optimal solution for the maximised profit for solar power producers.

7.6 Methodology

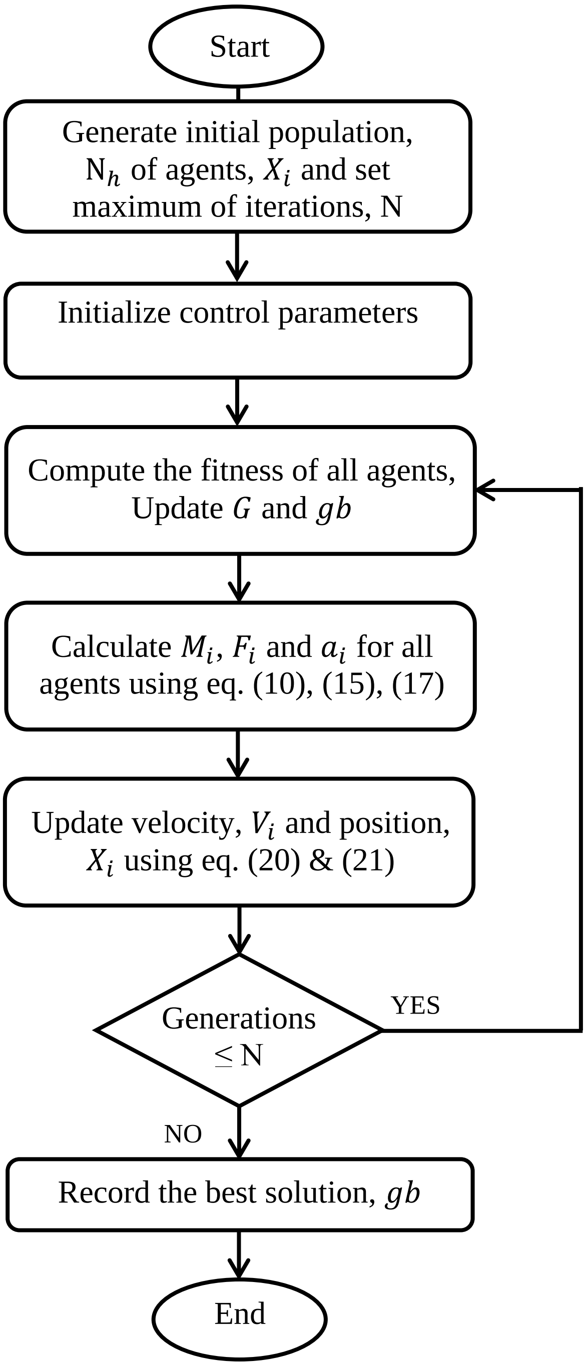

Fig.7.1: Flow chart for HPSO-GSA for designing the optimal bidding strategy for solar PV producers

Table 7.1: Control Parameters of RCGA, PSO, GSA and HPSO-GSA algorithm for Bidding problem

Parameters	**RCGA**	**PSO**	**GSA**	**HPSO-GSA**
Population size	50	50	50	50
Maximum iterations	1200	1200	1200	1200
Tolerance	10^{-8}	10^{-8}	10^{-8}	10^{-8}
Elite count	2	--	--	--
Crossover fraction	0.80	--	--	--
Crossover function	Heuristic	--	--	--
Selection function	Tournament	--	--	--
Mutation function	Adaptive Feasible	--	--	--
Social parameter	--	2.0	--	2.0
Cognitive parameter	--	2.0	--	2.0
$v_i^{\min}$	--	0.01	--	0.01
$v_i^{\max}$	--	1.0	--	1.0
$w_{\min}$	--	0.2	--	0.2
$w_{\max}$	--	0.9	--	0.9
G	--	--	20	20
G_0	--	--	100	100

7.7 Result and Discussion

For investigation of effectiveness of proposed algorithm for designing of optimal bidding strategy for solar PV producers, the simulations are executed in Window XP professional, OS environment using Intel core i5, 3.20 GHZ, 4 G RAM memory and codes are developed in MATLAB. The algorithms have been tested on numerical data of JNNSM phase 2. In this section, designing of optimal bidding strategy for solar PV producers is described with a better profit and reduced error using the new fitness function. Simulations have been executed for selection of the control parameters through the implemented algorithms which are shown in Table 7.1. Additionally, the design of bidding strategy is performed for two different cases, with different number of limits. The optimum set of control parameters of RCGA, PSO, GSA, and HPSO-GSA for designing of optimal bidding are shown in Table 7.1. Best outcomes are shared for the proposed work after extensive trails with range of random parameter value. The parameter tuning is a distinctive job for bidding problem due intermittent nature of solar for which no specified methods available in the state of the art. Moreover, the parameter is not same for all problems. Therefore, the optimal parameter values are calculated after performing numerous simulations and the stated work is achieved using the acquired optimal results. For designing of optimal bidding for profit calculation, same dataset is considered for identical set of parameters for scrutinization of implemented optimization algorithms. Several aspects of bidding are considered during investigation of this work, such as past data of bid and rival bid data. The investigation is also performed for error convergence, statistical value of error, and computation time obtained for the four metaheuristic algorithms. A count of 100 independent trial runs are accomplished for all four optimization algorithms and the optimized values of *profit for HPSO-GS (2500 rs/unit maximum)* and (*1090 rs/unit minimum) values reported.*

The results of the HPSO-GSA algorithm were compared with RCGA, PSO, and GSA and it was found that the HPSO-GSA gives highest profit with lower computation time.

Table 7.2: Case I for maximum bid capacity 500 MW

Capacity	Profit(rs/unit)	Profit(rs/unit)	Profit(rs/unit)	Profit(rs/unit)
Bid size (MW)	RCGA	PSO	GSA	HPSO
50	230.56	234.07	232.30	246.92
100	402.55	408.36	410.27	460.55
150	600.29	612.83	650.05	690.67
200	860.30	880.22	860.60	920.63
250	1001.61	1050.75	1150.38	1190.73
300	1200.11	1230.28	1302.20	1380.33
350	1400.10	1457.00	1550.76	1660.30
400	1605.70	1690.00	1600.18	1840.00
450	1800.93	1800	1997.96	2070.00
500	2210.90	2400	2460.10	2500

Table 7.3: Case II for maximum bid capacity of 250 MW

Capacity	Profit(rs/unit)	Profit(rs/unit)	Profit(rs/unit)	Profit(rs/unit)
Bid size (MW)	RCGA	PSO	GSA	HPSO
50	233.16	228.87	232.10	240.12
100	396.00	390.36	402.27	430.55
150	580.29	582.10	600.05	600.67
200	845.30	880.22	877.60	900.63
250	991.91	997.95	1050.38	1090.93

7.7.1 Profit curve 1 for case I

Fig.2. is combined profit curve for RCGA, PSO, GSA and HPSO –GSA algorithm for real time data solar power producers. It shows that the profit calculated by HPSO –GSA is higher as compared to calculate by other algorithms. It shows that by combining HPSO and GSA algorithm works well for constrained optimization of bidding strategy for PV power producers. For higher rating of power block, the cost per of power block is higher and consequently the profit also higher and maximum for HPSO-GSA algorithm indicated with red color in Fig.7.2.

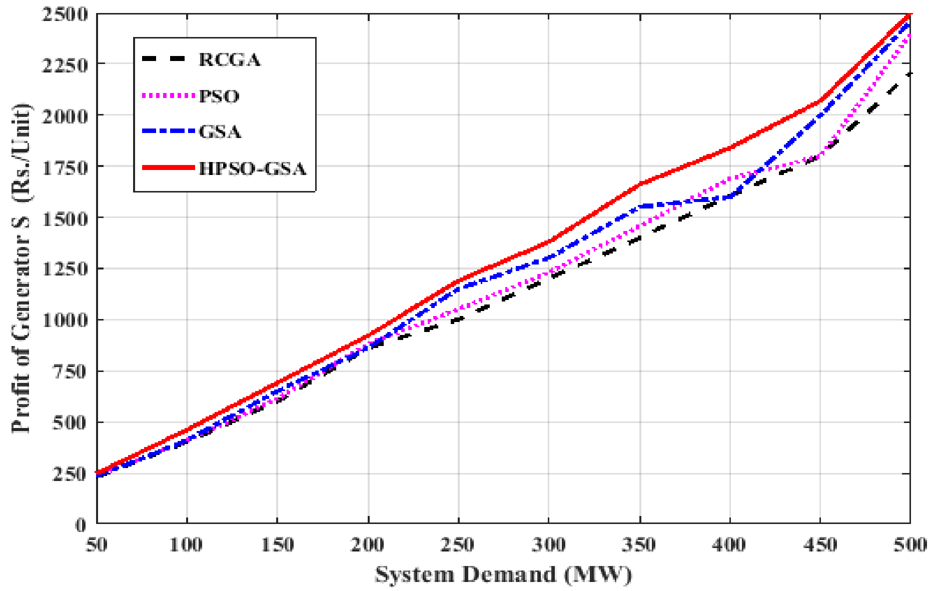

Fig.7.2: Profit Curve for case I of Generator S

7.7.2 Profit curve 2 for case II

Fig. 7.3. is combined profit curve for RCGA, PSO, GSA and HPSO –GSA algorithm for real time data solar power producers (Table 7.2). It validates the effectiveness of HPSO-GSA for example 2 which contains the real time data of solar power used for bidding in electricity market. the profit values for corresponding power block is shown in fig with red colour for HPSO-GSA, blue for GSA, pink for PSO and black for RCGA algorithm.

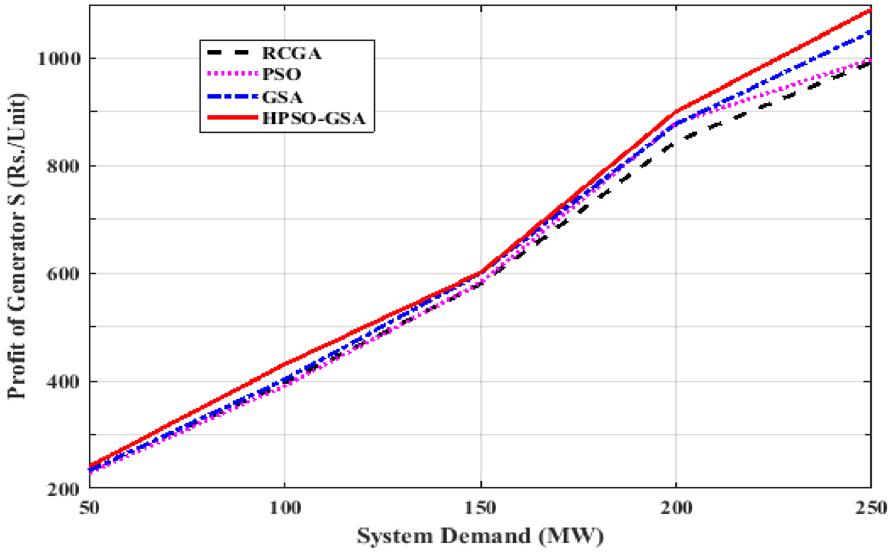

Fig.7.3: Profit Curve for case II of Generator S

7.7.3 Comparison graph

In fig.4. the difference obtained in profit for case I and case II are shown with bar graph. It can be observed that from the bar graph of comparative profit from employed algorithms, HPSO – GSA algorithm is giving us maximum profit for the four ranges of system demand (0MW - 50MW, 50MW – 100MW, 100MW – 150MW and 150MW – 200MW) except (200MW – 250MW) range. The profit obtained for the range (150MW – 200MW) by HPSO – GSA algorithm is maximum among all power volume and profit obtained for the range (200MW – 250MW) is equal for GSA and HPSO – GSA indicated by green and yellow color respectively in the bar graph.

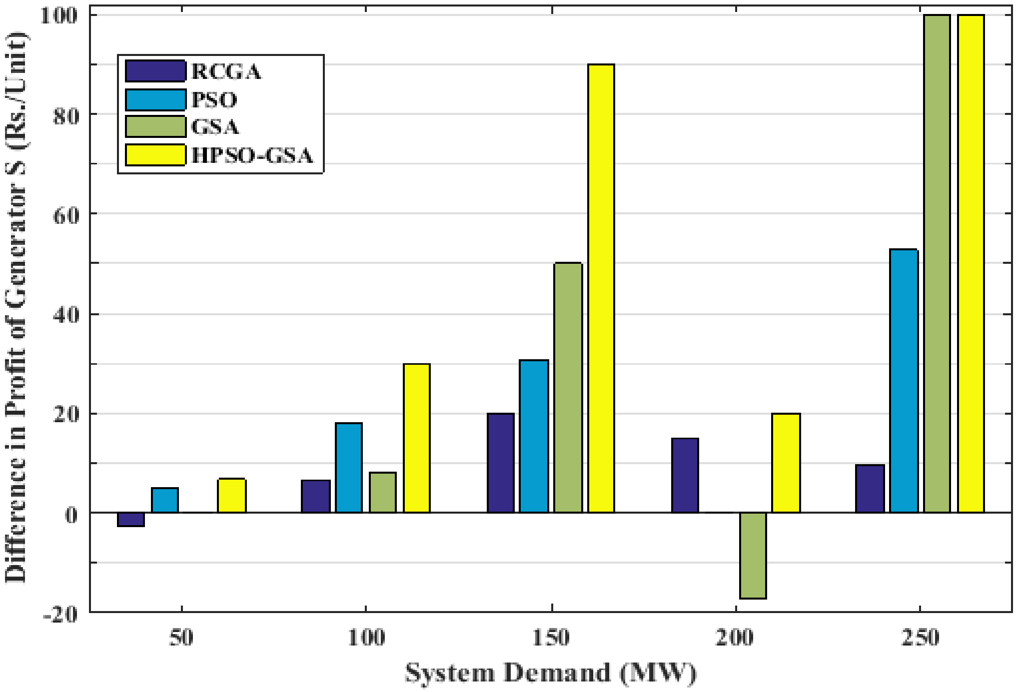

Fig. 7.4: Comparative bar graph for difference in profits for different algorithms

7.7.4 Improvement curve for case I

In Fig 7.5. improvement in profit for power producers employing different algorithms is presented with bar graph. The comparative percentage improvement in the profit for employed algorithms in designing of optimal bidding strategy is indicated with numerical value on the top of the bar in figure. Only the highest numerical percentage change for profit is highlighted in the figure for the data set of case I. In Fig. 7.4. and Fig. 7.5. blue colour bar graph is for showing the improvement in profit for PSO over RCGA, purple colour bar is for improvement in profit for GSA over RCGA, sky blue is for HPSO -GSA over RCGA, green colour bar is for GSA over PSO, pink colour bar is for HAPSO -GSA over PSO, yellow colour bar is for HPSO -GSA over GSA. The maximum percentage of profit is 18.88 reported for HPSO- GSA over RCGA algorithm at 250 MW demand. The minimum percentage of profit is 6.975 reported for HPSO – GSA over GSA algorithm.

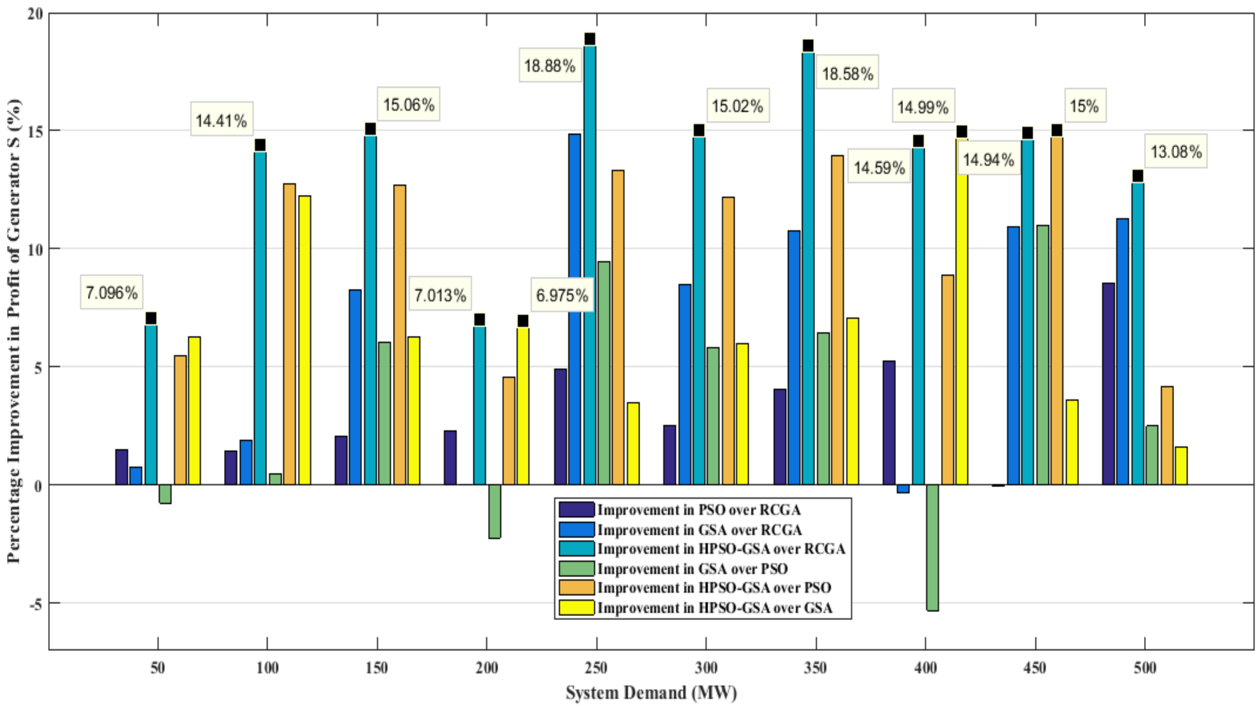

Fig. 7.5: Comparative improvement curve for RCGA, PSO, GSA and HPSO-GSA (Case I)

7.7.5 Improvement curve for case 2

In Fig. 7.6. Shows the percentage improvement in profit using employed algorithms for designing of optimal bidding for solar power producer of case II dataset. The maximum percentage improvement in the profit for solar power producer reported is 10.3 for HPSO – GSA over PSO for 100 MW power block and the minimum percentage improvement in profit is 3.512 for HPSO -GSA over RCGA at 150 MW. The HPSO -GSA algorithm shows maximum profit for optimal bidding design problem over GSA, PSO and RCGA algorithm.

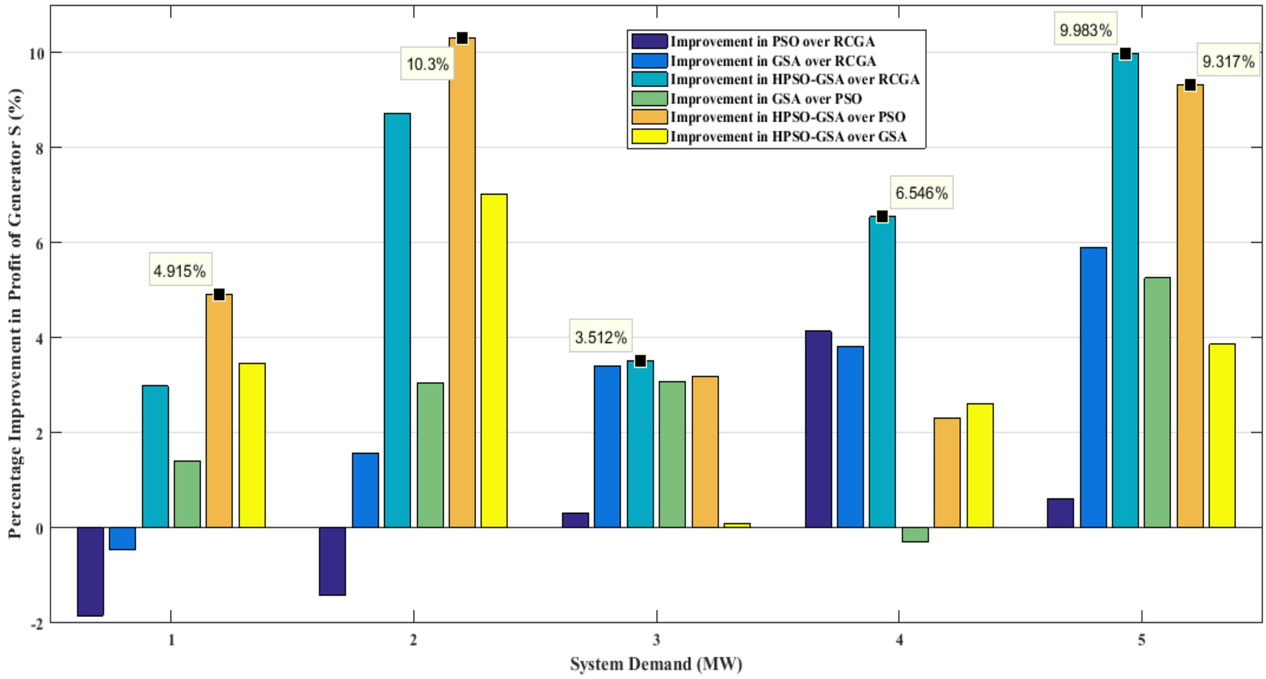

Fig.7.6: Comparative improvement curve for RCGA, PSO, GSA and HPSO-GSA (Case II)

As shown in Table 7.4. the comparison for computation time for employed algorithms to design the optimal bidding is presented. The HPSO – GSA algorithm found to be computationally efficient for both the dataset of solar PV bidding.

Table 7.4: Comparison of computation time

Parameters	Case I				Case II			
	RCGA	PSO	GSA	HPSO - GSA	RCGA	PSO	GSA	HPSO - GSA
Iterations	1200	1200	1200	1200	1200	1200	1200	1200
Minimum Time (sec)	6.386	4.983	4.793	4.778	4.274	3.372	3.311	3.294

7.8 Summary

Exploring the effectiveness of nature inspired optimization algorithms for the optimal bidding strategies in order to obtain maximized profit for power producers is the main objective of this chapter. In this chapter a novel bidding strategy for solar power PV producers considering the uncertainty and price imbalance constraints is proposed. Stochastic optimization-based problem HPSO-GSA have been implemented for the profit maximization of the PV producer for DA electricity market. The effectiveness of the method has been verified by comparison of the results of HPSO-GSA with RCGA, PSO and GSA. The HPSO – GSA outperforms in terms of profit per unit of bid size over RCGA, PSO and GSA, and at the same time HPSO – GSA is computationally efficient for the data set used in this study. The main feature of HPSO-GSA is that it performs parallel processing of both the algorithms. The HPSO-GSA captures the uncertainty in price and variability in solar energy output effectively so that producers can bid optimally to maximize their profit.

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Chapter 8

CONCLUSION

The renewable energy is one of the appropriate possible solution to mitigate the issue of global warming and high demand across the globe. The world is driving towards the maximum utilization of untapped potential of renewable energy for sustainable future. The key concern in usage of renewable energy especially solar and wind energy is intermittent nature. Intermittency associated with wind and solar power generation is main hurdle in achieving higher penetration into the grid. Apart from these, reform in market structure is necessary to expand the renewable energy trading. Electricity price forecasting is concurrent aspect of power system. Electricity price forecasting (EPF) helps in liberalizing electricity market in different ways by providing information for market players to bid suitably, improving demand side management. EPF is important task for power system planner in RE grid integrated market and designing of bidding strategy for solar power producers is also important to promote the competition among generators and maximize the profit.

The solar energy sector in India is expanding widely in terms of capacity addition and grid interconnection. A proper market model and operating mechanism needs to be developed to expand the market of solar power to meet the demand and fulfills the energy gap. Hence, solar power electricity market model is designed and operating mechanism is also suggested for Indian scenario. To cope up with the uncertainty use of advanced forecasting, Virtual power plant and advanced storage technologies are suggested. The practical feasibility and possible challenges are highlighted in chapter 2. Additionally, the various trading models for trading the solar power in open market to create healthy competition and improve the quality of power is proposed in chapter 3.

Price forecasting is an important aspect of power system planning. The electricity price is volatile in nature and it depends on many factors such as electricity load, fuel price, type of market and weather parameter. ANN is widely accepted tool by researchers to forecast the load and price. The feature selection-based price forecasting of Australia electricity market has done and it was found that price is highly co related with electricity load and the accuracy of ANN model is accurate for the dataset with MAPE value of 1.94 for April month. Further the study has been extended for renewable energy market. The impact of solar energy and wind energy penetration on electricity price is investigated using different machine learning models (LSTM, XGBOOST, LASSO, Decision tree, Random forest, linear regression, DNN and SVR). In chapter 4, LSTM model is developed and proposed for the investigation of impact of solar energy on electricity price. A good forecasting accuracy is demonstrated using this method and the uncertainty in the solar energy is evaluated using confidence interval values. The confidence interval value for LSTM model is 0.80 for 6.00 MAPE value is achieved. For investigating the impact of wind energy penetration on electricity price Decision tree model is proposed in chapter 5, and it is found very accurate for forecasting of price in wind energy interactive grid. The MAPE value for forecasted price with wind energy as input parameter is 5.802. though price forecasting with solar and wind energy as input projects reliability the prediction accuracy can be improved using hybrid ensemble learning methods and by considering more input parameters in the dataset.

Accurate price forecasting is important for designing the appropriate bidding strategy for power producers. As it provides the important information about the market and helps the bidder to bid optimally in the electricity market to maximize their profits. In view of large penetration of solar energy into the grid, and to promote the competition among solar power producers, Optimal bidding strategy is designed for Indian market scenario in chapter 7. The dataset of Jawahar lal Nehru solar mission is used for testing the algorithm. The HPSO – GSA algorithm is modeled for designing the bidding strategy for solar power producers. The uncertainty in the solar energy is also considered as one of the constraints in the objective function and profit calculation is performed for different cases of data set. HPSO – GSA algorithm outperformed in profit calculation and shows superior result for the dataset. The profit calculated by HSPO -GSA is compared with RCGA, PSO and GSA algorithm for calculating the effectiveness of the model in Chapter 7.

Appendix

Sample training and testing data used from Austria electricity market

load_actual_entsoe_transparency	load_forecast_entsoe_transparency	solar_generation_actual
8816.4	8474.6	26.195
8991.6	8513.7	15.034
9199.2	8566.09	3.54
9531.6	8729.51	2.537
9406.8	8753.69	1.606
9419.6	8752.37	0.675
9458	8714.91	0
9257.6	8541.23	0
9158.8	8447.96	0
9086.4	8436.49	0
6023.2	6085.86	0
5933.2	6034.43	0
5946.4	6028.5	0
5925.2	5981.03	0
5855.2	5981.89	0
5784	5960.83	0
5790.8	5940.92	0
5751.6	5906.61	0
5801.6	5890.68	0
5812.4	5875.98	0
5768	5869.9	0
5790.8	5882.84	0
5897.6	5985.5	0
5992.8	6017.53	0
7528	7246.43	1.927
7580.8	7377.46	2.728
7748.8	7486.18	3.875
8176	7987.82	23.045
8314	8078.26	36.142
8388.8	8170.43	49.582
8479.6	8215.68	62.819
8700	8356.35	86.413
8750.4	8378.37	110.611
8741.2	8402.14	135.108
8724.4	8425.38	160.341
8752	8357.09	187.995
8818	8396.92	216.287
8851.6	8422.69	244.156

Sample training and testing data used from US wind farms

load_actual_entsoe_transparency	load_forecast_entsoe_transparency	solar_generation_actual	price_day_ahead	wind generation
8816.4	8474.6	26.195	41.32	796.544
8991.6	8513.7	15.034	51.3	802.868
9199.2	8566.09	3.54	60.89	854.471
9531.6	8729.51	2.537	47.23	875.665
9406.8	8753.69	1.606	50.91	953.952
9419.6	8752.37	0.675	49.96	983.39
9458	8714.91	0	49	929.674
9257.6	8541.23	0	59.08	838.834
9158.8	8447.96	0	46.8	785.085
9086.4	8436.49	0	42.1	716.314
6023.2	6085.86	0	43.26	669.663
5933.2	6034.43	0	33.51	595.122
5946.4	6028.5	0	30.22	537.268
5925.2	5981.03	0	26.6	464.194
5855.2	5981.89	0	34.59	434.786
5784	5960.83	0	35.09	377.008
5790.8	5940.92	0	32.74	325.639
5751.6	5906.61	0	29	315.675
5801.6	5890.68	0	32.4	323.898
5812.4	5875.98	0	28.12	319.189
5768	5869.9	0	32.72	319.633
5790.8	5882.84	0	35.04	321.013
5897.6	5985.5	0	23.1	319.53
5992.8	6017.53	0	27.92	333.357
7528	7246.43	1.927	37.56	323.95
7580.8	7377.46	2.728	52.6	347.985
7748.8	7486.18	3.875	62.25	338.432
8176	7987.82	23.045	44.56	315.835
8314	8078.26	36.142	54.11	299.951
8388.8	8170.43	49.582	57.28	302.635
8479.6	8215.68	62.819	58.27	309.839
8700	8356.35	86.413	69.71	303.992
8750.4	8378.37	110.611	64.04	279.613
8741.2	8402.14	135.108	51.21	278.209
8724.4	8425.38	160.341	44.89	273.013
8752	8357.09	187.995	65	271.706

Sample training and testing data used from Austrian electricity market

Load in MW	Price in $/MW	solar power generation in MW	wind power generation in MW
5977	18	0	152
5727	17	0	110
5407	14	0	56
5314	13	0	39
5401	14	0	34
5406	16	0	32
5761	18	8	34
5954	23	13	32
6325	26	37	42
6645	27	71	50
6797	29	100	46
6727	29	116	50
6589	28	114	50
6552	28	87	57
6604	29	45	60
6903	32	15	52
7382	37	7	46
7438	38	7	44
7163	36	0	58
6831	32	0	110
6460	28	0	103
6552	27	0	50
6214	24	0	20
5975	26	0	14
5680	25	0	29
5531	22	0	50
5379	20	0	101
5462	16	0	148
5784	17	0	159
6091	19	0	146
6714	25	8	159
7182	27	14	207
7545	29	36	292
7732	29	61	408
7870	28	79	448
7691	26	87	532
7714	24	81	601
7557	24	60	605
7664	22	31	652

Data links

https://data.open-power-system-data.org/time_series/2019-05-15

https://aemo.com.au/en/energy-systems/electricity/national-electricity-market-nem/data-nem/aggregated-data

Answers to the questions and suggestions of the examiners

We would like to take this opportunity to thank both the Examiner for providing the valuable and informative comments to our work **"Designing of market model, effective price forecasting tool and bidding strategy for Indian electricity market."** Given below is our response to each query/comment of the respected examiner.

Comments of Reviewer 1 and Response

Comment 1: There is huge non uniformity in using the upper and lower cases words in abbreviations, in running text, sections, subsections, subsections of the chapters. Be uniform throughout the thesis.

Response 1: The manuscript has been thoroughly revised as per the suggestion.

Comment 2: "table x.x" should be written as Table X.X. similarly do for figures as well.

Response 2: All the table nos. in the revised manuscript are corrected as Table x.x as suggested.

Comment 3: there are many grammatical mistakes, which need to be corrected.

Response 3: The grammatical mistakes have been corrected in the revised manuscript as per suggestion.

Comment 4: there are several variables in the running text are not in the math fronts. It should be corrected throughout the thesis

Response 4: All the mathematical variables are now corrected in math fonts in the revised manuscript.

Comment 5: references are not formatted

Response 5: In the revised manuscript, the references have been formatted according to the IEEE format.

Comment 6: the data in chapter 2 are old. It may be updated.

Response 6: The data used in the chapter 2 consists of Table 2.1 (Electricity Deficit States in India as on 2019), Table 2.2 (Largest Solar Photovoltaic Power Plants Worldwide as on June 2017) and Table 2.3 (Top solar states in India as on 31.03.2018). The data pertaining to Table 2.1 was obtained from NTPC upon special request and the request for latest data regarding electricity deficit states in India was not considered.

Comment 7: KWH and KWh should be written as kWh.

Response 7: The word KWH and KWh are replaced by kWh throughout the revised manuscript.

Comment 8: Page – 71, Table 1 is written tow paces (not Table 4.1). it seems that it is copied from paper. This mistake is throughout the thesis.

Response 8: Table 1 has been modified and formatted in the revised manuscript.

Comment 9: Page 81, fig 3 and fig 4 are mentioned whereas it is Figure 4.3 and 4.4. This mistake is throughout the thesis

Response 9: Proper numbering of figures has been done as per the suggestions.

Comment 10: sometime eq. and sometime Eq. Be uniform throughout the thesis. It seems that candidate is not serious in writing the thesis.

Response 10: This mistake has been corrected by writing Eq. throughout in the revised manuscript.

Comment 11: Many figures axis texts are not clear.

Response 11: Figures resolution have been improved and imported in tiff format for proper visibility**.**

Reviewer 1 query

Query 1: Does solar energy price include solar capacity price?

Response 1: solar energy price does not consist solar capacity price directly in the dataset. However, the solar capacity price may be included in the solar energy price but individual share is not shown in the dataset.

Query 2: Which one is more volatile, solar or wind? Which one has more adverse effect on the system operation?

Response 2: The wind is more volatile over the solar energy. The predictability of solar over the wind energy is more due to weather effect. Wind energy has more adverse effect on the system operation due to its intermittent nature, which affects the grid operation and reliability.

Query 3: why is wake effect not considered?

Response 3: Wake effect is an important factor for consideration in wind energy farm because it reduces the wind energy output. The dataset is not available for wake effect consideration used in the chapter six. Sincere thanks for raising this point. We will include this point in future scope and investigate the impact of wake effect on price forecasting in wind integrated grid.

Query 4: Once we go for community or rural level the energy storage is an important aspect. Why is this not considered.

Response 4: For community or rural level storage is an integral part to cope up with uncertainty. Advanced forecasting, virtual power plant and advanced storage has been suggested in chapter 3.

Query 5: What will be impact of shadowing on solar forecasting?

Response 5: The forecasting accuracy will be affected due to shadowing in solar forecasting. Due shadowing generation of the solar PV will be affected, and if the percentage or range of shadowing is not included in the input parameter of forecasting model the forecasting accuracy will be affected. Hence, it leads to deteriorate the forecasting accuracy.

Query 6: How are the hidden layers decided and its corresponding neuron?

Response 6: The hidden layers and corresponding neuron has been decided using the grid search methods for decision tree and random forest algorithm in chapter 5 and chapter 6, and for the rest of algorithm (LSTM, XGBOOST, Linear regression, LASSO, SVM, DNN) heat and trial method is used for the parameter tuning and best result has been shared .

Comments of Reviewer 2

Comments 1: There is room for significant improvement of the PhD thesis presentation. There are numerous language mistakes throughout the thesis; for example, in each countable noun singular, a definite article or an indefinite is required, and there are many mistakes of this kind. In the reference list, a consistent format should be followed; some references do not include complete information. There are also many editing and formatting mistakes throughout the PhD thesis.

Response 1: The kind suggestions have been implemented in the revised manuscript. Language, grammatical and formatting mistakes have been corrected throughout.

Reviewer 2 query

Query 1: Will a renewable electricity market be established, in addition to the conventional day ahead and real time electricity markets?

Response 1: The renewable electricity market is proposed in this thesis for Indian scenario. The reason and motivation of renewable energy-based electricity market has been discussed in introduction section (chapter 1) of the thesis. The following are the major reason for the need of renewable energy electricity market in India.

1. The growing electricity demands
2. Environmental aspects
3. Depleting fossil fuel
4. Solar and wind energy capacity addition
5. Establishment of India Energy exchange for trading of energy.
6. Commencement of green day ahead market trading.