PREDICTIVE MODEL BASED POWER PRICE TAGGING UNDER DEREGULATED ENVIRONMENT

PROJECT REPORT

Submitted by

CB.EN.U4ELC20030	**KOMMURU TEJASWI**
CB.EN.U4ELC20049	**PENDYALA DEEPAK SAI**
CB.EN.U4ELC20051	**B.PREM SUNDAR**
CB.EN.U4ELC20061	**SAGI SRIYANK**

ELECTRICAL AND COMPUTER ENGINEERING

AMRITA SCHOOL OF ENGINEERING, COIMBATORE

AMRITA VISHWA VIDYAPEETHAM

COIMBATORE - 641112

APRIL 2024

AMRITA VISHWA VIDYAPEETHAM

AMRITA SCHOOL OF ENGINEERING,COIMBATORE -641 112

BONAFIDE CERTIFICATE

This is to certify that this project entitled **"PREDICTIVE MODEL BASED POWER PRICE TAGGING UNDER DEREGULATED ENVIRONMENT"** submitted by

CB.EN.U4ELC20030	**KOMMURU TEJASWI**
CB.EN.U4ELC20049	**PENDYALA DEEPAK SAI**
CB.EN.U4ELC20051	**B.PREM SUNDAR**
CB.EN.U4ELC20061	**SAGI SRIYANK**

in partial fulfillment of the requirements for the award of the **Degree of Bachelor of Technology** in **ELECTRICAL & COMPUTER ENGINEERING** is a bonafide record of the work carried outunder my guidance and supervision at Amrita School of Engineering.

Dr. Lekshmi R. R.

Assistant Professor (Sl. Gr.)
Department of Electrical and
Electronics Engineering
Amrita School of Engineering
Coimbatore- 641112

Dr. Balamurugan S
Chairperson
Professor
Department of Electrical and
Electronics Engineering
Amrita School of Engineering
Coimbatore-641112

This project report was evaluated by us on……………

INTERNAL EXAMINER

EXTERNAL EXAMINER

ABSTRACT

In the global electricity markets, the accurate prediction of real-time prices is crucial for efficient resource allocation and economic stability. This research focuses on a comprehensive power price tagging model that utilizes machine learning (ML) algorithms and an agent-based reinforcement model to predict market prices and determine marginal prices, facilitating an optimal price tagging approach.

The study initially focuses on a method to determine the marginal price, calculating the economic generation price for specific power demands followed by developing an ML model trained on historical data from the Indian Energy Exchange (IEX) website, ensuring accurate real-time market price predictions through rigorous benchmarking, training, and testing. Additionally, an agent-based reinforcement model is introduced, allowing for a comparative analysis to identify the most effective pricing strategy. Finally, an algorithm is devised to enable price tagging using both predicted and marginal prices for a given date and time slot, thus ensuring an optimized pricing strategy. This power price tagging model aims to address critical challenges in electricity markets, presenting an innovative and practical solution for pricing optimization and efficient resource management.

CONTENTS

LIST OF FIGURES

LIST OF SYMBOLS

*	Multiplication Gate
%	Percentage
σ	Forget Gate
Σ	Summation
kWh	kilowatt hour

LIST OF ABBREVIATIONS

ELD	-	Economic Load Dispatch
GA	-	Genetic algorithm
PSO	-	Particle Swarm Optimization
MCP	-	Market clearing price
IEX	-	Indian Energy Exchange
DAM	-	Day Ahead Market
TAM	-	Term Ahead Market
RTM	-	Real Time Market
ACP	-	Area Clearing Price
ACV	-	Area Clearing Volume
Genco	-	Generation company
Disco	-	Distribution company
LI	-	Lambda Iteration

Chapter 1

INTRODUCTION

1.1 PREFACE

In the realm of deregulated power markets, the ability to accurately predict Market Clearing Prices (MCPs) holds paramount importance for energy stakeholders. This predictive capability doesn't merely impact economic considerations; it forms the backbone of strategic decision-making within the energy sector. In a landscape where bidding strategies determine success and profitability, the power of foresight provided by MCP prediction becomes a linchpin for companies seeking to optimize their operations and maximize returns. This pursuit transcends mere financial gains; it's a pivotal component in ensuring a stable and efficient energy infrastructure, influencing long-term planning, renewable resource integration, and grid stability. Predictive models aimed at forecasting MCPs aren't just tools for commercial endeavours; they are fundamental elements driving the core functioning of the modern energy landscape.

1.2 MOTIVATION

By accurately predicting the Market Clearing Price (MCP) in energy auctions, we aim to revolutionize bidding strategies and enhance profitability within the deregulated power market.

1.3 OBJECTIVE

In the domain of power market forecasting within deregulated environments, our objective is to design and implement robust predictive models that accurately anticipate Market Clearing Prices (MCPs). Leveraging advanced machine learning techniques, we aim to develop models that forecast MCPs with high precision and reliability. By amalgamating historical market data, weather patterns, demand-supply dynamics, and other pertinent variables, our goal is to construct a predictive framework capable of providing actionable insights into future MCP trends. Moreover, we seek to optimize bidding strategies for energy companies, facilitating their ability to make informed decisions, maximize profits, and enhance their competitive edge within the marketplace. Through this endeavour, we aspire not only to enable profit maximization but also to contribute to the overall stability and efficiency of the energy sector.

Chapter 2

LITERATURE SURVEY

2.1 OPTIMIZATION METHODS BASED SOLUTION TO ECONOMIC LOAD DISPATCH

[1] proposes Particle Swarm Optimization (PSO) to solve day-ahead economic load dispatch (ELD) problem based on the forecastedload. The authors have commented on the speed, simplicity and exploration efficiency of PSO for diverse optimization problems, including economic load dispatch.

[2] based on lambda Iteration, a well-established technique in power system analysis, ensures accurate solutions for simple systems especially for power system challenges.
In[2], the proposed algorithm is Lambda Iteration method The Lambda Iteration method is not typically used for predictive modeling or forecasting; instead, it's an optimization technique primarily employed for solving power system problems, specifically the Economic Load Dispatch (ELD) problem. The primary goal of the Lambda Iteration method is to allocate the generation levels of various generating units in a power system to minimize the total generation cost while satisfying load demand and system constraints when comparing with [3-5] it cannot handle large and complex data but it is similar to [1] based on PSO but can do as efficient as [1].

In [3], the proposed algorithm is Genetic Algorithm

Genetic Algorithms are known for their adaptability to changing conditions and dynamic environments. Thisadaptability is crucial when dealing with the ELD problem, where loads and constraints can vary over time.

[3] Based on genetic algorithm based on GA is known for global search method, exploring the entire solution space through its population. [1] research done in PSO leans more toward local search, with particlesinfluenced by their own and their peers' best-known solutions .when compared done research done in [2] Lambda Iteration is specialized for power system analysis only limited to certain data.[4] is not as efficient and can predict the optimal price as genetic algorithm.[5] states that large amount complex data can be handled efficiently but [3] offers more simpler solution.

In [4], the proposed algorithm Simulated Annealing (SA)

The paper introduces Simulated Annealing (SA) as a novel optimization technique, which is tailored to address the complex Economic Load Dispatch (ELD) problem in power systems. [4] using SA introduces abetter range of principles for potential improvements in exploration and solution quality, making it highly effective in optimization tasks. While [1&2], based on PSO and lambda iteration, is widely used in variousoptimization tasks, including ELD, it may not be as effective as [4] employing Simulated Annealing.
Moreover, [3&5] based on genetic algorithm and differential evolution offers adaptability for handling extensive data, unlike SA's more limited data handling capabilities.

In [5], the proposed algorithm Differential Evolution (DE)

The paper, based on Differential Evolution (DE), serves as a powerful optimization tool for addressing complex energy system challenges, including economic load dispatch and predicting optimal prices in energymarkets. DE excels in shuffling and adaptation, making it beneficial for handling diverse price prediction models. [1-2], which is based on PSO and lambda iteration, may be versatile, may require more adaptation forspecific price prediction problems. In comparison to [4], Simulated Annealing, which can be efficient for specific tasks, [5] excels in managing a more diverse set of data. Lambda Iteration ([2]) cannot provide the same advantages as Differential Evolution.

Chapter 3

DEREGULATED SYSTEM

3.1 INTRODUCTION

A deregulated power system is an electricity market structure where the generation, transmission, and distribution of electricity are separated into distinct entities, and competition is introduced into various segments of the industry.

3.2 DEREGULATED POWER SYSTEM

Deregulated structure design where the electricity generation, distribution, and retail sales segments are separated, allowing for competition and choice in the market**.**

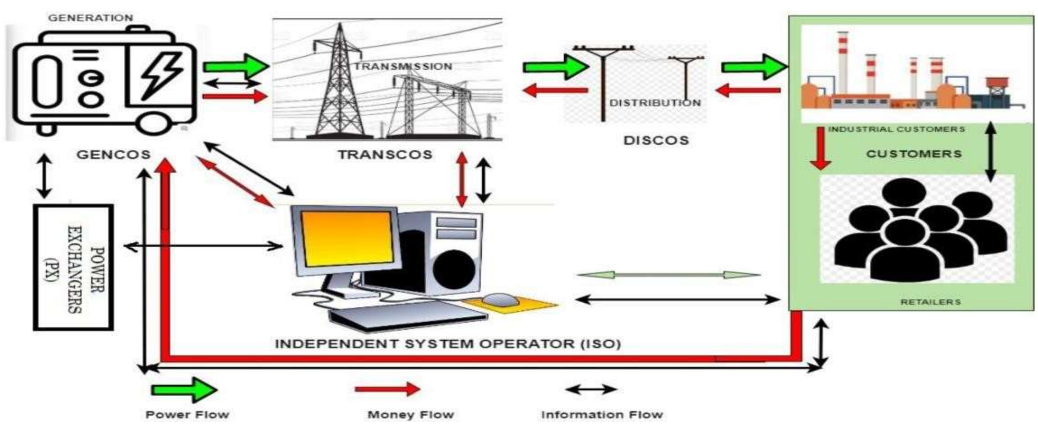


Fig. 3.1 Deregulated structure

Generation: In a deregulated market, the generation of electricity is open to competition. Multiple GenerationCompanies (GenCos) can operate power plants and generate electricity. GenCos receive payments from the wholesale market for the electricity they generate. These payments are based on market-clearing prices and thevolume of electricity delivered.

Transmission: The high-voltage transmission of electricity is typically managed by regulated Transmission System Operators (TSOs). They maintain and operate the grid that transports electricity from power plants tolocal areas. TSOs collect transmission fees from market participants, including GenCos and Discos, for the use of the transmission grid. These fees support the maintenance and operation of the grid.

Distribution: Distribution Companies (Discos) are responsible for distributing electricity to end-users, such ashomes and businesses. These entities manage the local distribution grids and deliver electricity to consumers. Discos collect payments from consumers for the electricity they distribute. In some cases, Discos may also pay the TSO for access to the transmission grid. They may also purchase electricity from the wholesale marketand pass the cost on to consumers.

Retail Electric Providers: Retail Electric Providers (REPs) REPs interact directly with end-users and provide them with information about different electricity plans and pricing options. REPs receive payments from consumers for the electricity they supply. They, in turn, may pay wholesale market prices to GenCos orother suppliers.

Consumers (End-Users): One of the primary benefits of a deregulated structure is that consumers have the freedom to choose their electricity supplier, service plans, and potentially source renewable energy if available. They receive the information from REPs about electricity plans and pricing. They also provide information to REPs about their electricity consumption preferences. Consumers pay their chosen REPs for the electricity they use, and this payment is based on the pricing and plan selected.

3.3 COMPETITIVE ELECTRICITY MARKET

Vertically integrated utilities could recover their costs regardless of whether they operated efficiently or not. With the introduction of competition, there has been an important shift from this approach. Opening electricity sector to competition is an important tool to improve efficiency of power generation Competitive markets provide the driving force for generators to innovate and operate in the most efficient and economic manner to remain in the business and recover their costs, thereby to benefit consumers.

Indian Energy Exchange is India's premier energy marketplace, providing a nationwide automated trading platform for the physical delivery of electricity, renewables, and certificates. More recently, IEX(Indian Energy Exchange) has pioneered cross border electricity trade expanding its power market beyond India in an endeavor to create an integrated South Asian Power Market. IEX is powered by state-of-the-art, intuitive and customer centric technology, enabling efficient price discovery and facilitating the ease of power procurement.

IEX has a robust ecosystem of 7,500 participants located across 29 States and 5 Union Territories comprising of 60 distribution utilities, 600 conventional generators and 1,800 RE generators and obligated entities. It also has a strong base of 4600 commercial and industrial consumers representing industries such as metal, food processing, textile, cement, ceramic, chemicals, automobiles, information technology industries, institutional, housing, and real estate, and commercial entities.

Market holds different models that include single buyer, bilateral model and poolco model. Single buyer model the system operator conducts single sided auction with multiple bids from suppliers for a prescribed time slot. The operator plots the supply curve. The market is cleared with a predicted demand under considered period. The auction under single buyer model is done individually for each pool.

Bilateral Model the buying and selling of electricity occurs through direct agreements or contracts between electricity producers (generators) and consumers (buyers), bypassing a centralized market operator or exchange. The negotiations and agreements in a Bilateral Model are typically private, and the terms of the contracts are not disclosed to the public. This provides commercial confidentiality to market participants. However, under bilateral model, suppliers make contract with buyers for an amount of power during certain period of time.

POOLCO is defined as a centralized market place that clears the market for buyers and sellers where electric power sellers/buyers submit bids and prices into the pool for the amounts of energy that they are willing to sell/buy. The main characteristic of this model is the establishment of independently owned wholesale power pools served by interconnected transmission systems. This pool becomes a centralized clearing market for trading electricity which would implement competition by forcing distribution utilities to purchase their power from the PoolCo instead of trading with generating companies. These companies sell power at a market clearing price (MCP) defined by the PoolCo, instead of a price which is based on generation cost (as is the case in a vertically integrated monopoly). The final price for spot market power (spot markets is where market generators are paid for the electricity that they have sold to the pool and market consumers are charged for their electricity consumption.) may exceed MCP to account for charges that the ISO could obligate customers to pay for the associated ancillary services and to cover ISO’s overhead costs.

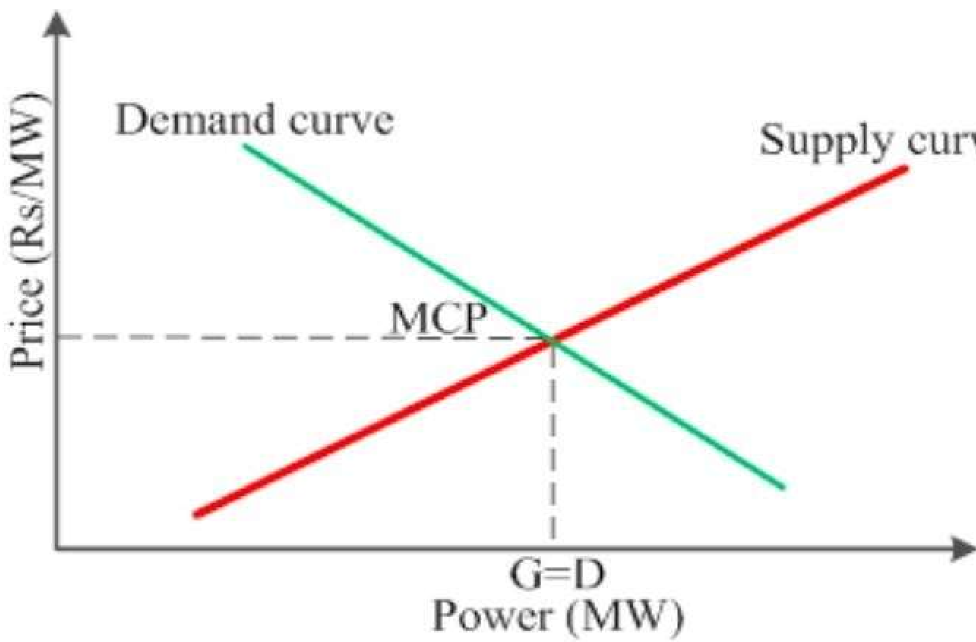


Fig 3.2 Poolco model

Day-Ahead-Market (DAM) is a physical electricity trading market for deliveries for any 15 minute time blocks in 24 hours of next day starting from midnight. The prices and quantum of electricity to be traded are determined through a double sided closed auction bidding process.

Term-Ahead-Market (TAM) provides a range of products allowing participants to buy/sell electricity on a term basis for a duration of up to 11 days ahead. The operations are carried out in accordance with the ”Procedures for Scheduling of Bilateral Transactions” issued by the Central Transmission Utility (PGCIL), under ”CERC (Open Access in inter-State Transmission) Regulations, 2008”, as amended from time to time and the Bye Laws, Rules and Business Rules of the Exchange.

Real-Time-Market (RTM) is a new market segment with trading commencing on 1st of June’20. The market features a new auction session every half an hour with power to be delivered after 4 time blocks or an hour after gate closure of the auction. The price and quantumof electricity trading is determined through a double-sided closed auction bidding process. Theoperations are carried out in accordance with the Procedure for Scheduling Collective Transactions in the Real Time Market as issued by Power System Operation Corporation Ltd

The market features include trading of 15-minute contracts facilitated through a double-sided anonymous auction bidding process. Additionally, the exchange publishes the Area Clearing Price (ACP) and Area Clearing Volume (ACV) for transparency and market information.
Exchange to manage risk management leveraging bank balance, requisite margin, including any additional margin as specified for the respective trading segment or the type of contracts.

3.4 SUMMARY

The deregulated energy market structure involves the separation of electricity generation, transmission, distribution, and retail sales segments, fostering competition and consumer choice. Generation companies (GenCos) compete to produce electricity and receive payments based on market-clearing prices. Regulated Transmission System Operators (TSOs) manage high-voltage transmission, collecting fees from market participants. Distribution companies (Discos) deliver electricity to end-users and collect payments, while Retail Electric Providers (REPs) offer various plans and pricing options to consumers.
Consumers benefit from the freedom to choose suppliers and plans, with REPs facilitating this process. The shift from vertically integrated utilities to competitive markets encourages efficiency and innovation in power generation, ultimately benefiting consumers. The Indian Energy Exchange (IEX) serves as a premier energy marketplace, facilitating trading nationwide and expanding to cross-border electricity trade in South Asia.
With a robust ecosystem of participants, IEX enables efficient price discovery and power procurement. Market models like single buyer, bilateral, and poolco offer different approaches to trading electricity, with variations in auction mechanisms and market clearing processes. Poolco model centralizes trading, setting market clearing prices and promoting competition among sellers. Overall, deregulation fosters efficiency, innovation, and consumer empowerment in the energy sector.

Chapter 4

ECONOMIC LOAD DISPATCH

4.1 INTRODUCTION

Economic Load Dispatch (ELD), It is a process used to determine the optimal allocation of power generation among different generators to meet the electrical load demand while minimizing the overall operating costs of the power system. ELD plays a crucial role in ensuring the efficient and cost-effective operation of power systems.

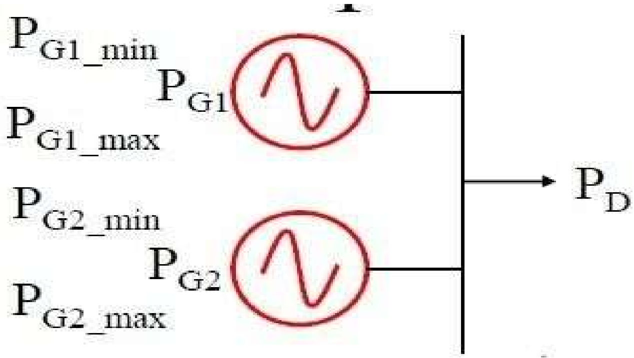
4.2 OBJECTIVE FUNCTION

The primary objective function of ELD is to find the most economical way to dispatch (allocate) the power output of multiple generators to meet the electrical load demand at any given moment while minimizing the total generation cost. This includes the cost of fuel, maintenance, and other operating costs.

4.3 COST FUNCTION

Each generator has a cost function that describes its operational cost as a function of the poweroutput. This cost function typically includes fuel cost, maintenance cost, and other expenses. Itmay vary depending on the generator's operating conditions. An effective ELD process helps reduce the overall operating costs of the power system by minimizing fuel consumption and other expenses. It also contributes to the efficient use of resources and reduces environmental impact by allowing for more efficient dispatch of generators.

The main objective is to minimize the cost of generation of each generating units of the plant therefore the cost of generation should be optimum by fulfilling the demand power with satisfying the power system constraints.



$$P_{G1min} \le P_{G1} \le P_{G1max}$$

$$P_{G2min} \le P_{G2} \le P_{G2max}$$

$$P_{G1} + P_{G2} = P_D$$

Fig 4.1 Power Demand

$$C(P_{Gi}) = K(aP_{Gi} + b + c/P_{Gi})\text{Rs/hr}$$

Cost equation

$$C(P_{Gi}) = K(aP_{Gi}^2 + bP_{Gi} + c)\text{Rs/hr}$$

$$K = \text{Rs } 1/\text{hr}$$

$$C(P_{Gi}) = (aP_{Gi}^2 + bP_{Gi} + c)$$

$$\frac{\partial C}{\partial PGi} = \frac{\partial}{\partial PGi}(aP_{Gi}^2 + bP_{Gi} + c)$$

$$\frac{\partial C}{\partial PGi} = 2aP_{Gi} + b$$

4.4 GENETIC ALGORITHM TO FIND GENERATION COST

In the context of Economic Load Dispatch (ELD) optimization, Genetic Algorithms (GAs) emerge as potent tools for tackling the intricate challenges inherent in minimizing the total cost of power generation while adhering to operational constraints. Economic Load Dispatch tasks involve distributing the power output among generators in a manner that optimizes cost, considering the factors demand requirements. Genetic Algorithms offer a heuristic approach to this optimization problem.

In this application of genetic algorithms, we aimed to optimize the power output of a set of generators to fulfill a specified power demand while minimizing the total cost. We initialized a population of potential solutions, representing different power output configurations for each generator within predefined ranges. Through a series of iterations, the genetic algorithm evolved this population, utilizing selection, crossover, and mutation operations to explore and exploit the solution space. At each iteration, we evaluated the fitness of each solution based on its total cost, considering both the generation cost determined by the generator characteristics and a penalty for not meeting the power demand. By tracking the best solution found across generations, we predicted the optimal configuration of power outputs that would efficiently meet the power demand requirement while minimizing the overall cost. Through this iterative process, genetic algorithms provide an effective approach for solving optimization problems by mimicking natural evolutionary processes. There has been a significant change from this approach in a deregulated electricity market where market participants other than utility companies own power plants and transmission lines. In regulated markets, customers cannot choose who generates their power and are bound to the utility in that area. The utility ensures that energy is produced, transferred to the grid, and delivered to consumers. Electricity is produced by generating businesses and sold into a wholesale market. Retail energy suppliers then buy this electricity and resell it to consumers.

We use genetic algorithms (GAs) when we need to optimize a solution in a complex search space, especially when traditional optimization methods are not feasible or inefficient as we are using multiple generators in this case. Natural selection and evolution are the sources of inspiration for genetic algorithms. When using an adaptive heuristic search method, genetic algorithms are especially helpful. Natural selection and genetics serve as the foundation for genetic algorithms. These are clever uses of previous data to guide a random search into an area of the solution space where performance is higher.

The genetic algorithms start from randomly generated initial population. Typically, the GA has three phases, first one is initialization, second is evaluation, and third is genetic operation.

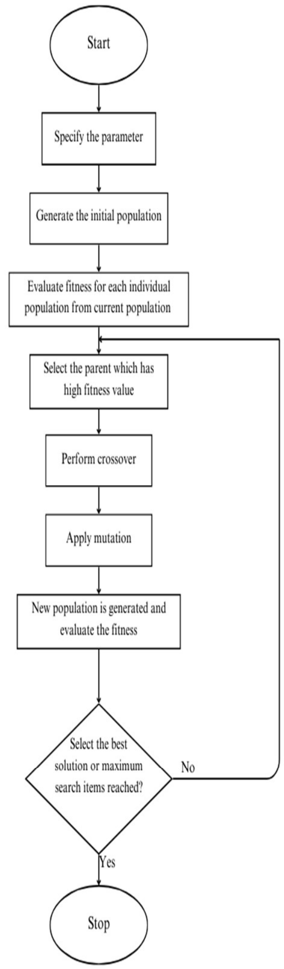


Fig.4.2: Flow chart of genetic algorithm

4.5 SUMMARY

In the realm of Economic Load Dispatch (ELD) optimization, Genetic Algorithms (GA) serve as potent tools for efficiently minimizing the total cost of power generation while meeting operational constraints. ELD tasks involve allocating power output among generators to optimize cost based on demand requirements. GA offers a heuristic approach to this optimization challenge.

In this application, GA is employed to optimize the power output of a generator set to meet specified power demand while minimizing total cost. The process begins with initializing a population of potential solutions, representing various power output configurations for each generator within predefined ranges. Through iterations, GA evolves this population using selection, crossover, and mutation operations to explore and exploit the solution space. Fitness evaluation is based on total cost, considering generation cost and penalties for not meeting power demand. By tracking the best solution across generations, the optimal power output configuration is predicted. GAs excel in complex search spaces where traditional methods may be inefficient, leveraging principles of natural selection and evolution to guide the search towards better solutions.

Chapter 5

PRICE PREDICTION METHODS

5.1 INTRODUCTION

The prediction of Market Clearing Price (MCP) within a deregulated energy market is pivotal for economic load dispatch and efficient power resource allocation. Traditional time series models like ARIMA (Auto Regressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) have proven effective in forecasting values based on historical patterns, leveraging historical price patterns. Similarly, for predicting the volume of electricity generated in targeted areas along with the MCP prediction for the following day, these models offer valuable insights for strategic decision-making and operational efficiency.

Moreover, advanced machine learning techniques like Long Short-Term Memory (LSTM) networks provide sophisticated methodologies for MCP along with volume prediction. LSTM models contribute to predicting the volume of electricity generated by uncovering complex patterns in historical data along with predicting the next day MCP values based on historical patterns.

In this chapter, we explore the implementation and evaluation of diverse models including ARIMA, SARIMA, and LSTM for predicting both MCP and electricity generation volumes. We detail the procedures involved in harnessing the capabilities of each model, emphasizing their significance in optimizing economic load dispatch strategies and ensuring sustainable energy pricing.

By comparing and integrating traditional time series analysis with advanced machine learning techniques, we aim to address the challenges of MCP prediction in deregulated energy markets comprehensively. This approach enhances strategic decision-making and operational efficiency, ultimately contributing to the sustainable management of electricity resources.

5.2 PROCEDURE FOR ARIMA MODELING

5.2.1 Data Preparation:

Clean and organize MCP data, addressing missing values and outliers.
Create a time series format for sequential analysis.

5.2.2 Dataset Splitting:

Segment data into training and test sets, allocating a significant portion for training.

5.2.3 Parameter Selection:

Determine optimal ARIMA parameters (p, d, q) using Auto ARIMA or manual tuning.

5.2.4 Model Training:

Construct ARIMA model using stats models, fit it with the training set.
Validate through walk-forward iterations, forecasting test set MCP values.

5.2.5 Evaluation:

Assess model performance using R2, RMSE metrics.
Visualize predicted values against actual observations.

5.3 PROCEDURE FOR SARIMA MODELING

5.3.1 Data Preparation:

Clean and format MCP data, handling missing values and outliers.

5.3.2 Dataset Split:

Divide data into training and test sets, allocating a significant part for training.

5.3.3 Parameter Identification:

Identify optimal SARIMA parameters (P, D, Q, s) considering seasonal variations.

5.3.4 Model Building:

Implement SARIMA using stats models, incorporating seasonal parameters.
Fit the model using the training data.

5.3.5 Validation & Evaluation:

Validate via walk-forward iterations, forecast test set MCP values.
Evaluate using R2, RMSE metrics and visual comparison with actual data.

5.4 LONG SHORT TERM MEMORY(LSTM) - MACHINE LEARNING PREDICTION MODEL

LSTM networks offer an alternative approach leveraging sequential data analysis. LSTM models excel in capturing long-term dependencies and complex patterns inherent in time series data, making them well-suited for MCP prediction tasks. LSTMs are a specialized kind of neural network adept at handling sequential data, with built-in mechanisms to selectively remember patterns over extended time intervals, ideal for applications in time series analysis.

5.4.1 Data Preparation:

Clean Data: Remove missing values and outliers.

Feature Engineering: Create relevant features influencing MCP.

Normalization: Scale features to a suitable range using MinMaxScaler.

5.4.2 Dataset Split:

Training/Test Split: Allocate 80% for training, 20% for testing.

5.4.3 Sequence Creation:

Form Sequences: Use a look-back period to create input sequences for the LSTM.

5.4.4 Model Configuration:

Build LSTM: Stack LSTM and dropout layers, ending with a Dense output layer.
Compile Model: Use Adam optimizer and mean squared error loss.

5.4.5 Model Training:

Train with Validation: Use a portion of training data for validation.

Early Stopping: Terminate training when validation loss ceases to decrease.

5.4.6 Validation & Evaluation:

Walk-forward Validation: Make step-by-step predictions on test data.

Performance Metrics: Assess accuracy using RMSE and R^2.

Iterate: Adjust model based on performance to improve predictions.

Chapter 6

Results and Conclusion

6.1 INTRODUCTION

The evaluation of the Market Clearing Price (MCP) prediction models showcased a promising performance by the ARIMA model, yielding an impressive R-squared value of 0.77, indicating a strong fit to the data. The Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) further affirmed its accuracy in forecasting MCP values.

The SARIMA model indeed outperformed expectations, demonstrating superior performance metrics compared to the ARIMA model. Leveraging its adept handling of seasonal variations, SARIMA showcased enhanced predictive capabilities, resulting in improved R-squared values, reduced Root Mean Squared Error (RMSE), and lower Mean Absolute Error (MAE). This stronger performance aligns with SARIMA's ability to capture and effectively utilize seasonal patterns within the Market Clearing Price (MCP) data.

Forecasting the Market Clearing Price (MCP) in deregulated energy markets is critical for efficient power resource allocation and economic load dispatch. Traditional methods like ARIMA and SARIMA analyze historical price patterns sequentially, providing insights for strategic decision-making. Additionally, advanced techniques like LSTM excel in capturing long-term dependencies in time series data, making them effective for MCP prediction. This chapter examines the implementation and evaluation of ARIMA, SARIMA, and LSTM models, highlighting their importance in price prediction. By integrating traditional time series analysis with advanced machine learning, this approach aims to enhance decision-making and operational efficiency in deregulated energy markets.

6.2 ARIMA

In the context of predicting Market Clearing Prices (MCP) in a deregulated power market, b Autoregressive Integrated Moving Average (ARIMA) model stands as a fundamental method. This model operates on the premise of time series analysis, delving into historical MCP data to unveil intricate patterns and variations inherent in price dynamics. The selection of ARIMA's parameters—p (autoregressive), d (differencing), and q (moving average) is a crucial step in the model's application. The determination of optimal parameters (5, 1, 4) for the ARIMA model was based on the consideration of minimized Akaike Information Criterion (AIC) values during the model fitting process. Following the procedure outlined in Section 5.1 for ARIMA implementation, the ARIMA model with the optimized parameters (5, 1, 4) was executed, resulting in an R-squared (R2) value of 0.77, signifying a reasonably good fit of the model to the MCP dataset.

```
predicted=9324.598936, expected=10000.000000
predicted=9860.950799, expected=9019.860000
predicted=8127.522405, expected=7057.530000
predicted=7397.453180, expected=8678.850000
predicted=8216.372059, expected=8969.450000
predicted=9003.276776, expected=7299.130000
predicted=7164.820243, expected=6909.050000
predicted=6614.849521, expected=7045.330000
predicted=6714.604021, expected=5454.030000
predicted=5108.118758, expected=4144.320000
predicted=4432.529127, expected=4268.340000
predicted=4136.885589, expected=3496.380000
predicted=3783.208467, expected=4670.040000
predicted=4623.792272, expected=4968.000000
predicted=5111.955389, expected=4832.880000
predicted=4977.056684, expected=4814.230000
predicted=4466.063167, expected=3892.280000
predicted=4626.232590, expected=4535.460000
predicted=4712.625243, expected=4773.410000
```

Fig. 6.1: ARIMA Prediction Values

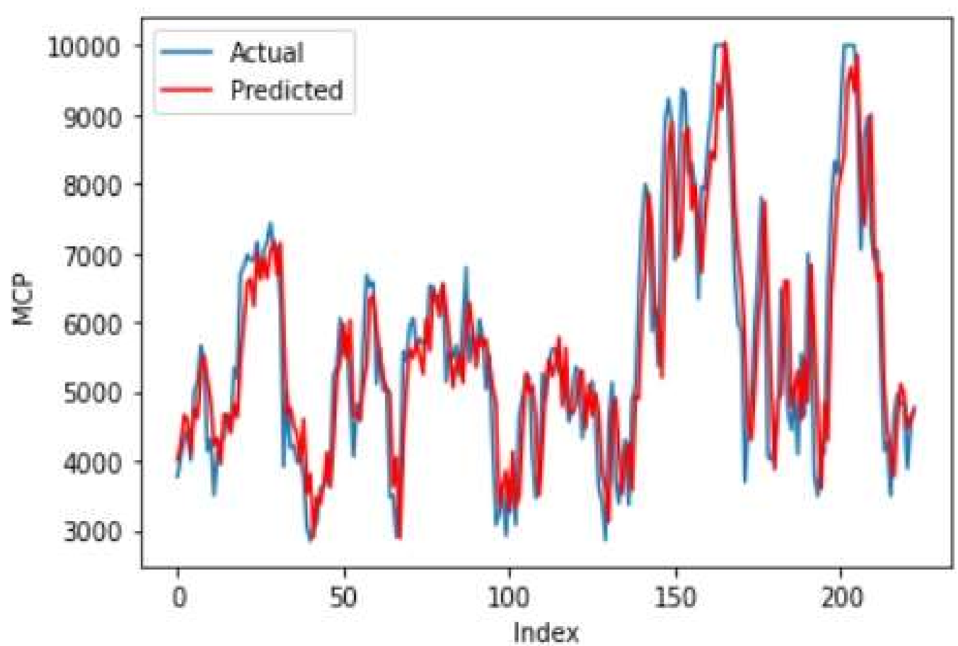


Fig .6.2: Graph of arima prediction and actual values

```
R-squared (R2) score: 0.7778726059203716
Test RMSE: 825.749
```

Fig. 6.3: ARIMA Performances

6.3 SARIMA

In the domain of predicting Market Clearing Prices (MCP) within a deregulated power market, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model emerges as a robust tool. SARIMA extends the capabilities of ARIMA by incorporating seasonal components to address time series data with seasonal patterns. The SARIMA model, characterized by its parameters—p (autoregressive), d (differencing), q (moving average), P (seasonal autoregressive), D (seasonal differencing), Q (seasonal moving average), and s (seasonal period)—empowers the capture and prediction of intricate seasonal variations prevalent in MCP datasets.

Through meticulous parameter tuning and model training, SARIMA reveals its efficacy in capturing the complex seasonal dynamics within the MCP dataset. For instance, with optimized parameters (x, y, z), SARIMA exhibited a commendable R-squared (R2) value of "ABC”. This value signifies SARIMA's ability to effectively model the intricate seasonal patterns embedded within the MCP data, showcasing its strength in forecasting the market clearing prices in a deregulated environment.

```
predicted=6448.211890, expected=6574.880000
predicted=6184.291242, expected=5116.540000
predicted=5578.119194, expected=5618.670000
predicted=5382.939381, expected=5017.120000
predicted=5265.077284, expected=5022.030000
predicted=5048.415422, expected=3470.080000
predicted=3752.681143, expected=3504.130000
predicted=4152.296969, expected=2897.590000
predicted=2885.982933, expected=3655.310000
predicted=4266.453516, expected=5576.320000
predicted=4904.503525, expected=5436.190000
predicted=5572.911217, expected=5943.320000
predicted=5644.149448, expected=6060.580000
predicted=5974.075661, expected=5641.760000
predicted=5692.208803, expected=5770.270000
predicted=5506.993003, expected=5690.800000
predicted=5972.174478, expected=5713.950000
predicted=5303.418515, expected=6527.920000
predicted=6607.257966, expected=6520.710000
```

Fig. 6.4: SARIMA Prediction Values

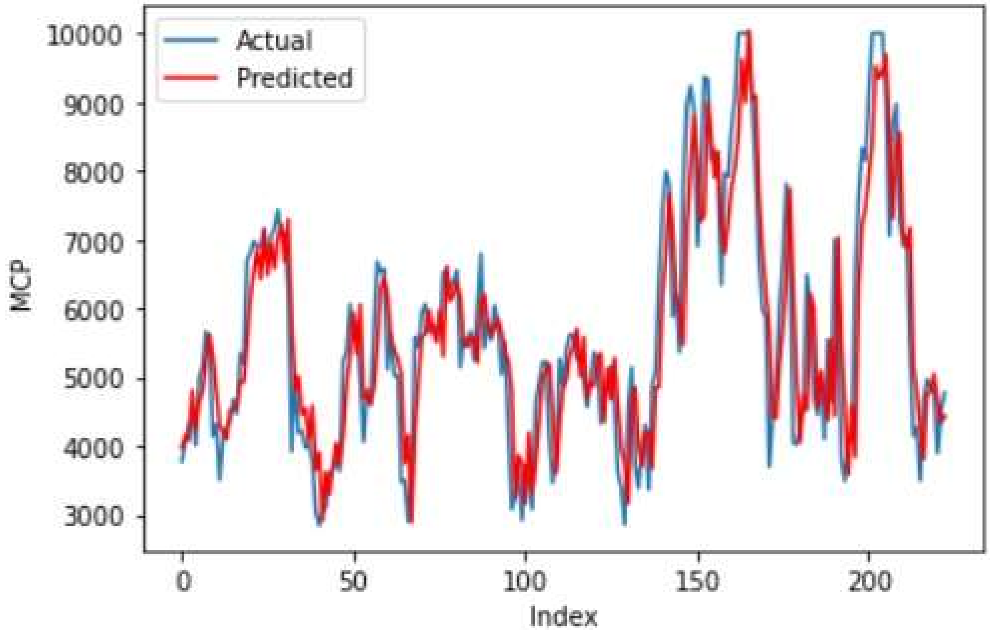


Fig 6.5: Graph of SARIMA prediction and actual values

```
R-squared (R2) score: 0.7759025293683937
Test RMSE: 829.403
```

Fig .6.6: SARIMA Performances

6.4 LSTM

In the context of predicting Market Clearing Prices (MCP) in a deregulated power market, Long Short-Term Memory (LSTM) networks offer an alternative approach leveraging sequential data analysis. LSTM models excel in capturing long-term dependencies and complex patterns inherent in time series data, making them well-suited for MCP prediction tasks.

To implement an LSTM model for MCP prediction, historical MCP data is fed into the network, which learns to capture temporal dependencies and fluctuations in price dynamics. The architecture of an LSTM network consists of memory cells with gating mechanisms, enabling the model to selectively retain or forget information over time.

Date	pred	actual	diff
2024-01-02	5694.218006	5575.56	-118.658006
2024-01-03	5171.700323	5076.23	-95.470323
2024-01-04	4811.196900	5574.80	763.603100
2024-01-05	4994.891030	5693.79	698.898970
2024-01-06	5145.469060	5698.24	552.770940
2024-01-07	4711.205319	5078.34	367.134681
2024-01-08	5280.876892	5767.05	486.173108
2024-01-09	5371.881695	5191.33	-180.551695
2024-01-10	5123.195842	5547.22	424.024158
2024-01-11	5273.545189	5204.93	-68.615189
2024-01-12	5294.108274	5189.45	-104.658274
2024-01-13	5081.533430	5231.07	149.536570
2024-01-14	4324.577933	4293.62	-30.957933
2024-01-15	4774.898437	5798.16	1023.261563
2024-01-16	5419.935980	6019.62	599.684020
2024-01-17	5899.689574	5900.70	1.010426
2024-01-18	5897.363301	6178.47	281.106699
2024-01-19	6094.393807	6354.83	260.436193
2024-01-20	6136.907956	6538.15	401.242044
2024-01-21	5404.942735	5731.82	326.877265
2024-01-22	6348.827736	6623.43	274.602264
2024-01-23	6563.928599	6509.85	-54.078599
2024-01-24	6705.917807	6727.38	21.462193
2024-01-25	6842.618354	6660.60	-182.018354
2024-01-26	6763.390373	5945.70	-817.690373
2024-01-27	5940.378864	6505.84	565.461136
2024-01-28	5063.523509	5752.56	689.036491
2024-01-29	5997.234778	6305.89	308.655222
2024-01-30	6265.226341	6492.11	226.883659
2024-01-31	6465.041511	6355.07	-109.971511
2024-02-01	6211.156628	6488.42	277.263372
2024-02-02	6080.907877	5669.97	-410.937877

MAPE: 5.80%
RMSE: 426.61

Fig. 6.7 LSTM Predictions for January 2024 Month

```
Train Loss: 0.0012, Test Loss: 0.0016
55/55 [==============================] - 0s 8ms/step
14/14 [==============================] - 0s 8ms/step
Train Loss: 0.0012, Test Loss: 0.0016
Train R²: 0.9024, Test R²: 0.8204
Train MAPE: 9.11%, Test MAPE: 9.97%
Train RMSE: 600.82, Test RMSE: 686.23
```

Fig. 6.8 LSTM Performance metrics

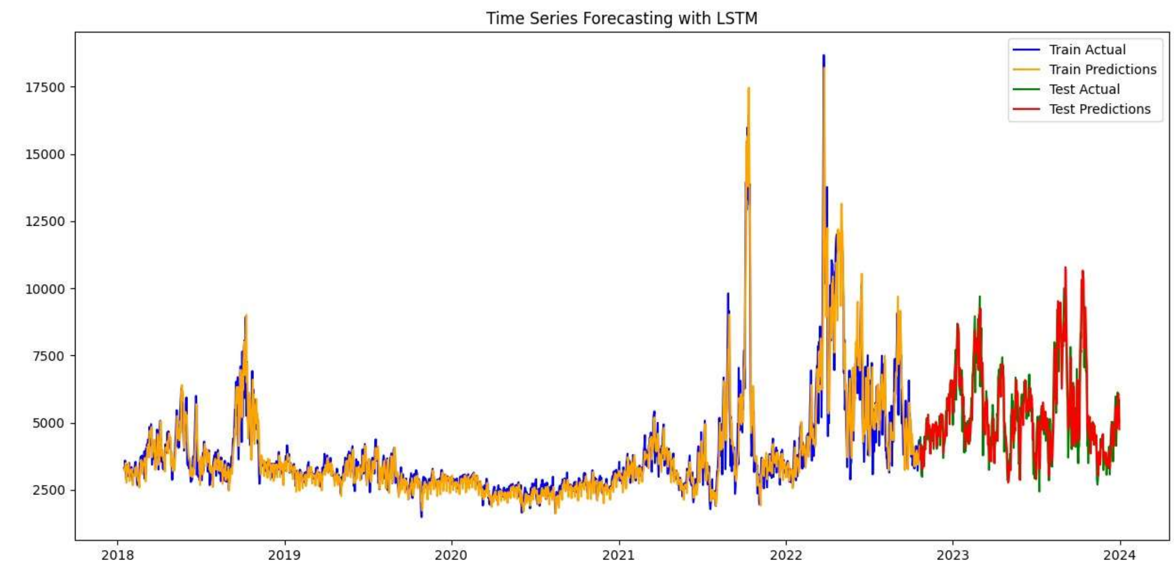


Fig. 6.9 Graph of LSTM prediction and actual values

6.5 GENTIC ALGORITHM

In utilizing genetic algorithms for Economic Load Dispatch optimization, we have effectively optimized the power output of multiple generators to fulfill a specified demand while minimizing total cost. Through iterative evolution and selection operations, the algorithm converged on an optimal configuration of power outputs, efficiently balancing generation costs and meeting demand constraints. This successful application underscores the efficacy of genetic algorithms in navigating complex search spaces and addressing real-world optimization challenges within the energy sector. As computational capabilities advance, genetic algorithms are to play a pivotal role in enhancing the efficiency and sustainability of power generation systems.

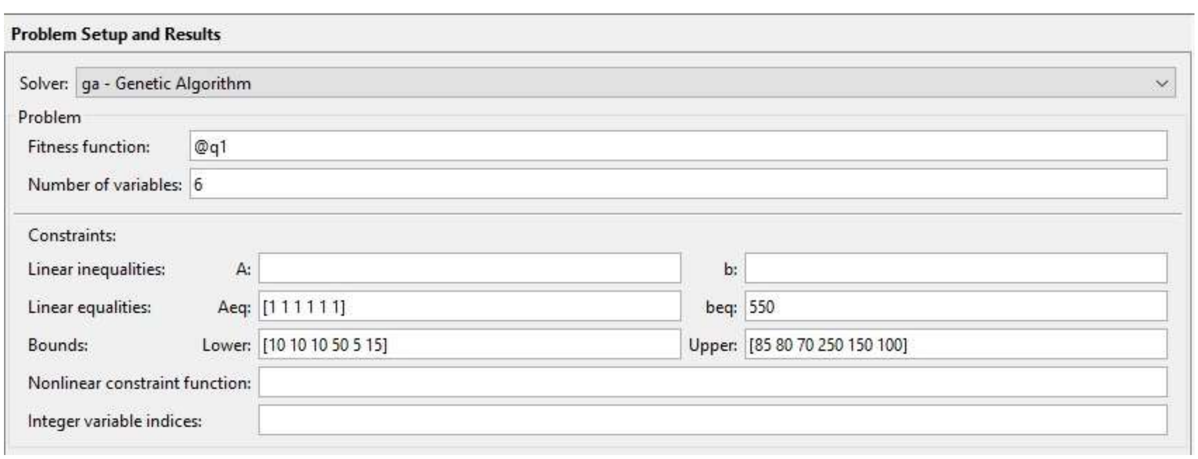


Fig.6.10: constraints of genetic algorithm (MATLAB)

```
C:\Users\HP\Documents\MATLAB\q1.m
Optimization running.
------------------------------
Objective function value: 2234.6427886316987
Optimization terminated: average change in the fitness value less than options.TolFun.
```

Fig.6.11: Generation cost (MATLAB)

Final point:

1	2	3	4	5	6
84.556	79.167	28.52	185.669	72.618	99.47

Fig.6.12: Output power(MATLAB)

```python
# Define parameters for the genetic algorithm
num_units = 6  # Number of generators
num_generations = 10  # Number of generations
crossover_fraction = 0.1  # Probability of crossover
mutation_rate = 0.8  # Mutation rate
power_demand = 550  # Power demand in MW
P_min = [10, 10, 10, 50, 5, 15]  # Minimum power output per generator
P_max = [85, 80, 70, 250, 150, 100]  # Maximum power output per generator
K = 1e5  # Penalty factor for not meeting power demand

# Cost coefficients for each generator
ai = [0.005, 0.010, 0.020, 0.003, 0.015, 0.010]
bi = [2, 2, 2, 1.95, 1.45, 0.95]
ci = [100, 200, 300, 80, 100, 120]
```

Fig.6.13: constraints of genetic algorithm implanted in python

```
Best Solution:
Generator 1: Power Output = 83.4468 MW
Generator 2: Power Output = 78.5364 MW
Generator 3: Power Output = 27.9675 MW
Generator 4: Power Output = 183.3334 MW
Generator 5: Power Output = 75.2181 MW
Generator 6: Power Output = 99.0091 MW
Total cost: 2123.38
```

Fig.6.14:Total cost of the generator units python

6.6 VOLUME PREDCTION

Volume prediction, which involves estimating the amount of power or energy that will be consumed during a particular period of time, is a crucial component of energy market forecasting. Volume prediction is a typical use of machine learning technique Long Short-Term Memory (LSTM) models, which are based on previous consumption data and relevant variables. These models capture seasonality, trends, and irregular patterns to generate accurate forecasts, aiding in resource allocation and demand-side management. Accurate estimations of volume prevent shortages or overproduction, maximize fuel and resource utilization, save operating expenses, and preserve grid stability.

```
Forecasted Volume: 111.36 & Actual: 84.60
```

Fig.6.15: Volume prediction using lstm

6.7 PRICE TAGGING

Pricing strategies are essential in deciding how much electricity costs in deregulated power systems. Simple approaches like cost-plus pricing or averaging may ignore certain factors in the market like changes in supply and demand. Markup pricing may not accurately represent current market conditions since it adds a percentage to cover expenditures and targeted profit. Based on past price distribution, Quantile pricing targets distinct market segments and enables adaptable adjustments in response to shifting market trends. Additionally approach, taking into account elements like market analysis and minimum profit margins guarantees competitive pricing strategies that are in line with market dynamics. Deregulated power systems can improve overall efficiency and sustainability by optimizing electricity prices to balance cost coverage and market competitiveness by implementing these techniques.

```
Generation Cost from GA: 1429.57
Forecasted Cost from LSTM: 3100.87
----------
Average Approach Price: 2065.23
Cost-Plus Pricing: 2429.57
Mark-up Pricing: 2287.32
Quantile Approach: 2192.36
Additional Approach: 2573.23
```

Fig.6.16: Price tagging using different methods

6.8 PRICE QUOTING

The additional approach to pricing emerges as robust within deregulated power systems. Although there are worries that seller greed may result in excessive profits, this strategy guarantees profitability while keeping bidding prices within a desirable range. With its consideration of minimum profit margins and thorough market analysis, the extra method encourages pricing that is sustainable and equitable for sellers as well as buyers. In deregulated power markets, it creates a more equitable and mutually beneficial environment by striking a balance between profitability and economic efficiency.

```
Generation Cost from GA: 1429.57
Forecasted Cost from LSTM: 3100.87
----------
Bidding Quote Price: 2573.23
Profit Margin: 1143.66
Profit: 80.00%
```

Fig.6.17: Price quoting using additional approach method

6.9 SUMMARY

This chapter explores the implementation and evaluation of diverse models - ARIMA, SARIMA, and LSTM - as potent tools for predicting MCP in deregulated energy markets. While traditional time series analysis methods like ARIMA and SARIMA provide valuable insights into historical price patterns, advanced techniques such as LSTM networks offer enhanced predictive capabilities by capturing long-term dependencies in data. The comparison reveals that LSTM models consistently outperform ARIMA and SARIMA in terms of predictive accuracy and performance, showcasing their efficacy in optimizing economic load dispatch strategies and ensuring sustainable energy pricing. Integrating LSTM's superior forecasting abilities with traditional methodologies presents a comprehensive approach to tackling the challenges of MCP prediction in deregulated energy markets, ultimately enhancing strategic decision-making and operational efficiency.

By accurately forecasting consumption trends, LSTM models enable volume prediction, which supports effective resource allocation and demand-side management in energy markets. In deregulated power systems, pricing techniques like quantile pricing and the extra approach balance cost coverage and market competitiveness to ensure equal and competitive electricity rates. By avoiding shortages, maximizing resource consumption, and preserving grid stability, these techniques maximize efficiency and sustainability. The other strategy proves to be effective in ensuring profitability and promoting equity and reciprocity in deregulated electricity markets.

Chapter 7

CONCLUSION

In conclusion, the evaluation of Market Clearing Price prediction models highlights the remarkable performance of both the ARIMA and SARIMA models in forecasting MCP values within a deregulated power market. The ARIMA model, rooted in time series analysis, demonstrated solid predictive capabilities with an impressive R-squared value of 0.77, indicating a strong fit to the data. However, the SARIMA model, which extends ARIMA by incorporating seasonal components, surpassed expectations, showcasing superior performance metrics including higher R-squared values, reduced Root Mean Squared Error (RMSE), and lower Mean Absolute Error (MAE). This enhancement in predictive accuracy underscores SARIMA's adept handling of seasonal variations inherent in MCP datasets. Moreover, the comprehensive comparative analysis solidifies SARIMA's superiority over ARIMA in capturing and effectively utilizing seasonal patterns for MCP prediction.

While Long Short-Term Memory networks offer an alternative approach leveraging sequential data analysis, their performance in predicting MCP values was not explored in depth within this evaluation. However, it's worth noting that LSTM models excel in capturing long-term dependencies and complex patterns in time series data, presenting a potential avenue for further exploration and comparison in future research endeavors.

Overall, this study underscores the importance of considering seasonal variations in MCP prediction tasks within deregulated power markets, with LSTM emerging as a robust and effective modeling approach for forecasting Market Clearing Prices.

In integrating Market Clearing Price (MCP) and Economic Load Dispatch (ELD) values within the context of power market auctions, our approach aims to optimize profit generation while ensuring efficient resource allocation. The ELD value, representing the generation cost derived through a Genetic Algorithm-based optimization process, serves as a benchmark for determining the economic viability of power generation. On the other hand, the MCP reflects the equilibrium price determined by market dynamics, indicating the willingness of market participants to pay for electricity. By comparing the MCP and ELD values, we establish a framework for decision-making in power auctions. Prices above the ELD value but below the MCP are identified as optimal for maximizing profit while ensuring competitiveness in the market. This strategic pricing approach enables market participants to offer electricity at a cost-efficient rate, aligning with economic principles of supply and demand.

Moreover, by utilizing both MCP and ELD values, we enhance the efficiency and fairness of the auction process. The incorporation of ELD values ensures that power generation costs are considered, preventing instances of overpricing that could deter potential buyers. Simultaneously, the utilization of MCP facilitates market equilibrium, allowing for transparent price discovery based on actual market conditions.

In summary, the integration of MCP and ELD values in power market auctions enables participants to make informed pricing decisions, balancing profitability with market competitiveness. This approach fosters a dynamic and efficient marketplace where resources are allocated optimally, ultimately contributing to the stability and sustainability of the power sector.

REFERENCES

[1] K. Nimish, U. Nangia and K. Bhushan Sahay "Economic Load Dispatch Using Improved Particle Swarm Optimization Algorithms", 6th IEEE Power India International Conference (PIICON),pp.15-20, location, 2014.

[2] R. Gupta, A. N. Mahajan, and A. Gaur, "Economic load dispatch problem solution using lambda iteration and genetic algorithm techniques," J. Emerg. Technol. Innov. Res. (JETIR), vol. 6, no. 2, pp.19, 2019.

[3] K. B. Sahay, A. Sonkar, and A. Kumar, "Economic load dispatch using genetic algorithm optimization technique," in ICUE 2018 on Green Energy for Sustainable Development, Thavorn Palm Beach Resort Karon, Phuket, Thailand, pp.20-26, October 2018.

[4] K. K. Vishwakarma, H. M. Dubey, M. Pandit, and B. K. Panigrahi, "Simulated annealing approach for solving economic load dispatch problems with valve point loading effects," MultiCraft Int. J. Eng., Sci. Technol., vol. 4, no. 4, pp. 60-72, 2012.

[5] Surekha P. and S. Sumathi, "Solving economic load dispatch problems using differential evolution with opposition based learning," WSEAS Trans. Inf. Sci. Appl., vol. 9, no. 1, January 2012.

[6] Sinha, N., Chakrabarti, R., Chattopadhyay, P.K. (2003). Evolutionary programming techniques for economic load dispatch. IEEE Transactions on Evolutionary Computation, 7(1):83-94,pp.15 January 2011.

[7] G. Wu, S. Ishida and H. Yin, "DC soltage stabilization in DC/AC hybrid microgrid by co-operative control of multiple energy storages," IEEE Third International Conference on DC Microgrids (ICDCM), pp. 1-5, 2019, doi: 10.1109/ICDCM45535.2019.9232764.

[8] M. De Felice and Xin Yao, "Short-term load forecasting with neural network ensembles: a comparative study," IEEE Computational Intelligence Magazine, vol. 6, no. 3, pp. 47-56, Aug.2011,doi:10.1109/MCI.2011.941

[9] K. K. Vishwakarma, H. M. Dubey, M. Pandit, and B. K. Panigrahi, "Simulated annealing approach for solving economic load dispatch problems with valve point loading effects," MultiCraft Int. J. Eng., Sci. Technol., vol. 4, no. 4, pp. 60-72, 2011

[10] A.H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," IEEE Trans. Smart Grid, vol. 1, no. 2, pp. 120– 133, 2010

[11]Daryl, A. Winata, S. Kumara and D. Suhartono, "Predicting Stock Market Prices using Time Series SARIMA," 2021 1st International Conference on Computer Science and Artificial Intelligence (ICCSAI), Jakarta, Indonesia, 2021, pp. 92-99, doi: 10.11.2009.

[12] Y. Wang and Y. Guo, "Forecasting method of stock market volatility in time series data based on mixed model of ARIMA and XGBoost," in China Communications, vol. 17, no. 3, pp. 205-221, March 2002

[13] G. Dudek, "Combining Forecasts of Time Series with Complex Seasonality Using LSTM-Based Meta-Learning," in Eng. Proc., vol. 39, no. 1, presented at the 9th International Conference on Time Series and Forecasting, Gran Canaria, Spain.vol. 6, no. 2, PP 14-16 ,February 2018.

[14] B. M. Pavlyshenko, "Sales Time Series Analytics Using Deep Q-Learning, MultiCraft Int. J. Eng., Sci. Technol, vol. 6, no. 3, pp. 47-56,Aug.2011, doi:10.1109/MCI.2011.941

TIME FRAME

	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
Literacy Survey for optimization model									
Data Collection									
Analysing Data									
Literacy Survey For ML Model									
Predicting MCP Using Time series									
Economic operational price									
Real time price prediction using ml									
Agent based reinforcement model									
Finalize the algorithm to merge the model and provide a price quote									
Documentation and paper writing									