ELECTRICITY PRICE FORECASTING IN RESTRUCTURED POWER MARKETS

Manoj kumar[1], Amritpal Singh,[2] Fouqat Ishaq[3]

[1,2],Assistant Professor, Department of Electrical Engineering, Desh Bhagat University

Department of Electrical Engineering

Desh Bhagat University, Mandi Gobindgarh, Punjab (147301)

ABSTRACT

The electricity market is particularly complex due to the different arrangements and structures of its participants. If the energy price in this market is presented in a conceptual and well-known way, the complexity of the market will be greatly reduced. Drastic changes in the supply and demand markets are a challenge for electricity prices (EPs), which necessitates the short-term forecasting of EPs. In this study, two restructured power systems are considered, and the EPs of these systems are entirely and accurately predicted using a Gaussian process (GP) model that is adapted for time series predictions. In this modeling, various models of the GP, including dynamic, static, direct, and indirect, as well as their mixture models, are used and investigated. The effectiveness and accuracy of these models are compared using appropriate evaluation indicators. The results show that the combinations of the GP models have lower errors than individual models, and the dynamic indirect GP was chosen as the best **model.**

Keywords: Electricity Prices (EPs), Gaussian Process (GP)

1. INTRODUCTION

Since 1980, changes have been implemented in several areas of the global economy, including banking, ports, railroads, food services, and communication. The applications listed above are required to reduce government control and replace it with free market forces. Similar to this, global restructuring in the electrical sector is occurring. The three somewhat distinct parts of the electrical sector are generation, transmission, and distribution. All three of these vertically related sectors have historically been integrated into one utility in the traditional power system. Numerous power producers were compelled to switch from a single utility structure to a free market system during the 1990s. Due to a variety of factors, markets have changed from being regulated to being unregulated, and modifications have been made in numerous nations. The various countries are impacted by the significant demand increase, inefficient system management, and inconsistent tariff regulations. The financial resources needed to upgrade the production utilities have been impacted by this. This has caused numerous producers to restructure the power market. The utilities offer electricity at discounted rates and have lots of options for buying cheap energy. This reform aims to increase competition, provide consumerswith more options, and provide them with financial advantages (Borenstein et al. 2000). Three principles form the foundation of the reforms. The first concept encourages separating the marketing, transmission, and generation of electricity. These duties are not monopolistic in character and can be carried out by businesses on a competitive basis in place of the government. The second tenet holds that those businesses might be privatized. The privatized businesses are more effective and have improved management techniques. The third principle encourages the creation of institutions to regulate market participants and safeguard the general welfare. Chile implemented the market reforms for electricity first in 1982, after which Norway, Sweden, the United Kingdom, and Finland began the process. More respondents now think that consumer gains from liberalization are significant. Electricity market growth has received a lot of attention in recent years (Hu 2010). The physical characteristics of the electrical market and the fluctuating cost of electricity contribute to market risk. Forecasting of various market indicators, such as the hourly electricity price of the spot market, has become vital to handle such risks in the electrical market. An energy-generating company's ability to make decisions based on an accurate estimate of market prices is crucial.

1.1 ELECTRICITY PRICE FORECASTING

A subset of energy forecasting known as electricity price forecasting (EPF) aims to forecast spot and forward electricity market prices. The price paperions have developed into a key component of the decision-making process for energy corporations. In a market for deregulated electricity, pricing decisions carry risk. Prior knowledge is necessary for marketers to have a competitive advantage while managing risk (Catalao et al. 2007). Electricity, on the other hand, is a particularly unique commodity because it cannot be economically stored and requires an equal balance between supply and demand. The generated electricity must be used because it cannot be stored (Mosbah and El-Hawary 2016). As a tradable commodity, the prices can be purchased and sold. Due to their instability, volatility, seasonality, transportability, and unreasonable tariff regulations, the prices are crucial. Accordingly (Nitin and Mohanty 2015), the price of energy is treated onpar with other commodity markets. First of all, unlike short-term forecasting, mid-term forecasting by definition cannot use the trend from the recent past. Furthermore, it is quite challenging to identify and estimate electricity price peaks for both the short- and long-term future. Finding the peak pricing is typically highly accurate since short-term forecasting may make use of recent trend data. The duration of the historical data required to train the forecasting model is the primary distinction. Typically, the data from the previous few daysare all that are required to train the power price model for short-term forecasting. But in order to train the forecasting model, mid-term and long-term forecasting models need one year of historical data. Short-term planning is therefore taken into account in this context because it is more significant and essential in the open power market. The time frame for the immediate future is a few hours to a few weeks. EPF is a significantly more difficult technique compared to load forecasting. It is because energy has unique qualities that set it apart from other commodities, like its elasticity of demand, which keeps the balance between supply and demand for power constant. Fig. 1.1 (Pandey and Upadhyay 2016) illustrates a straightforward method for price forecasting.

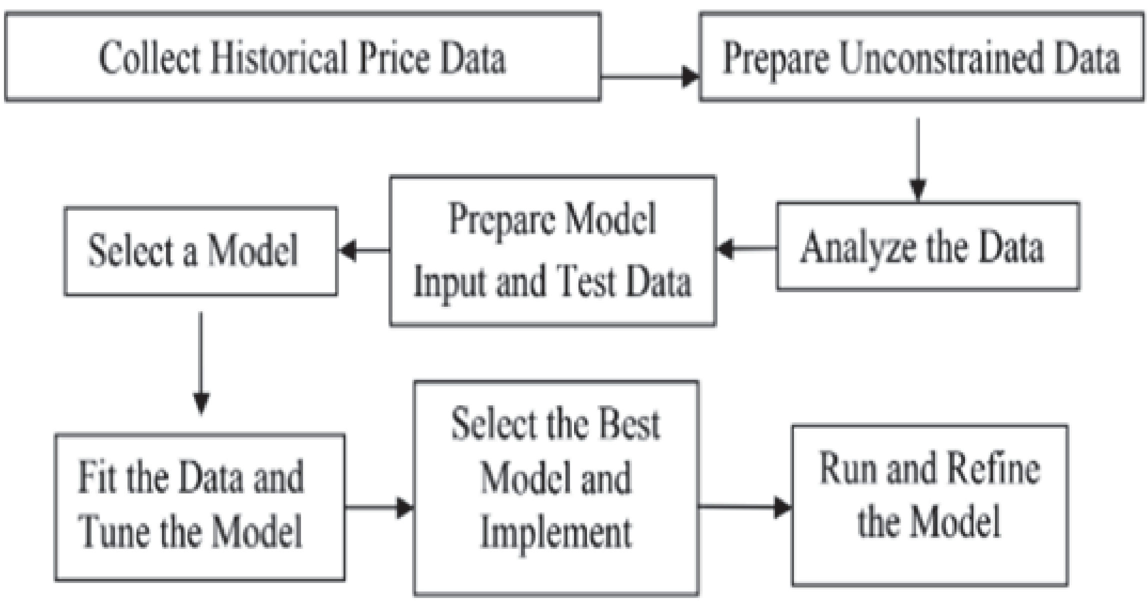


Fig. 1.1 Process of Price Forecasting

1.2 ELECTRICITY PRICE CLASSIFICATION

The demand side actors are more involved when the market structure develops and becomes more sophisticated, such as with smart grids, because they have the freedom and opportunity to react to changes in price above and below specific thresholds. Price classification based on thresholds is preferable to identifying exact numerical values of future prices if marketers opt to manufacture their own power from the market on the basis of market price exceeding a particular price threshold (Shrivastava et al. 2016). Therefore, for market participants, Electricity Price Classification (EPC) is more significant than predicting. For the purpose of classifying pricing, the entire data set is taken into account. A threshold value is used to categorise the prices. The annual price average is used to calculate the threshold value. In order to dynamically classify future, unknowable electricity market prices in relation to user- defined criteria, price categorization and thresholding is used. Because not every market participant must be aware of the precise value of future prices, the price classifications are significant. In electrical markets, it is not necessary to have exact prices in order to reduce the price forecasting problem to a subproblem of price classification, where the class of future prices is of interest. Typically, market prices for energy are categorized in accordance with pre-established price thresholds. Pattern recognition algorithms are typically used toclassify prices.

1.3 INTRODUCTION TO MACHINE LEARNING

Computer science includes the discipline of machine learning (ML). Additionally, it is a sort of artificial intelligence (AI) that makes it possible for programmers to develop programs quickly. More emphasis is placed on creating algorithms that train computers to adapt to new data. In order to grasp and apply the approaches, machine learning (ML) uses an algorithm to complete the task automatically and without human intervention. A "field of study that gives computers the ability to learn without being explicitly programmed" is machine learning (ML). The advantages of ML are the ML will eventually improve itself from its own mistakes. Faster than people. So, it saves time. There are numerous reasons why ML is being used more frequently. The primary explanation is that ML has a system that, after being trained on a few datasets, would eventually learn and get better when given a certain task. The machine learning algorithm puts time into learning from the data that is sent to it or from the errors that it makes. In disorganized datasets, ML is utilized to identify the characteristics of pertinent data. By effectively forecasting future data, the generalization property of ML enables the system to perform well on instances of unknown data. The ML task is carried out in the following manner, step by step:

i. Data collection: Excel or text files with the data that have been gathered. It creates the learning data. The learning component of the learning approach would be better if the quantity of the pertinent data was better.

ii. Data preparation: The analytical procedure is assessed for the quality of the data. The data quality is determined, and a few problems like missing data and handling outliers arise. For a thorough data analysis that expands on the data content, an exploratory methodology is required.

iii. Building a model: This part of the process entails choosing the training set of data. Two subsets of the data are used to train and test the model. Data is trained in order to enhance the model. Test data are utilized as a source of reference.

iv. Evaluating the model: In test data, evaluation is done. This step decides the appropriate method by its output. By building the model, the performance is done. In this step, various models are developed by introducing the set of data to augment the efficiency. The process of ML workflow is shown in Fig. 1.2

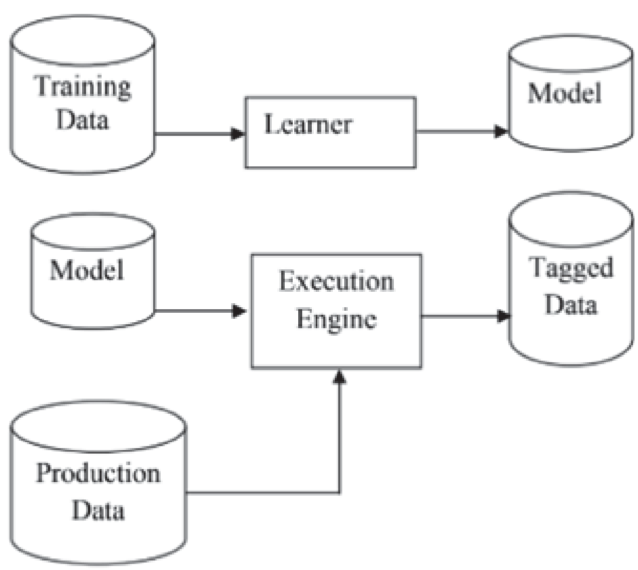


Fig. 1.2 Operational Model of Machine Learning

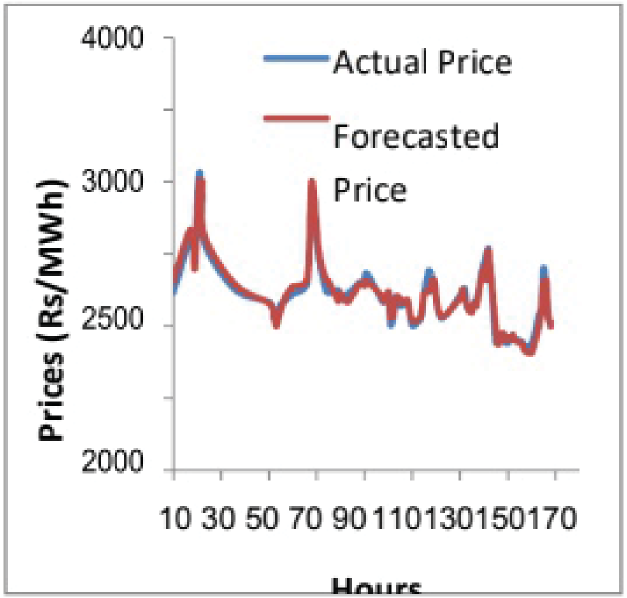
1.4 SUPPORT VECTOR MACHINE

The Support Vector Machine (SVM), the subsequent generation of NNs, is taken into consideration in an effort to decrease the amount of time and knowledge needed to create and train the forecasting models. SVM is one of the ML approaches that Vapnik, (1982), presented. An important tool for classification and regression processes that optimizes the training data is support vector machines (SVM). In comparison to NNs, SVM has less obvious tuneable parameters, therefore effective forecasting performance may depend less on parameter value selection. To solve the SVM problem, various methods are employed. However, due to memory issues, classic optimization algorithms like the Newton technique are rarely used for the classification problem of huge data. As a result, the SVM classification problem is frequently solved using the decomposition method. The initial price series is changed into a sub-optimization problem. The decomposition technique's primary goal is to choose the data set. The working set is limited to two members (Chang 2008). The SVM method is used in Vapnik's work, which involves statistical learning. In order to improve accuracy, the NN classification approach employs structural risk minimization (SRM). SVM can strike a balance between the SRM and a learning machine's capacity for learning. So, according to Zhao et al. (2005), the SVM applies the minimizing of structural risk concept. For linear patterns, SVM applies the aforementioned technique. Kernel functions are utilized for patterns that are not linear. Non-linear data sets can be mapped by SVM into a high-dimensional space. Linear functions are used to identify this new large-dimensional space's borders. SVM provides a problem with an exhaustive solution (Alshejari and Kodogiannis 2017).

RESULTS

The main goal of this research is to quickly assess electricity pricing in various marketplaces using ML approaches. The features from the entire data set are reduced, with some of the characteristics being eliminated as noise from the entire data set, in order to increase computing speed and efficiency. Using feature selection methods, only crucial features are chosen. The aforementioned process is applied to the markets of Austria and India to demonstrate the potential of the ML techniques and FS approaches to generalize. The data set is divided into training and testing data for the Austrian and Indian markets. In the Austrian market, 80% of the data (292 samples) is used for training and 20% for testing (73 samples). The Indian market which consists of 366 days is split as the training data (293 samples) and test data (73 samples).

The leading electricity trading platform in India is called the Indian Energy Exchange (IEX). For players in the energy market, including those in open-access industries, IEX facilitates effective price discovery and price risk management by offering a transparent neutral, demutualized, automated platform for the physical supply of electricity. There are around 4000 participants in this exchange, including utilities from 29 states, 5 U.S. union territories, and more over 1000 private generators. In this study, the training period is based on the prices from the previous 42 days, producing 1008 training instances. The information for energy pricing was gathered from hourly, hourly-presented daily trading reports of an Indian market that were tailored to annual reports. Winter: October 26–November 1, Spring: February 5–11, Summer: June 22–28, and Rainy: September 21–27 are the test dates for the seasons. Given that the test period is one week long and a day has a length of 24 hours, a week has a total of 168 hours. The SFS Algorithm is used to reduce the total number of variables from 168 to 83. The proposed work is examined on an Indian market and the results show the effectiveness of the proposed RVM approach.



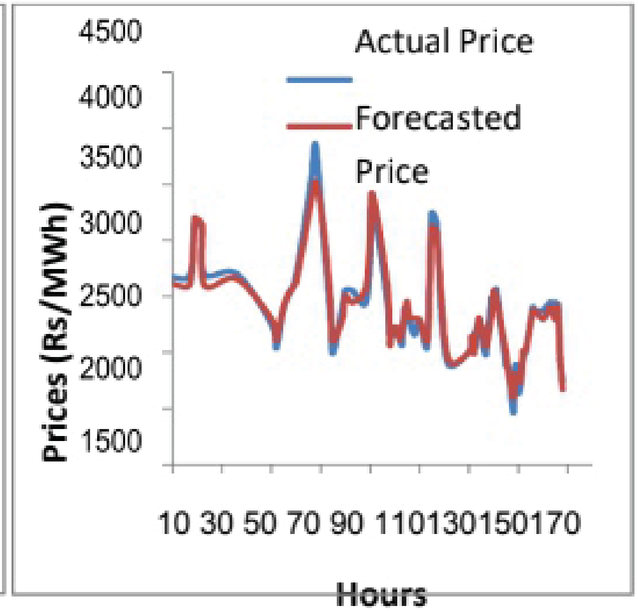
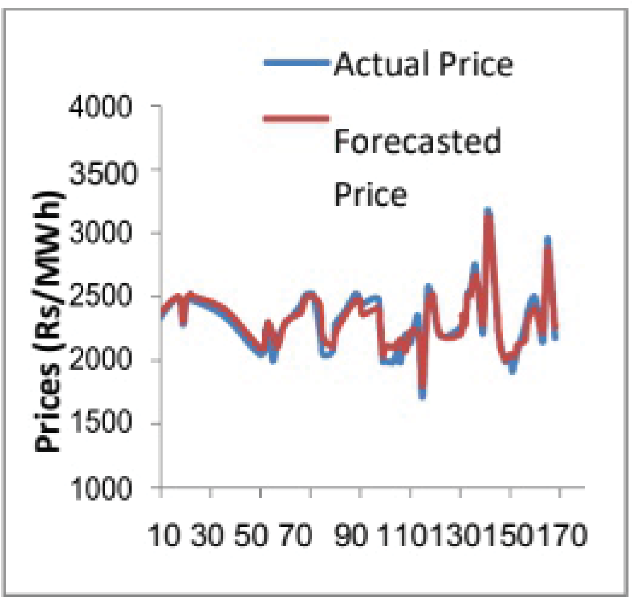


Fig.1.3 Forecasting Results of Oct26-Nov1 Fig.1.4 Forecasting Results of Feb5-11



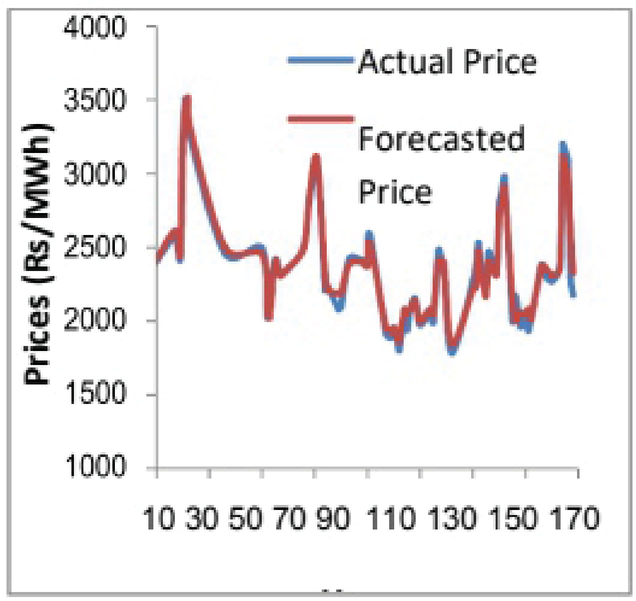


Fig.1.5 Forecasting Results of Jun22-28 Fig.1.6 Forecasting Results of Sep 21-27

The forecasted price obtained with the RVM-SFS during the winter, spring, summer, and rainy seasons along with the actual price as well as the mean absolute value of forecasted errors are shown in Figures 1.5 – 1.6. It can be seen from Figures 1.5 – 1.6 that the predicted prices of each seasonal week are accurately matching with the actual price. Short-term forecasts have become increasingly important since the rise of the competitive electricity markets. It is also required by the producers and consumers to derive their bidding strategies to the electricity market. As given in Figs. the high prices are considered for forecasting daily errors. The period from 150 to 200 days and 310 to 350 days belong to the months of June and December respectively, are considered.

CONCLUSION

The electricity supply has been transformed into a private, unregulated product as a result of the power market reform. Profitability following privatization has evolved into the primary goal for all market participants in such a market setting. Therefore, an initial classification of electricity pricing was done to determine the costs that have an impact on marketers. Based on a threshold value, the prices have been divided into low and high-class pricing. Thresholds have been developed by numerous demand-side market actors to categorize power prices. However, as individuals make decisions based on their decision-making, marketers typically need to know the exact worth of prices. So, in order to compete for market share and to either bid or hedge against volatility in the current upheaval of the deregulated electricity market, electricity price forecasting has been conducted. The price prediction was made in conjunction with the impending price increase. After then, the increase was discovered to lessen the impact of prices on the markets. As a result, a novel method of machine learning-based classifiers for the categorization and forecasting of electricity prices has been developed and described in this study . It has given timely assessments of electricity market pricing. The forecasting has been assessed and spike values have been determined based on the classification. The work is examined in depth and debated. Future Tasks are also provided. Investigated are the results of price classifiers using NN, SVM, CVM, IVM, and RVM for various markets both with and without feature selection. The suggested RVM has been found to be extremely superior in classification compared to other leading machine learning algorithms due to higher classification accuracy and fewer misclassifications in a shorter amount of time. A set of input features have been chosen and applied as input variables to machine learning classifiers using the Sequential Feature Selection (SFS) Algorithm, producing better results than previous feature selection methods. Conclusion: The proposed RVM classifier using the SFS algorithm for feature selection has produced reasonably accurate classification and forecasting results, particularly during periods when the price does not vary significantly between hours and days. The proposed approach's adaptability and robustness have been demonstrated by market testing and the application of a variety of ML algorithms for EPF.

SCOPE FOR FUTURE WORK

The investigation could be extended further to look into mid-term and long-term price forecasts.The choice of more suitable data categorization techniques may be part of future studies; for instance, the input training data may be divided into working days, weekend days, and public holidays. Hybrid models using integrated machine learning techniques may be used to test their further efficacy. Combining decision-making and spike forecasting may be used to better predict spikes and prevent them.

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