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Machine Learning Models for Prediction of Energy Prices in Indian Power-Energy Trading Market

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Abstract:

The Indian day-ahead electricity market operates through power exchanges, such as the Indian Energy Exchange (IEX) and Power Exchange India Limited (PXIL), using a double-sided auction mechanism. However, the market faces challenges in ensuring smooth operations and effective price determination. This paper discusses the complexities and challenges of the Indian day-ahead market and explores the role of machine learning techniques in improving price forecasting accuracy. The challenges include market concentration, infrastructure constraints, renewable energy integration, incomplete market integration, limited demand response mechanisms, and the need for accurate forecasting. To address these challenges, a multi-faceted approach involving policy interventions, regulatory reforms, infrastructure investments, and technological advancements is required. Machine learning techniques, with their ability to capture non-linear relationships, handle high-dimensional data, adapt to changing market dynamics, incorporate multiple data sources, and handle time-series data, offer significant potential for enhancing price forecasting accuracy. The paper also discusses various predictive models, including autoregressive models, moving average models, ARIMA, seasonal ARIMA, and SARIMAX, along with their applications in the Indian electricity market. Additionally, basic ensemble techniques such as weighted averaging, max voting, and averaging are introduced as powerful methods to improve prediction accuracy. By addressing the challenges and leveraging machine learning techniques, the Indian day-ahead market can achieve robust and efficient operations, facilitating efficient electricity trading and delivery.

Keywords: *Electricity Price prediction, Forecasting, Machine learning, Ensemble approaches*

I. INTRODUCTION

The Indian day-ahead market operates within a structured framework, aiming to ensure efficient electricity trading and delivery for the next day. However, it faces several challenges and complexities that need to be addressed for smooth operations and effective price determination. In the Indian day-ahead market, electricity is traded through power exchanges, primarily the Indian Energy Exchange (IEX) and Power Exchange India Limited (PXIL). The market follows a double-sided auction mechanism, where buyers and sellers submit their bids and offers for electricity quantity and price. The market clearing price is determined through the matching of bids and offers, establishing a supply-demand equilibrium. In our daily life, we trade different commodities. One of them, but different and special is electricity. It is a non-storable and requires equilibrium between demand and supply. India is the world's 6th largest energy market. In India, the gross electricity produced in 2019-2020 was 1383.5 TWh. Thermal power plants basically use non-renewable resources such as coal to produce two-third of this total energy. The gross electricity consumed in 2019-2020 was 1208 per capita. The electricity supply still not satisfies the actual requirement of the country.

In many countries power exchanges are formed to trade the electricity. Power exchanges are the auction points where sellers and buyers can bid to trade electricity for their submitted quantity and price. There are two power exchanges functioning in India for power trading named: Power Exchange India Limited (PXIL) and Indian Energy Exchange Limited (IEX). The power exchanges allow the power traders to find a good deal and optimal buyer and seller for trade. Power exchanges directly controls the energy market such as Day Ahead Market, Term Ahead Market, Real Time Market, Green Term Ahead Market, etc. For technical clearance, power exchanges are working in co-ordination with Transmission System Operator (TSO). TSO operates and control the transmission grids and also clears the amount of energy to be transacted over the grid for an instance of time.

IEX is a power exchange in India. Under Electricity Act 2003, Central Electricity Regulatory Commission (CERC) is a statutory authority which approves and regulates the IEX and its activities by various regulations and procedures including Power Market Regulation 2010.

Now the days, IEX enables traders to trade in following segments:

1. Day-ahead market
2. Term-ahead market
3. Renewable Energy Certificates (REC)

In day-ahead trading, traders can quote their offers and bid a day ahead of physical delivery. The exchange aggregates the offers and bids separately and clears the market on the basis of demand supply equilibrium. The intersection point of the demand and supply curve determines the MCP and MCV. This point is called the equilibrium point. For a bid to be cleared the bid price should be higher than or equal to MCP and for a offer to be cleared, the offer price should be lower than or equal to MCP. The orders can be executed fully or partially as per the trader's instructions.

DAM allows traders to trade next-day (D) energy deliverables in one-day (D-1) advance. In day-ahead market, 24 hours of the day is divided into 96 time blocks of 15-15 minutes. These 96 time blocks of the delivery day are start from the midnight i.e. 00:00-00:15, 00:15-00:30, 00:30-00:45, 00:45-01:00, 01:00-01:15 ... and so on. The order (new entry, modification and cancellations) for any, some or all 15 minutes time block of delivery day are placed a day before from 10 o'clock morning to 12 o'clock noon everyday irrespective of holiday. For DAM, IEX defined 13 bid areas. After congestion management through market splitting, IEX determine the price for each area called Area Clearance Price (ACP). Cleared volume for each area is also determined and termed as Area Clearing volume (ACV).

Accurate forecasting can help the participant to understand future behavior of the energy prices. With an accurate price forecast, producer can develop an appropriate strategy to maximize its profit, or a consumer can maximize its utilization. Price prediction is a very complex task; several statistical techniques are available for price forecasting but accuracy are again questionable. Consequently, the evaluation of energy price forecasting models is important step to increase the production and consumption of electricity. Additionally, this ensures a certain level of accuracy. A lot of factor affects energy prices as well as wide range of bidding techniques are in practice of participants. It’s complicates energy prediction.

Despite the progress made, the Indian day-ahead market encounters several challenges:

Market Concentration: The market is characterized by a relatively low number of market participants, leading to limited competition. This concentration can influence price formation and hinder the efficient functioning of the market. Encouraging more players to participate in the market can foster competition and enhance market liquidity.

Infrastructure Constraints: Inadequate transmission infrastructure and grid congestion pose significant challenges for the Indian day-ahead market. Transmission bottlenecks restrict the optimal utilization of generation resources and result in higher costs. Investments in grid infrastructure and expansion are necessary to address these constraints and facilitate efficient electricity trading across regions.

Variable Renewable Energy Integration: The increasing penetration of variable renewable energy sources, such as solar and wind, presents challenges in the day-ahead market. The intermittent nature of renewable generation makes it difficult to accurately forecast and schedule their availability, leading to potential imbalances between supply and demand. Integrating advanced forecasting techniques and implementing flexible market mechanisms can help manage the variability and uncertainty associated with renewable energy integration.

Incomplete Market Integration: The Indian electricity market consists of multiple regional markets that operate with varying rules and regulations. The lack of harmonization and coordination between these regional markets limits the ability to optimize resource allocation and trade electricity seamlessly across regions. Establishing a more unified and integrated market structure can unlock significant benefits in terms of market efficiency and price discovery.

Demand Response and Demand-Side Management: The Indian day-ahead market has limited mechanisms for demand response and demand-side management. Encouraging consumers to actively participate by adjusting their electricity consumption patterns in response to price signals can enhance market efficiency and facilitate better demand-supply matching. The development of demand response programs and incentives can promote consumer engagement and support grid stability.

Forecasting Accuracy: Accurate load forecasting and price forecasting are crucial for the effective functioning of the day-ahead market. However, accurate forecasting becomes challenging due to the inherent uncertainties associated with factors such as weather conditions, consumer behavior, and policy changes. Developing more accurate forecasting models, leveraging advanced data analytics techniques, and incorporating real-time data can help improve forecasting accuracy and enable efficient market operations.

Addressing these challenges requires a multi-faceted approach involving policy interventions, regulatory reforms, infrastructure investments, and technological advancements. Enhancing market transparency, promoting competition, fostering regional market integration, and incentivizing demand response initiatives are essential for ensuring a robust and efficient day-ahead market in India.

II. MACHINE LEARNING FOR EPF

Machine learning techniques play a crucial role in capturing the complexities of the Indian electricity market and improving price forecasting accuracy. The Indian electricity market is characterized by dynamic and non-linear relationships between various factors, such as demand, supply, fuel prices, weather conditions, and government policies. Machine learning algorithms have the capability to analyze large volumes of data, identify intricate patterns, and adapt to changing market dynamics, making them well-suited for addressing the challenges of price forecasting in this context. Here are the key reasons why machine learning techniques are important in capturing the complexities of the Indian electricity market and enhancing price forecasting accuracy:

Non-linear Relationships: Traditional statistical models often assume linear relationships, which may not adequately capture the non-linear dynamics present in the electricity market. Machine learning algorithms, such as support vector machines (SVM), random forests, and neural networks, have the ability to model and learn complex non-linear relationships between input variables and price outcomes. They can capture intricate patterns and correlations that traditional models may overlook, leading to more accurate price forecasts.

Handling High-Dimensional Data: The Indian electricity market involves a wide range of variables that influence price outcomes, including historical price data, demand patterns, weather conditions, fuel prices, renewable energy generation, and economic indicators. Machine learning techniques can handle high-dimensional data effectively and extract relevant features to improve forecasting accuracy. Dimensionality reduction methods, such as principal component analysis (PCA) or feature selection algorithms, can help identify the most influential variables for price prediction.

Adaptability to Changing Market Dynamics: The Indian electricity market is subject to various uncertainties, such as changes in policy, fuel availability, or weather patterns. Machine learning models can adapt to these changes by continuously learning and updating their predictions based on new data. They can capture short-term and long-term trends, identify seasonality, and adjust their forecasts in response to evolving market conditions, enabling more accurate price predictions.

Incorporating Multiple Data Sources: Machine learning techniques allow for the integration of diverse data sources, including historical price data, weather data, economic indicators, and market fundamentals. By incorporating these multiple data sources, machine learning models can capture the interdependencies and interactions among different factors influencing electricity prices in the Indian market. This holistic approach enhances the accuracy of price forecasting by considering a broader range of variables.

Handling Time-Series Data: Price forecasting in the Indian electricity market involves analyzing time-series data, where past prices are indicative of future behavior. Machine learning algorithms, such as autoregressive integrated moving average (ARIMA), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, are specifically designed to handle time-series data. These algorithms can capture temporal dependencies, seasonality, and trends in price data, enabling more accurate predictions for future price movements.

Improved Forecasting Performance: Machine learning techniques have demonstrated superior performance compared to traditional statistical models in electricity price forecasting. They have been shown to provide higher prediction accuracy, better capture extreme events, and exhibit robustness in the face of changing market conditions. By leveraging advanced algorithms and learning from historical data, machine learning models can generate more precise and reliable price forecasts in the Indian electricity market.

PREDICTIVE MODELS

Autoregressive Model (AR)

In an auto regression model, we forecast the variable of interest using a linear combination of past values of the variable. The term auto regression indicates that it is a regression of the variable against itself. Thus, an autoregressive model of order p can be written as

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

where ε_t is white noise. This is like a multiple regression but with lagged values of y_t as predictors. We refer to this as an AR (p) model, an autoregressive model of order p. Autoregressive models are remarkably flexible at handling a wide range of different time series patterns. Changing the parameters $\phi_1 \dots \phi_p$results in different time series patterns. The variance of the error term ε_t will only change the scale of the series, not the patterns.

Moving Average Models (MR)

Rather than using past values of the forecast variable in a regression, a moving average model uses past forecast errors in a regression-like model.

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{q-1},$$

where ε_t is white noise. We refer to this as an MA (q) model, a moving average model of order q. Of course, we do not observe the values of ε_t, so it is not really a regression in the usual sense. Notice that each value of y_t can be thought of as a weighted moving average of the past few forecast errors. However, moving average models should not be confused with the moving average smoothing. A moving average model is used for forecasting future values, while moving average smoothing is used for estimating the trend-cycle of past values.

ARIMA

If we combine differencing with auto regression and a moving average model, we obtain a non-seasonal ARIMA model. ARIMA is an acronym for Autoregressive Integrated Moving Average (in this context, "integration" is the reverse of differencing). The full model can be written as

y′t=c+ϕ1y′t−1+⋯+ϕpy′t−p+θ1εt−1+⋯+θqεt−q+εt,

$$y'_t = c + \varepsilon_t + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q},$$

where y'_t is the differenced series (it may have been differenced more than once). The "predictors" on the right hand side include both lagged values of y_t and lagged errors. We call this an ARIMA (p,d,q) model, where

p = order of the autoregressive part;

d = degree of first differencing involved;

q = order of the moving average part.

The same stationarity and inevitability conditions that are used for autoregressive and moving average models also apply to an ARIMA model

SARIMA

A seasonal ARIMA model is formed by including additional seasonal terms in the ARIMA models we have seen so far. It is written as follows:

SARIMA	(p, d, q)	$(P, D, Q)_m$
	↑↑	↑↑
	Non-seasonal part of the model	Seasonal part of the model

where m= number of observations per year. We use uppercase notation for the seasonal parts of the model, and lowercase notation for the non-seasonal parts of the model.

The seasonal part of the model consists of terms that are similar to the non-seasonal components of the model, but involve backshifts of the seasonal period. For example, an SARIMA (1,1,1)(1,1,1)$_4$ model (without a constant) is for quarterly data (m=4), and can be written as

$$(1-\phi_1 B)\,(1-\Phi_1 B^4)(1-B)(1-B^4)y_t = (1+\theta_1 B)\,(1+\Theta_1 B^4)\varepsilon_t$$

The additional seasonal terms are simply multiplied by the non-seasonal terms.

SARIMAX

SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Variables) is an extension of the SARIMA model that incorporates exogenous variables to improve time series forecasting. SARIMAX combines the autoregressive, integrated, and moving average components of SARIMA with the inclusion of external predictors. These exogenous variables capture additional information that may influence the time series, such as economic indicators, weather data, or demographic factors. By including these variables, SARIMAX can account for their impact on the time series and provide more accurate and robust predictions. SARIMAX is widely used in various fields, including finance, economics, and demand forecasting, where exogenous factors play a significant role in influencing the time series behavior.

ENSEMBLE METHODS (EMs)

I. BASIC ENSEMBLE TECHNIQUES

In this section, we discuss 3 basic but powerful ensemble methods, namely:

- Weighted averaging (WA)
- Max voting (MV)
- Averaging.

Max voting (MV)

The primary application of MV is for a classification task. In the MV technique, several single classifier models are employed to decide on every data-point. The output of every individual or single classifier is taken as a 'vote', the final output (decision) is based on the majority's answer. Let M_1, M_2 and M_3 represent single different classifier models, and x_{train} and y_{train} be training datasets, independent and dependent variables respectively. While x_{test} and y_{test} be independent variables and target variables of the testing dataset, respectively. Let M_1, M_2 and M_3 be trained separately with the same training dataset, thus, M_1.fit(x_{train} and y_{train}), M_2.fit(x_{train} and y_{train}) and M_3.fit(x_{train} and y_{train}), respectively. Let y_{M_1}, y_{M_2} and y_{M_3}, represent the predicted output of the respective models. Then, the final prediction (F_p) is a simple majority vote among the predicted output.

Averaging

The averaging technique is very similar to the MV technique; however, an average of the outputs of all individual or single classifiers represents the final output (decision). However, unlike the MV, the averaging technique can be used for both regression and classification machine learning task. With models {M_1, M_2 and M_3} separately trained and tested with the same dataset, final prediction (F_p)) is the average of individual models.

$$F_P = \sum_{i=1}^{n} \frac{y_i}{n}$$

where $y_1, y_2, \dots, y_n$ are the predicted output of individual models.

Weighted average (WA)

The WA is an extension of the averaging techniques. In WA technique, different weights are assigned to every model signifying the prominence of an individual model for prediction. However, with WA, M_1, M_2 and M_3 are assigned with different weights of say (0.5, 0.2 and 0.7) respectively, then, the final prediction (F_P).

$$F_P = (0.5 \times y_1) + (0.2 \times y_2) +, \dots, + (0.7 \times y_n)$$

II. ADVANCED EL TECHNIQUES

The following section discusses three advanced combination techniques in brief.

Stacking (STK)

Stacking is an EL technique that makes use of predictions from several models ($m_1, m_2, \ldots, m_n$) to construct a new model, where the new model is employed for making predictions on the test dataset. STK seeks to increase the predictive power of a classifier. The basic idea of STK is to "stack" the predictions of ($m_1, m_2, \ldots, m_n$) by a linear combination of weights $a_j, \ldots,$ ($i = 1, \ldots, n$).

$$f_{STK}(x) = \sum_{i=1}^{n} a_i f_i x$$

where the weight vector "a" is learned by a meta-learner.

Blending (BLD)

The blending ensemble approach is like stacking technique. The only difference is that, while stacking uses test dataset for prediction blending uses a holdout (validation) dataset from the training dataset to make predictions. That is predictions take place on only the validation dataset from the training dataset. The outcome of the predicted dataset and validation dataset is used for building the final model for predictions on the test dataset.

Bagging (BAG)

Bagging also called bootstrap aggregating involves combining the outcome of several models (for instance, N number of K-NNs) to acquire a generalized outcome. Bagging employs bootstrapping-sampling techniques to create numerous subsets (bags) of the original train dataset with replacement. The bags created by the bagging techniques severs as an avenue for the bagging technique to obtain a non-discriminatory idea of the sharing (complete set). The bags' sizes are lesser than the original dataset. Some machine learning algorithms that use the bagging techniques are bagging meta estimator and random forest. BAG seeks to decrease the variance of models.

Boosting (BOT)

Boosting also called "meta-algorithm" is a chronological or sequential process, where each successive model tries to remedy or correct the errors of the preceding model. Here, every successive model depends on the preceding model. A BOT algorithm seeks to decrease the model's bias. Hence, the boosting techniques lump together several weak-learners to form a strong leaner. However, the single models might not achieve better accuracy of the entire dataset; they perform well for some fragment of the dataset. Therefore, each of the single models substantially improves (boosts) the performance of the ensemble. Some commonly boosting algorithms are AdaBoost, GBM, XGBM, Light GBM and CatBoost.

IV. CONCLUSION

In conclusion, the Indian day-ahead market operates through power exchanges, such as the Indian Energy Exchange (IEX) and Power Exchange India Limited (PXIL), using a double-sided auction mechanism. However, the market faces various challenges that hinder its efficiency and price determination. These challenges include market concentration, infrastructure constraints, variable renewable energy integration, incomplete market integration, limited demand response and demand-side management mechanisms, and forecasting accuracy. To address these challenges, a multi-faceted approach is required involving policy interventions, regulatory reforms, infrastructure investments, and technological advancements. This paper has explored the application of machine learning techniques in electricity price prediction and analyzed the current state of the field. Through an extensive examination of literature and research studies, several key findings have emerged. Firstly, it is evident that machine learning algorithms offer significant potential in accurately forecasting electricity prices. Machine learning techniques play a crucial role in capturing the complexities of the Indian electricity market and improving price forecasting accuracy. Traditional statistical models may not adequately capture the non-linear relationships and high-dimensional nature of the market. Machine learning algorithms, such as support vector machines (SVM), random forests, and neural networks, can handle non-linear relationships, high-dimensional data, and adapt to changing market dynamics. They can also incorporate multiple data sources, handle time-series data, and provide improved forecasting performance compared to traditional models. Some of the predictive models used in the Indian day-ahead market include autoregressive models (AR), moving average models (MA), autoregressive integrated moving average models (ARIMA), seasonal ARIMA models (SARIMA), and SARIMAX models (seasonal ARIMA with exogenous variables). These models capture different aspects of the market dynamics and help in generating accurate price forecasts. Ensemble methods, such as weighted averaging, max voting, and averaging, are also employed in the Indian day-ahead market. These methods combine the predictions of multiple individual models to improve the overall forecasting performance and enhance decision-making. These models leverage historical price data, weather information, economic indicators, and other relevant factors to capture the complex dynamics of electricity price fluctuations. Secondly, the feature selection process plays a crucial role in improving the performance of electricity price prediction models. Effective feature selection techniques, such as correlation analysis, recursive feature elimination, and principal component analysis, help identify the most influential variables and reduce dimensionality, leading to more accurate and efficient predictions. Furthermore, the integration of external factors, such as renewable energy generation, demand-side management, and policy changes, has been shown to enhance the predictive capabilities of machine learning models. Incorporating these factors provides a more comprehensive understanding of the electricity market dynamics and improves the accuracy of price forecasts. However, challenges remain in the field of electricity price prediction using machine learning. The limited availability of high-quality and up-to-date data, data preprocessing issues, and model interpretability concerns are some of the hurdles that researchers and practitioners need to address. Furthermore, the dynamic nature of electricity markets necessitates continuous model adaptation and retraining to maintain accuracy over time. In conclusion, machine learning techniques have demonstrated great potential in accurately predicting electricity prices. Continued research and advancements in data availability, feature selection methods, and model interpretability will contribute to further improvements in the accuracy and applicability of electricity price prediction models. As these models continue to evolve, they hold the promise of enabling more informed decision-making, risk management, and efficient utilization of electricity resources in various sectors, such as energy trading, renewable energy integration, and demand response programs.

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