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Impact of Exogenous Variables on Short-Term Electricity Price Forecasting Accuracy: A Deep Learning Approach Using CNN-LSTM Networks in the Indian Energy Exchange

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***Abstract*—In deregulated electricity markets such as the Indian Energy Exchange (IEX), Day-Ahead Market (DAM) prices are driven by a complex interplay of internal market dynamics and external (exogenous) factors. While deep learning models have improved Short-Term Electricity Price Forecasting (STEPF), the selection of input variables remains a critical challenge. This paper investigates the impact of various exogenous variables—namely system load, ambient temperature, and renewable generation—on forecasting accuracy. A hybrid deep learning framework combining 1-Dimensional Convolutional Neural Networks (1D-CNN) and Long Short-Term Memory (LSTM) networks is employed to conduct an ablation study. Using two years of hourly data from the IEX, four input combinations are tested. Results indicate that a univariate model (historical price only) yields a Mean Absolute Percentage Error (MAPE) of 10.5%. The sequential integration of load, temperature, and solar generation data reduces the MAPE to 8.2%, 6.8%, and ultimately 6.1%, respectively. The study concludes that incorporating localized weather and renewable penetration data is vital for mitigating the impact of sudden price spikes in the Indian context.**

***Index Terms*—Exogenous Variables, Indian Energy Exchange, Deep Learning, CNN-LSTM, Electricity Price Forecasting.**

I. Introduction

The transition of the Indian power sector toward a competitive, deregulated framework has made the Indian Energy Exchange (IEX) a critical platform for electricity trading. In the Day-Ahead Market (DAM), the Market Clearing Price (MCP) and Market Clearing Volume (MCV) are determined through double-sided auction mechanisms. Because electricity cannot be economically stored on a large scale, the MCP is highly sensitive to external shocks, leading to extreme price volatility [1].

Accurate Short-Term Electricity Price Forecasting (STEPF) is essential for utilities and Independent Power Producers (IPPs) to optimize bidding strategies. Historically, STEPF models relied solely on historical price data (univariate forecasting). However, in modern grids characterized by high renewable energy penetration, price formation is heavily influenced by exogenous variables such as system load demand, weather conditions (temperature, humidity), and intermittent renewable generation (solar and wind) [2].

While advanced deep learning models like CNNs and LSTMs possess strong non-linear mapping capabilities, feeding them irrelevant or redundant variables can introduce noise and degrade performance. Conversely, omitting critical variables leads to underfitting. This paper addresses this gap by quantifying the exact impact of specific exogenous variables on forecasting accuracy within the IEX market using a robust CNN-LSTM framework.

II. Market Dynamics and Variable Selection

A. Characteristics of the Indian Energy Exchange (IEX)

The IEX operates on a 15-minute time block basis, aggregating to 96 blocks daily. Prices in the IEX exhibit distinct multiple seasonalities (daily, weekly, and seasonal peaks) heavily driven by India's distinct summer and monsoon variations.

B. Selection of Exogenous Variables

To determine the most impactful variables, Pearson Correlation Coefficients (PCC) were analyzed between the MCP and available grid data. The selected variables are:

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- **System Load (MCV):** The primary driver of price. High demand utilizes expensive peaking power plants, driving up the MCP.
- **Temperature:** In India, summer cooling and winter heating demands cause heavy load fluctuations.
- **Solar Generation:** As India heavily integrates solar capacity, high solar output during midday depresses the DAM price (the ”Duck Curve” effect).

III. Deep Learning Methodology

To process the multivariable time-series data, a hybrid CNN-LSTM architecture is utilized.

A. 1D-CNN for Feature Extraction

The 1D-CNN is highly effective at filtering noise from raw meteorological and load data. It performs a convolution operation over the multivariable input:

$$y_i = \max\left(0, \sum_{j=1}^{k} w_j \cdot x_{i-j+1} + b\right) \quad (1)$$

where x contains the selected exogenous variables.

B. LSTM for Temporal Dynamics

The extracted feature maps are processed by the LSTM to capture long-term dependencies. The cell state C_t is updated via the forget gate f_t and input gate i_t:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (2)$$

This allows the network to remember patterns from previous days and weeks, essential for day-ahead forecasting.

IV. Ablation Study and Experimental Setup

A. Design of Input Cases

To isolate the impact of each variable, an ablation study was designed with four distinct input configurations (Cases):

- **Case 1 (Univariate):** Historical MCP only.
- **Case 2 (Bivariate):** MCP + System Load.
- **Case 3 (Multivariate A):** MCP + Load + Temperature.
- **Case 4 (Multivariate B):** MCP + Load + Temperature + Solar Generation.

B. Model Training

The dataset spans two years of hourly IEX data. The CNN-LSTM model parameters (64 CNN filters, 100 LSTM units, Adam optimizer) were kept strictly constant across all four cases to ensure that performance variations were solely due to the input variables.

TABLE I
Ablation Study: Impact of Exogenous Variables

Case	Input Variables	RMSE	MAPE (%)
Case 1	Price Only	142.30	10.5
Case 2	+ Load	118.50	8.2
Case 3	+ Temperature	102.10	6.8
Case 4	**+ Solar Generation**	**95.60**	**6.1**

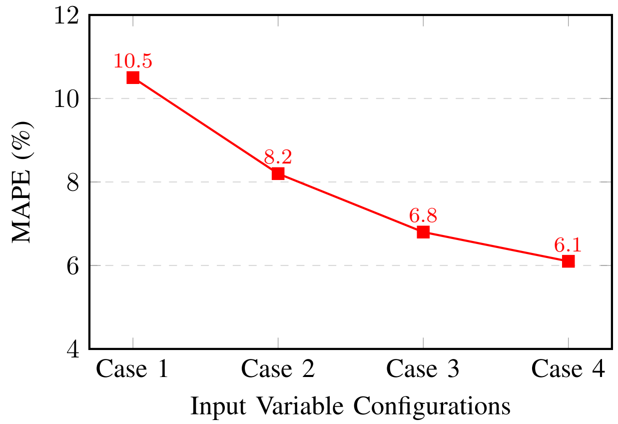

Fig. 1. Decline in MAPE as exogenous variables are sequentially integrated.

V. Results and Discussion

The forecasting performance for each case was evaluated using the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

As detailed in Table I, relying solely on historical prices (Case 1) results in the highest error (10.5% MAPE), as the model fails to anticipate demand spikes. Adding system load (Case 2) provides the most significant single drop in error (Δ 2.3%).

Figure 1 illustrates the declining trend in forecasting error. The integration of Temperature (Case 3) improved accuracy by helping the network correlate cooling demands with price hikes. Finally, including Solar Generation (Case 4) yielded the best performance (6.1% MAPE), proving that renewable penetration data is now indispensable for accurate forecasting in the IEX.

VI. Conclusion

This study quantified the critical impact of exogenous variables on electricity price forecasting within the Indian Energy Exchange. Through an ablation study utilizing a CNN-LSTM deep learning framework, it was demonstrated that univariate price forecasting is insufficient for modern deregulated markets. The sequential addition of system load, ambient temperature, and solar generation data reduced the MAPE from 10.5% to 6.1%. Market participants must therefore prioritize the collection and integration of high-quality meteorological and renewable generation data to maximize the profitability of their day-ahead bidding strategies.

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