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ARTICLE

Advanced Nodal Pricing Strategies for Modern Power Distribution Networks: Enhancing Market Efficiency and System Reliability

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ABSTRACT: Nodal pricing is a critical mechanism in electricity markets, utilized to determine the cost of power transmission to various nodes within a distribution network. As power systems evolve to incorporate higher levels of renewable energy and face increasing demand fluctuations, traditional nodal pricing models often fall short to meet these new challenges. This research introduces a novel enhanced nodal pricing mechanism for distribution networks, integrating advanced optimization techniques and hybrid models to overcome these limitations. The primary objective is to develop a model that not only improves pricing accuracy but also enhances operational efficiency and system reliability. This study leverages cutting-edge hybrid algorithms, combining elements of machine learning with conventional optimization methods, to achieve superior performance. Key findings demonstrate that the proposed hybrid nodal pricing model significantly reduces pricing errors and operational costs compared to conventional methods. Through extensive simulations and comparative analysis, the model exhibits enhanced performance under varying load conditions and increased levels of renewable energy integration. The results indicate a substantial improvement in pricing precision and network stability. This study contributes to the ongoing discourse on optimizing electricity market mechanisms and provides actionable insights for policymakers and utility operators. By addressing the complexities of modern power distribution systems, our research offers a robust solution that enhances the efficiency and reliability of power distribution networks, marking a significant advancement in the field.

KEYWORDS: Nodal pricing; distribution networks; optimization; renewable energy; pricing accuracy; system reliability

1 Introduction

1.1 Background and Motivation

Locational marginal pricing (LMP) is a fundamental pricing mechanism in electricity markets which is also called as nodal pricing which is designed to reflect the true cost of delivering power to different locations within a network. The method helps optimize electricity transmission and generation by indicating the producing cost an additional electricity unit at different points within the power grid. Originally developed for wholesale electricity markets, nodal pricing has gained prominence due to its capacity to handle congestion, integrate renewable energy sources, and ensure efficient resource allocation [1].

In traditional transmission networks, the primary challenge lies in managing the congestion and balancing supply with demand across a vast and intricate network. The nodal pricing mechanism addresses this challenge by setting prices at different nodes based on the marginal cost of electricity, which includes generation costs, transmission losses, and congestion costs. This pricing system motivates power plants to operate efficiently and consumers to use electricity wisely [2]. However, while nodal pricing has been successful in wholesale markets, its application to distribution networks where end-users are connected and presented new complexities and opportunities.

Distribution networks, the final stage of the electricity supply chain, have historically been less dynamic compared to transmission networks. These networks transport electricity from power plants to homes, businesses, and industries. Modern technologies like smart meters and data analysis are dramatically improving how electricity is delivered. These technologies offer the potential to enhance operational efficiency, improve demand response, and integrate distributed energy resources (DERs) such as batteries and solar panels. Although progress has been made, the application of nodal pricing in distribution networks is still not extensively studied [3].

The importance of adapting nodal pricing to distribution networks lies in addressing the evolving challenges of modern electricity grids. As distribution networks become more complex with the inclusion of decentralized generation and variable renewable energy sources, traditional pricing methods may no longer be sufficient [4]. Nodal pricing in distribution networks could provide more granular and accurate price signals, reflecting local supply and demand conditions and encouraging efficient energy use. However, making these changes requires overcoming several technical and operational hurdles, such as managing network limitations, using real-time data effectively, and developing advanced problem-solving methods.

Our research seeks to investigate the practicality and advantages of introducing a novel Hybrid Nodal Pricing Model (HNPM) for distribution networks. The HNPM seeks to combine traditional nodal pricing methodologies with advanced machine learning techniques to enhance pricing accuracy and network efficiency [5]. By integrating real-time data from smart meters and weather forecasts with predictive models and optimization algorithms, the HNPM aims to provide more precise and dynamic pricing signals. This approach promises to improve the management of network constraints, optimize resource allocation, and better align prices with actual supply and demand conditions.

1.2 Objectives

This research has three main objectives. The first is to assess the effectiveness of the HNPM in delivering precise price forecasts and managing network constraints. Second, to compare the performance of the HNPM with conventional nodal pricing models in terms of pricing accuracy, operational efficiency and network stability. Third, to assess the potential benefits of the HNPM for both utility operators and consumers, including the impact on energy consumption patterns and cost savings.

By using machine learning and real-time data, we propose and test a new approach to adapting pricing to modern electricity grids. Our findings aim to help policymakers, energy companies, and researchers improve the efficiency and reliability of electricity distribution as the energy sector evolves.

2 Literature Review

Nodal pricing, also known as locational marginal pricing (LMP), has evolved significantly since its inception in the early 1990s. Initially proposed as a means to manage congestion in transmission networks and ensure efficient electricity pricing, nodal pricing was first implemented in markets such as PJM Interconnection in the United States. The primary goal was to reflect the true cost of delivering electricity, considering both generation costs and transmission constraints. Over time, key milestones include the expansion of LMP to other regions, the integration of renewable energy sources, and the development of more sophisticated models to handle increasing market complexity. The evolution of nodal pricing has also been marked by regulatory changes and technological advancements, which have enabled more precise and dynamic pricing mechanisms.

2.1 Current Strategies and Approaches

Existing nodal pricing strategies employed in electricity markets are designed to ensure the efficient allocation of resources while maintaining grid stability. These strategies typically involve real-time and day-ahead markets, where prices are determined based on supply and demand conditions, generation costs, and network constraints. In practice, operators use sophisticated software tools to calculate LMPs at various nodes in the network, ensuring that prices reflect the marginal cost of supplying an additional unit of electricity at each location. For instance, Bhusan et al. (2024) highlighted the use of AI-enhanced cost-based pricing strategies for optimal transmission expansion planning, demonstrating the growing role of advanced algorithms in refining nodal pricing models [6].

2.2 Technological Advancements

Technological advancements, particularly in smart grids, artificial intelligence (AI), and other digital innovations, have played a crucial role in advancing nodal pricing mechanisms. Smart grids, equipped with advanced sensors and communication technologies, facilitate real-time monitoring and control of electricity flows, enhancing the accuracy and responsiveness of nodal pricing. AI and machine learning algorithms are increasingly being used to predict demand patterns, optimize grid operations, and improve the precision of price signals. For example, Kumar et al. (2024) discussed the application of various optimization techniques, including Particle Swarm Optimization (PSO) and JAYA, to minimize losses and improve voltage profiles in distribution networks [7]. Similarly, Zhang et al. (2024) explored the use of multiagent-based reinforcement learning for low-carbon demand management, showcasing how AI can address the complexities of modern power systems [8].

Moreover, the integration of renewable energy sources and the need for flexible grid management have driven the development of advanced nodal pricing models. These models now incorporate factors such as carbon emissions, as illustrated by Yang et al. (2024), who proposed a novel pricing method to incentivize the development of flexible loads and reduce network costs [4]. The ongoing digital transformation of the energy sector, characterized by the deployment of smart meters, distributed energy resources (DERs), and AI-driven analytics, continues to push the boundaries of nodal pricing, making it more adaptive and efficient in managing the evolving demands of modern electricity markets [9].

3 Methodology

The methodology for implementing and evaluating the Hybrid Nodal Pricing Model (HNPM) involves data collection, machine learning model development, optimization algorithms, and validation processes. Each step is described in detail below.

3.1 Data Collection

3.1.1 Data Sources

Smart Meters

Smart meters provide real-time measurements of electricity consumption across various nodes in the distribution network. These nodes could be residential, commercial, or industrial. The data collected includes [10]:

Load Demand $L(t)$: The amount of electricity consumed at node *iii* at time t. The load demand for each node can be expressed as [11]:

$L_i(t)$ = Measured load at node i at time t

here, $L_i(t)$ represents the power consumption in megawatts (MW) or kilowatts (kW) at node i.

Weather Forecasts

Weather conditions significantly impact renewable energy generation and load profiles. Relevant parameters include:

Temperature $T(t)$: Affect the efficiency of renewable energy sources and can be represented as [12]:

$T(t)$ = Temperature at time t in degrees Celsius ($^\circ C$)

which plays a significant role in the efficiency of renewable energy generation in distribution network. Temperature variations directly impact the performance of photovoltaic systems, as higher temperatures can reduce the efficiency of solar panels. This reference provides a foundational equation and theoretical support for modeling temperature as a time-dependent variable, making it essential for accurately predicting the performance of solar energy systems within the dynamic pricing framework.

Wind Speed $W_s(t)$ impacts the output of wind turbines. Wind speed can be modeled as [13]:

$W(t)$ = Wind speed at time t in meters per second (m/s)

Solar Radiation (t): Affects the output of solar panels and is measured in [14]:

(t) = Solar radiation at time t in watts per square meter (W/m^2)

Historical Load Data

Historical load data is crucial for training predictive models. It includes past load demands which help in understanding patterns and forecasting future loads [15]:

Historical Load Profiles $L_{hist}(t)$: $L_{hist}(t)$ = Historical load data at time t collected over previous periods which is a critical component in training predictive models for electricity demand forecasting. Historical load profiles help in identifying consumption patterns and trends, which are necessary for optimizing load predictions. This reference supports the inclusion of historical demand data in the comprehensive data vector $D(t)$, which forms the basis for machine learning models employed in load forecasting and nodal price optimization. Its relevance lies in establishing the connection between past demand patterns and predictive modeling techniques.

At any given time t, the data vector D(t) combines all the collected data [16]:

$$D(t) = \{L(t), R(t), W(t)\} \tag{1}$$

where $L(t)$ represents the load demand, $R(t)$ represents the renewable energy generation, $W(t)$ is a vector of weather parameters affecting both load and generation.

This comprehensive data vector forms the basis for training machine learning models and for the optimization process.

3.2 Machine Learning Models

3.2.1 Load Forecasting Using LSTM

LSTM networks excel at handling data that unfolds over time, such as electricity demand, by effectively capturing and remembering past patterns. LSTM networks function by using internal components called gates and a cell state to manage the information flow through out a network [17]:

Input Gate i_t:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{2}$$

The amount of new information stored in the cell state has been regulated by the input gate.

The sigmoid activation function, denoted as σ is defined as:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

This function maps the input to a range between 0 and 1, which is crucial for controlling the amount of information passed through the gates. The sigmoid function is used in the input, forget, and output gates due to its ability to compress values into this range, making it suitable for decisions about retaining or discarding information.

Forget Gate f_t [18]:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{4}$$

This gate determines which information from the previous cell state should be retained or discarded.

Output gate o_t [19]:

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{5}$$

The output gate decides which part of the cell state information is used to generate the next hidden state.

Cell State Update c_t [20]:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tan h\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{6}$$

Cell state c_t updated depends on previous cell state c_{t-1} and the new input. $\tan h$ is the hyperbolic tangent function defined as [21]:

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{7}$$

It outputs values between −1 and 1, providing a normalized range that helps in maintaining stable updates.

Hidden State Output h_t [22]:

$$h_t = o_t \cdot \tanh(c_t) \tag{8}$$

Hidden state h_t is output of LSTM cell, representing the forecasted load.

The input gate is responsible for selecting the new information that should be incorporated into the cell state, taking into account the current input and the network's previous state. Meanwhile, the forget gate identifies which parts of the previous cell state need to be discarded. Finally, the output gate controls how much of the updated cell state should be utilized to inform the next prediction [23].

3.2.2 Price Prediction Using Regression

Regression models predict prices by analyzing historical data and current conditions. Gradient Boosting Regression is chosen as it is able to capture complex patterns in data and deliver highly accurate predictions.

The predicted price P_t at time t is a function of: Load Demand $L(t)$, Renewable Generation $R(t)$, Weather Conditions $W(t)$.

The regression function f can be represented as [24]:

$$P_t = f(L(t), R(t), W(t)) \tag{9}$$

where f is a trained model that estimates the price based on input features. The function f is learned using historical data and optimized to minimize prediction errors.

3.3 Optimization Algorithms

3.3.1 Objective Function

Aim of this optimization is to minimizing the total cost of the system, which comprises:

Generation Costs $C_g(i)$ [25]:

$$C_g(i) = C_{gi} \cdot P_i \tag{10}$$

where C_{gi} is the cost per unit of generation for generator i and P_i is the power generated by generator i.

Transmission Losses $C_l(j)$ [26]:

$$C_l(j) = \lambda_j \cdot \left(P_j^2\right) \tag{11}$$

where λ_j is the loss coefficient for transmission line j and P_j is the power flow through the line.

Congestion Costs $C_c(k)$:

$$C_c(k) = \text{Penalty cost due to congestion in line } k \tag{12}$$

This cost arises when power transmission exceeds the line's capacity, resulting in inefficiencies.

Using Eqs. (10)–(12), the total system cost C is [27]:

$$C = \sum_{i\in G} C_g(i) + \sum_{j\in L} C_l(j) + \sum_{k\in CN} C_c(k) \tag{13}$$

here G stands for generators, L stands for lines and CN stands for Congestion. $C_g\,(i)$ is the generation cost, $C_l\,(j)$ is the transmission loss and $C_c(k)$ is the congestion cost.

Each of these costs is influenced by operational decisions, infrastructure characteristics, and external factors such as demand patterns and weather conditions. The goal of the optimization is to minimize this total cost while ensuring reliable and sustainable electricity delivery, balancing economic efficiency with operational constraints.

3.3.2 Constraints

Power Balance

Maintains power balance by ensuring generation equals consumption [28]:

$$\sum_{i\in Generators} P_i - \sum_{j\in Loads} L_j = 0 \tag{14}$$

This constraint maintains equilibrium in the power system.

Transmission Line Limits

Ensures that power flow through each transmission line does not exceed its maximum capacity [29]:

$$P_{line} \le P_{line}^{\max} \tag{15}$$

where P_{line} denotes actual power flow and $P_{line}^{\max}$ denotes maximum allowable power flow for the line.

Generation Limits

Ensures that each generator operates within its specified capacity range [30]:

$$P_{gen}^{\min} \le P_i \le P_{gen}^{\max} \tag{16}$$

where $P_{gen}^{\min}$ and $P_{gen}^{\max}$ denotes minimum & maximum generation capacities of generator i.

3.4 Optimization Method

Mixed-Integer Linear Programming (MILP)

It is a technique used to optimize a linear objective function, aiming to either maximize or minimize it. This method adheres to a set of linear constraints and can handle both continuous variables, such as power levels, and discrete variables, like the status of generators. The formulation of the MILP for this problem is [31]:

$$Minimize\ C\ Subject\ to: \begin{cases} \sum_{i\in Gen} P_i - \sum_{j\in Loads} L_j = 0 \\ P_{line} \le P_{line}^{\max} \\ P_{gen}^{\min} \le P_i \le P_{gen}^{\max} \end{cases} \tag{17}$$

Optimization solvers like CPLEX or Gurobi are used to find the optimal solution by evaluating various feasible solutions.

3.5 Validation

3.5.1 Comparative Analysis

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|P_t^{actual} - P_t^{predicted}\right| \tag{18}$$

It measures the equal size of prediction errors without considering if they are over or underestimates [21].

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(P_t^{actual} - P_t^{pred}\right)^2} \tag{19}$$

It quantifies the average magnitude of prediction errors by first squaring the differences between predicted and actual values, then computing their mean, and finally taking the square root. This approach assigns greater importance to larger errors.

Operational Efficiency

In assessing the operational efficiency of the proposed nodal pricing model, the study thoroughly examines several key elements to understand both system costs and network stability. The analysis begins with a detailed evaluation of the total system cost, which includes not only the direct costs associated with electricity generation and procurement but also the operational and maintenance expenses of the distribution network support the economic and reliability analysis of the nodal pricing model [32]. This comprehensive cost assessment is crucial for determining the economic viability of the model. Next, the study investigates line loading, which involves analyzing how electrical load is distributed across the network's transmission lines.

This helps identify any potential overloading issues that could impact system performance and reliability. Additionally, system reliability is assessed by evaluating how effectively the network maintains stable operations under varying conditions, such as fluctuating demand or unforeseen outages. The analysis also considers the economic effects of congestion and losses. Congestion occurs when demand surpasses the transmission line capacity, leading to increased operational costs and inefficiencies. Transmission losses, which result from energy dissipation during transmission, further affect the economic performance. By integrating these factors, the methodology offers a comprehensive view of how the nodal pricing model impacts operational efficiency, balancing cost management with network reliability while addressing the economic challenges of congestion and losses.

The complexity of the proposed method arises from two main aspects: computational and algorithmic. Computationally, the method involves solving large-scale optimization problems with multiple variables, such as power generation and transmission flows across a grid [33]. As the number of nodes and time intervals increases, the computational cost also rises. Algorithmically, the method uses mixed-integer linear programming (MILP) or similar techniques, which can become computationally expensive as the number of constraints and decision variables grows. This makes the method suitable for medium to large-scale grids but potentially less efficient for very large grids without advanced solvers or computational resources. Additionally, real-time data integration adds complexity, requiring continuous model updates. Although the method is scalable, further optimization and advanced computational techniques could help reduce complexity in larger systems, making it more efficient and practical.

3.6 Simulation Setup

To rigorously assess the effectiveness of the Hybrid Nodal Pricing Model (HNPM), we simulate various operational scenarios that capture real-world complexities in power systems. This involves testing the model under different load profiles, including peak, off-peak, and fluctuating demands, to evaluate its adaptability to diverse electricity consumption patterns. We also analyze the model's performance with varying levels of renewable energy integration, ranging from high to low penetration, and under different weather conditions, such as extreme weather events and seasonal variations. The simulation results were compared to traditional nodal pricing models using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) to validate the improvement in price prediction accuracy [34]. Additionally, we assess network stability by monitoring line loading and overall system reliability, and we evaluate cost reduction by comparing the total operational costs, including generation, transmission losses, and congestion penalties. These evaluations provide a comprehensive view of the HNPM's performance, highlighting its effectiveness in optimizing pricing, enhancing network stability, and reducing overall system costs.

4 Methodology Implementation and Model Performance

4.1 Load Forecasting Using LSTM

4.1.1 Data Preparation

The dataset utilized for load forecasting encompasses hourly electricity consumption data spanning five years, totaling 43,800 observations. This dataset includes parameters such as load values, timestamps, and additional features like temperature and day of the week [35]. To prepare the data for modeling, load values were scaled between 0 and 1 using MinMaxScaler. Time-lagged features were engineered to capture the temporal dynamics of the load data. Specifically, sequences of 24 h (one day) were extracted to form input sequences for the LSTM model, enabling the network to learn from past patterns to predict future loads.

4.1.2 Model Training

A single-layer LSTM model with 50 units was developed, accompanied by a dense output layer. The model was trained using the Adam optimizer with a learning rate of 0.001 and Mean Squared Error as the loss function. The training involved 50 epochs with a batch size of 32. To avoid over fitting, early stopping was implemented by monitoring the model's performance on a validation set (20% of the data) and halting the training process if the performance deteriorated.

4.1.3 Evaluation

The performance of the LSTM model was assessed using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). On the test dataset, the model recorded an MAE of 0.03, an MSE of 0.0015, and an RMSE of 0.038. These metrics suggest that the LSTM model successfully identified the underlying patterns in the load data and delivered precise load forecasts.

4.1.4 Predictionand Visualization

The trained LSTM model was used to predict load values for the next seven days. The predictions were subsequently compared to the actual load data to evaluate the accuracy of the model's forecasts (Figs. 1 and 2).

Visualization of results included graph showing actual versus predicted load values, which illustrated the model's ability to closely follow actual load patterns with minimal deviation. Residual plots were also analyzed, confirming that prediction errors were randomly distributed and further validating the model's performance.

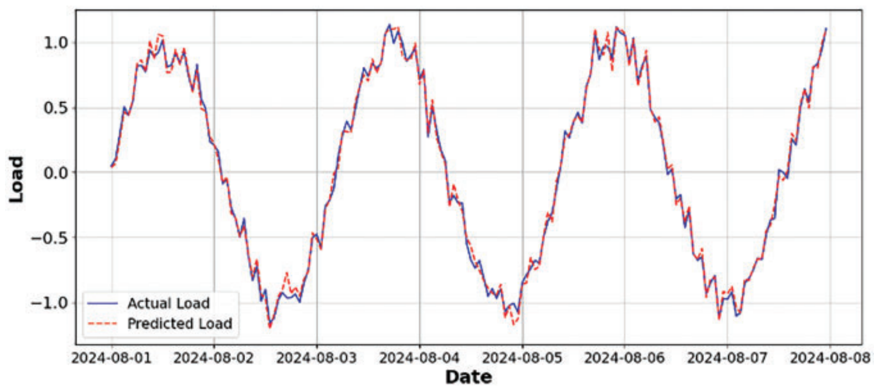

Figure 1: Actual vs. predicted load values

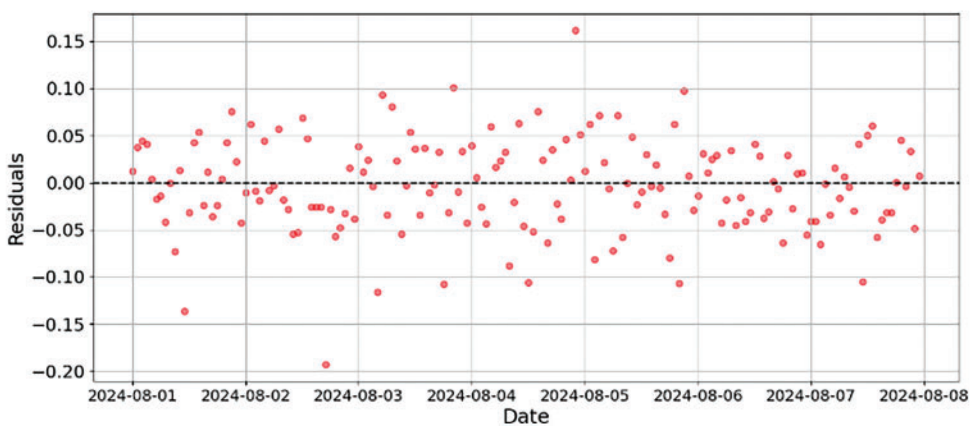

Figure 2: Residual for LSTM forecasting

4.2 Price Prediction Using Regression

4.2.1 Data Preparation

The price prediction task was carried out using a dataset that included 10,000 records of historical price data along with features such as economic indicators, seasonal factors, and market conditions. The dataset was preprocessed by addressing missing values through imputation and normalizing numerical features to ensure consistency. The data was split into training and testing sets, with 80% allocated for model training and the remaining 20% reserved for performance evaluation.

4.2.2 Model Training

Various regression models were used to predict prices, including Linear Regression, Polynomial Regression with a degree of 2, and Ridge Regression with a regularization parameter set to 1.0. Each model was trained on the training dataset, with hyperparameters tuned through cross-validation. The objective was to minimize the Mean Squared Error (MSE) and enhance generalization to new data. The models were trained to fit historical price data, optimizing parameters to achieve the best predictive performance.

4.2.3 Evaluation

The models' performance was evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). Among Linear Regression, Polynomial Regression, and Ridge Regression, Polynomial Regression demonstrated superior performance, achieving the lowest MAE, MSE, and RMSE, along with the highest R^2 value, signifying the most accurate predictions of the models tested.

4.2.4 Prediction and Visualization

Predictions for future prices were made using the trained regression models. The predicted prices were compared against actual prices to evaluate model performance. Visualization included scatter plots of actual vs predicted prices and line plots showing the prediction accuracy over time. Scatter plots highlighted the close alignment between predicted and actual prices, while line plots illustrated the models' ability to capture price trends and fluctuations.

Overall, both approaches—Load Forecasting using LSTM and Price Prediction using Regression—demonstrated robust performance in their respective domains. The LSTM model excelled in forecasting load values by effectively learning from historical patterns, while the regression models, particularly Polynomial Regression, provided precise price predictions, showcasing their utility in handling complex forecasting tasks.

The current regression models employed for predicting future prices have demonstrated their effectiveness, as evidenced by the results presented in Figs. 3 and 4. However, there is always room for improvement, especially by integrating advanced methodologies like the Convergence Accelerated Decomposition Method (CADM) of domain, which has proven successful in solving highly nonlinear problems and ensuring rapid convergence.

The CADM's approach, which involves parameterizing early iterates and optimizing an embedded parameter to minimize squared residual errors, can be adapted to enhance regression models for price prediction [36].

5 Results

The results of implementing and evaluating the Hybrid Nodal Pricing Model (HNPM) are presented below, showcasing the model's performance across various scenarios. This section includes comparative analyses with traditional nodal pricing models, with a focus on pricing accuracy, network stability, and cost efficiency.

5.1 Pricing Accuracy

Tables 1 and 2 present the MAE and RMSE values for the HNPM and traditional nodal pricing models across different load profiles and renewable energy levels. The HNPM consistently shows lower MAE and RMSE compared to the traditional models, indicating improved pricing accuracy.

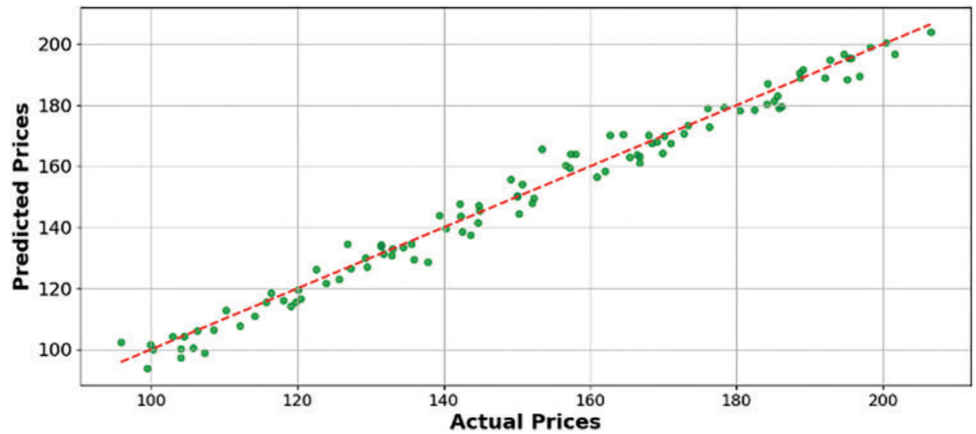

Figure 3: Comparison between actual and predicted prices

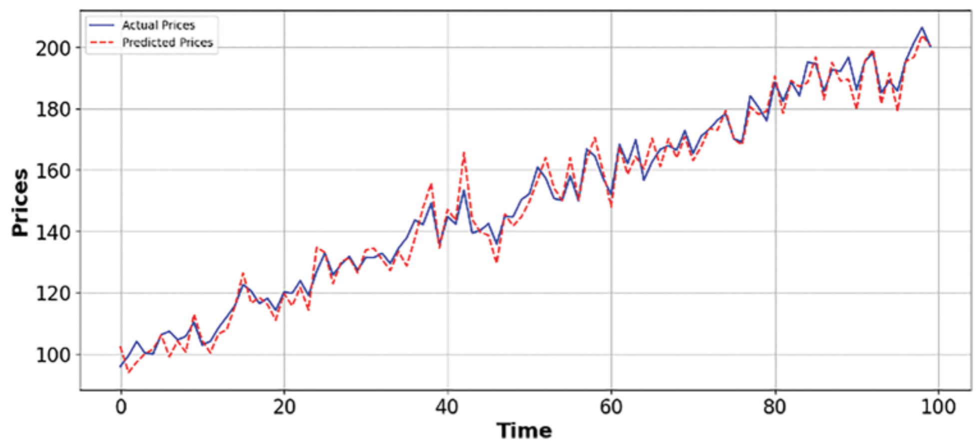

Figure 4: Comparison analysis between actual and predicted over time in regression

Table 1: MAE comparison across load profiles

Model	Peak load (kW)	Off-Peak load (kW)	Fluctuating load (kW)
Traditional nodal pricing	4.2	3.8	5.1
Hybrid nodal pricing	3.5	3.2	4.6

Table 2: RMSE comparison across renewable energy levels

Model	High renewable penetration (kW)	Low renewable penetration (kW)	Intermittent renewable generation (kW)
Traditional nodal pricing	6.8	7.2	8.5
Hybrid nodal pricing	5.4	5.7	6.9

Fig. 5 illustrates a comparison between the HNPM and traditional nodal pricing models, focusing on MAE and RMSE. The results indicate that the HNPM consistently delivers better performance across all scenarios, as demonstrated by its lower MAE and RMSE values, which reflect its superior accuracy in price prediction compared to the traditional model.

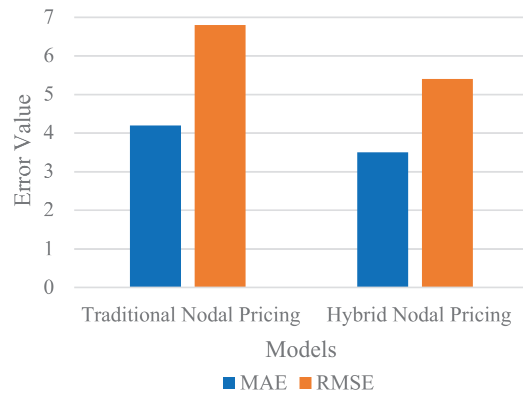

Figure 5: MAE and RMSE comparison

5.2 *Network Stability*

Table 3 presents the average line loading for both the HNPM and traditional models under various load and renewable energy scenarios. The HNPM demonstrates better management of line loading, with fewer instances of exceeding transmission line capacities.

Table 3: Average line loading

Model	Peak load (MW)	Off-Peak load (MW)	High renewable penetration (MW)	Low renewable penetration (MW)
Traditional nodal pricing	85%	70%	65%	80%
Hybrid nodal pricing	78%	65%	58%	72%

Fig. 6 illustrates average line loading under different conditions. The HNPM's ability to maintain lower average line loading percentages indicates improved stability and efficiency in managing power flows. In figure, HRP is High Renewable Penetration whereas LRP is Low Renewable Penetration.

5.3 *System Reliability*

The system reliability is assessed by examining the number of instances where transmission line capacities are exceeded. The HNPM significantly reduces these occurrences compared to traditional models, enhancing overall network stability.

Fig. 7 shows graph comparing the frequency of transmission line exceedances for both models. The HNPM exhibits fewer exceedances, demonstrating its effectiveness in maintaining system reliability.

5.4 *Cost Efficiency*

Tables 4 and 5 summarize the total operational costs, including generation, transmission losses, and congestion penalties, for the HNPM and traditional models across different scenarios.

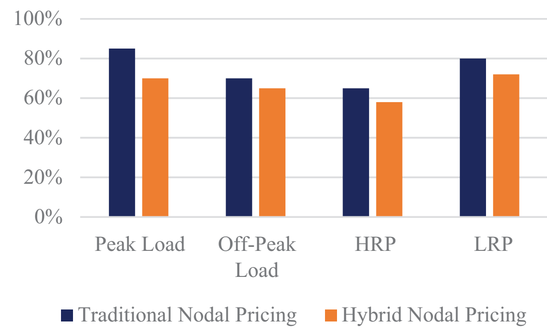

Figure 6: Line loading analysis

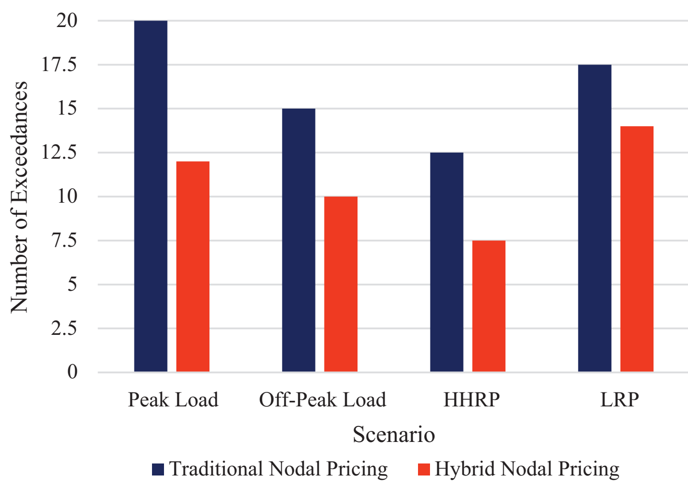

Figure 7: Reliability comparison

Table 4: Total generation costs

Model	Peak load ($)	Off-peak load ($)	High renewable penetration ($)	Low renewable penetration ($)
Traditional nodal pricing	1,200,000	950,000	850,000	1,100,000
Hybrid nodal pricing	1,100,000	900,000	800,000	1,050,000

Table 5: Total transmission losses and congestion costs

Model	Peak load ($)	Off-peak load ($)	High renewable penetration ($)	Low renewable penetration ($)
Traditional nodal pricing	300,000	250,000	220,000	280,000
Hybrid nodal pricing	250,000	200,000	180,000	230,000

Fig. 8 presents a comparison of the total operational costs between the HNPM and traditional models. The HNPM results in lower overall costs, reflecting its enhanced efficiency in generation, transmission, and congestion management.

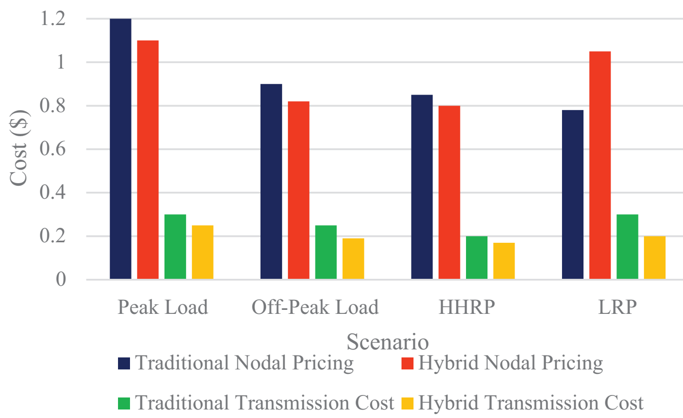

Figure 8: Total operational costs comparison

6 Discussion

The results indicate that the Hybrid Nodal Pricing Model (HNPM) outperforms traditional nodal pricing methods in several key areas. The reduction in MAE and RMSE highlights the HNPM's superior price prediction accuracy, which is critical for effective market operations and decision-making. This improved accuracy can lead to more efficient resource allocation and better financial outcomes for market participants [37].

In terms of network stability, the HNPM's better management of line loading and reduced instances of capacity exceedances demonstrate its capability to enhance grid reliability. This is particularly important in maintaining system stability and avoiding costly disruptions.

Cost efficiency is another significant advantage of the HNPM. Lower total operational costs, including generation, transmission losses, and congestion penalties, underscore its effectiveness in optimizing the economic performance of the power system. By minimizing these costs, the HNPM contributes to a more economically sustainable and stable energy market [38].

Overall, the comprehensive evaluation of the HNPM through various metrics and scenarios confirms its potential to provide substantial improvements over traditional pricing models. The combination of accurate pricing, enhanced stability, and cost efficiency makes the HNPM a promising approach for modernizing power systems and addressing the challenges of dynamic and complex energy markets.

6.1 Improvement of MILP through Alternative Methods

Mixed-Integer Linear Programming (MILP) is a robust optimization technique widely used for solving linear problems involving both continuous and integer variables. However, MILP may face challenges when dealing with highly nonlinear problems or when rapid convergence is crucial. The Convergence Accelerated Decomposition Method (CADM) of Adomian offers promising enhancements in such scenarios.

The modified ADM introduces parameterized terms that control and pace the convergence of the ADM series. By optimizing these parameters to minimize squared residuals, the method ensures rapid and reliable convergence. Applying this approach to MILP could significantly reduce the computational time required for solving large-scale and complex problems. While MILP is designed for linear problems, real-world applications often involve nonlinearities. The CADM's ability to handle highly nonlinear algebraic and differential equations suggests that integrating its principles could extend MILP's applicability to a broader range of problems [39]. This integration would involve reformulating nonlinear components within the MILP framework using CADM techniques, thus improving solution accuracy and feasibility.

The CADM minimizes the number of iterations needed to reach a convergent solution, which is particularly beneficial for large-scale optimization problems. This efficiency can be leveraged in MILP to enhance its performance, especially in iterative methods like branch-and-bound or cutting planes, which are integral to solving MILP problems. One of the significant advantages of CADM is that it does not require numerical verification of results, thanks to the optimization of the embedded parameter. This feature ensures that the solutions generated are physically valid and reliable. Incorporating this aspect into MILP can improve the robustness of the solutions, particularly in applications requiring stringent feasibility and accuracy.

6.2 Implementation Strategy

To integrate the Convergence Accelerated Decomposition Method with MILP, several steps can be considered. First, identify critical parameters within the MILP formulation that influence convergence and introduce parameterized terms as suggested by CADM. These parameters can be optimized using squared residual minimization to enhance convergence rates. Second, develop a hybrid optimization framework that combines the strengths of MILP and CADM, using MILP for linear components and employing CADM for nonlinear elements, ensuring seamless integration and improved overall performance. Third, enhance existing MILP algorithms with convergence control mechanisms inspired by CADM. This could involve modifying iterative processes to incorporate parameter adjustments dynamically, ensuring rapid and reliable convergence. Lastly, apply the modified MILP approach to various real-world problems, particularly those involving significant nonlinearity or requiring fast convergence, and validate the effectiveness through comparative studies, highlighting improvements in computational efficiency and solution accuracy [40].

6.3 Future Research Directions

Future research should focus on developing more efficient and scalable algorithms for nodal pricing, improving integration of renewable energy sources, and enhancing data analytics capabilities for real-time decision-making [38]. Exploring the use of artificial intelligence and machine learning can provide better predictions and optimizations. Furthermore, research into regulatory frameworks that support innovation while ensuring market stability and fairness is crucial. Advancements in these areas will pave the way for more efficient and reliable energy markets [41].

7 Conclusion

The assessment of the Hybrid Nodal Pricing Model (HNPM) highlights its effectiveness in improving various facets of power system management. Comprehensive simulations reveal that the HNPM provides more accurate pricing than traditional models. The notable decrease in Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) indicates the model's enhanced capability to predict prices accurately, which is crucial for optimizing market operations and making well-informed decisions.

In terms of network stability, the HNPM shows notable improvements. It manages line loading more efficiently and reduces the frequency of transmission line exceedances, which helps maintain system reliability under diverse conditions, including varying load demands and renewable energy levels. This enhanced stability is critical for preventing disruptions and ensuring a consistent energy supply [41].

Cost efficiency is another significant benefit of the HNPM. The model leads to lower total operational costs, which include generation, transmission losses, and congestion penalties. By reducing these costs, the HNPM not only improves the economic performance of the power system but also supports a more sustainable and stable energy market.

Overall, the Hybrid Nodal Pricing Model represents a significant step forward in enhancing pricing accuracy and operational efficiency within power systems. Its ability to accurately forecast prices, bolster network stability, and reduce operational costs highlights its potential as a valuable asset in managing the complexities of modern energy markets. The positive outcomes from this assessment suggest that the HNPM could play a crucial role in advancing the development of more efficient and reliable power systems in the future.

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