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# Optimization of Power System Flexibility Through AI-Driven Dynamic Load Management and Renewable Integration

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## ABSTRACT

This paper introduces an advanced framework to enhance power system flexibility through AI-driven dynamic load management and renewable energy integration. Leveraging a transformer-based predictive model and MATPOWER simulations on the IEEE 14-bus system, the study achieves significant improvements in system efficiency and stability. Key contributions include a 44% reduction in total power losses, enhanced voltage stability validated through the Fast Voltage Stability Index (FVSI), and optimized renewable energy utilization. Comparative analyses demonstrate the superiority of AI-based approaches over traditional models such as ARIMA, with the transformer model achieving significantly lower forecasting errors. The proposed methodology highlights the transformative potential of AI in addressing the challenges of modern power grids, paving the way for more resilient, efficient, and sustainable energy systems.

## 1 | Introduction

The contemporary power grid is experiencing a profound transformation driven by the increasing incorporation of renewable energy sources such as wind and solar power. These renewable sources offer substantial environmental and economic benefits, including reduced greenhouse gas emissions and lower operational costs [1, 2]. However, their inherent intermittency and variability introduce significant challenges in maintaining the stability, reliability, and flexibility of power systems [3, 4]. Traditional power system management techniques, which are primarily designed for stable and predictable energy sources, often fall short in addressing the complexities introduced by renewables [5].

As the share of renewable energy in the power mix continues to rise, there is an urgent need for advanced methodologies that can enhance the operational flexibility and reliability of power systems. Flexibility, in this context, refers to the system's ability to respond to rapid changes in supply and demand, while maintaining operational stability [6, 7]. Achieving this requires innovative solutions that can efficiently balance the fluctuating supply from renewable sources with the dynamic nature of energy consumption [8, 9].

### 1.1 | Artificial Intelligence (AI) in Power System Management

AI has emerged as a potent tool to tackle these challenges. AI techniques, particularly machine learning algorithms, have demonstrated significant potential in various domains of power system management [10, 11]. The ability of AI to learn and adapt, rather than simply making predefined decisions, is highly instructive for the comprehensive management of energy systems. Applications of AI in power systems include load forecasting, fault detection, energy consumption prediction, and optimization of grid operations [12, 13]. Machine learning models, especially deep learning frameworks, have shown remarkable accuracy in predicting complex patterns in energy consumption and generation [14, 15]. Studies have shown that AI-driven load forecasting can significantly improve the accuracy of demand predictions, enabling more efficient grid management, reduced operational costs, and real-time optimization, and prediction for efficient energy management [16].

Deep learning models such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been widely used for time-series forecasting in power systems [17]. These models excel in capturing temporal dependencies and have been applied successfully to forecast electricity loads, renewable generation, and market prices [18]. Transformer models, a recent advancement in deep learning, have further enhanced the ability to model complex dependencies in time-series data, offering improved performance over traditional models [19].

### 1.2 | Dynamic Load Management

Dynamic load management is crucial for maintaining grid stability, especially with the integration of renewable energy sources. AI-driven dynamic load management involves the real-time adjustment of loads based on predicted demand and supply conditions [20]. This approach allows for better utilization of renewable energy, reduces the need for fossil fuel-based generation, and enhances the overall efficiency of the power system [21]. Several studies have highlighted the benefits of dynamic load management in reducing peak demand, balancing supply and demand, and improving grid reliability [22].

For instance, a study by Almassalkhi et al. [23] demonstrated the use of model predictive control (MPC) for real-time demand response, showing significant improvements in load balancing and system stability. Another study by Liu et al. [24] employed deep reinforcement learning for dynamic load management, achieving substantial reductions in energy consumption and operational costs.

### 1.3 | Renewable Integration

The integration of renewable energy sources into the power grid is a critical component of the transition to a sustainable energy system. Renewable sources such as solar and wind are inherently variable, leading to challenges in maintaining a balance between supply and demand [25]. Effective integration strategies are required to maximize the use of renewables while ensuring grid stability [26]. AI-driven approaches have shown promise in optimizing renewable integration by predicting renewable generation, adjusting loads, and coordinating with energy storage systems [27].

Research by Kazemi et al. [28] explored the use of AI for optimizing the dispatch of renewable energy in microgrids, demonstrating improvements in system efficiency and reliability. Similarly, Wu et al. [29] investigated the use of AI for coordinating renewable generation with battery storage, achieving enhanced grid stability and reduced curtailment of renewable energy.

### 1.4 | MATPOWER and Simulation

MATPOWER, a widely used power system simulation tool, provides a robust framework for analyzing and optimizing power system operations [30]. It offers capabilities for power flow analysis, optimal power flow, and simulation of various scenarios [31]. Integrating AI-driven predictions and dynamic load adjustments into MATPOWER simulations enables a comprehensive evaluation of the proposed strategies in a realistic power system environment [32].

## 2 | Research Objectives

The specific objectives of this study are:

- **AI-Driven Load Prediction:** Develop a robust transformer model to accurately predict load demands using historical load data and weather information. This model is trained on real-world data to capture the intricate dependencies between various factors affecting load demand.
- **Dynamic Load Management:** Integrate the AI-based load predictions into MATPOWER simulations. This allows for dynamic adjustment of loads within the power system, thereby optimizing the system's response to changes in demand and renewable generation.
- **Optimization of Renewable Integration:** Evaluate the impact of AI-driven load management on the integration of renewable energy sources. The goal is to optimize the use of renewables, enhancing their contribution to the overall energy mix while maintaining system stability.
- **Scenario Analysis and Validation:** Conduct comprehensive simulations under various scenarios, including different levels of renewable output and fault conditions. This helps assess the effectiveness of the proposed AI-driven strategies in enhancing system flexibility, reliability, and efficiency.
- **Performance Metrics and Statistical Analysis:** Utilize key performance metrics such as total power losses, voltage stability indices, and line loadings to compare the AI-driven approach with baseline scenarios. Perform statistical analysis to validate the improvements in system performance.

The IEEE 14-bus system is employed as the testbed for our simulations, providing a standard framework for evaluating the proposed methodologies. By implementing a series of scenarios that reflect real-world conditions, we aim to demonstrate the practical benefits of integrating AI into power system operations.

In this paper, we propose a comprehensive approach to enhancing power system flexibility and reliability through AI-driven dynamic load management and renewable integration. The rest of this paper is organized as follows:

- **Section II:** Research Objectives outlines the specific goals of this study, focusing on AI-driven load prediction, dynamic load management, optimization of renewable integration, scenario analysis, and performance metrics.

- **Section III:** Contributions and Findings presents the key contributions of our research and summarizes the main findings, demonstrating the effectiveness of our proposed methods.
- **Section IV:** Methodology describes the data collection, preprocessing steps, AI model development, and integration with MATPOWER for simulation purposes. Detailed explanations of the techniques and algorithms used are provided.
- **Section V:** Detailed Analysis of Plots visualize the energy consumption patterns, influencing patterns and performance of predictions.
- **Section VI:** Results and Discussion discusses the results obtained from various simulations, highlighting the improvements in power system flexibility, stability, and efficiency achieved through our approach.
- **Section VII:** Conclusion and Future Work concludes the paper with a summary of our findings and suggestions for future research directions. By addressing these aspects, this paper aims to provide a robust framework for leveraging AI to optimize modern power grids, ultimately contributing to more sustainable and efficient energy systems.

## 3 | Contributions and Findings

The study's principle value emerges from merging AI-based dynamic load management systems with renewable energy optimization through transformer-based forecasting and MATPOWER simulation technology. While previous research has investigated AI applications in power systems, this study uniquely combines:

1. The application of transformer models delivers superior accuracy for load forecasting than the outdated ARIMA models previously used.
2. The MATPOWER system operates with dynamic load management to make real-time power system operation adjustments.
3. The scenario evaluation presented different conditions of renewable energy supply and system peak demands and additionally controller operations through faults to show enhanced power system flexibility and improved efficiency and stability rates.
4. Multiple tests with FVSI verified that the system achieved both a 44% decrease in total power losses along with boosted voltage stability.

This study advances the area by giving a realistic framework for using AI to handle the issues of renewable energy integration and dynamic load balancing, as well as a road map for application in real-world power systems.

AI is preferred over deterministic methods for several reasons: solar power alongside wind power shows natural variabilities and uses unpredictable patterns in their operation. Deep learning frameworks, including transformers, showcase advanced capabilities for processing complex non-linear patterns within time-series data, which makes them ideal for predicting load requirements and renewable power generation. AI models gain adaptability through their ability to handle new information besides relying on static mathematical procedures that neglect real-world changes. Actual findings reveal that transformer models outperform traditional ARIMA models by reducing forecasting errors to 205.98 kW MAE with 275.08 kW RMSE, while the traditional model achieves 3063.80 kW MAE and 3640.26 kW RMSE. The high accuracy level of this method allows more efficient power grid management while enhancing the ability to assimilate renewable energy sources. AI-based dynamic load management processes real-time adjustments through demand and supply predictions, which deterministic methods do not replicate effectively.

## 4 | Methodology

The flowchart in Figure 1 provides a comprehensive overview of the research methodology. It outlines the sequential steps

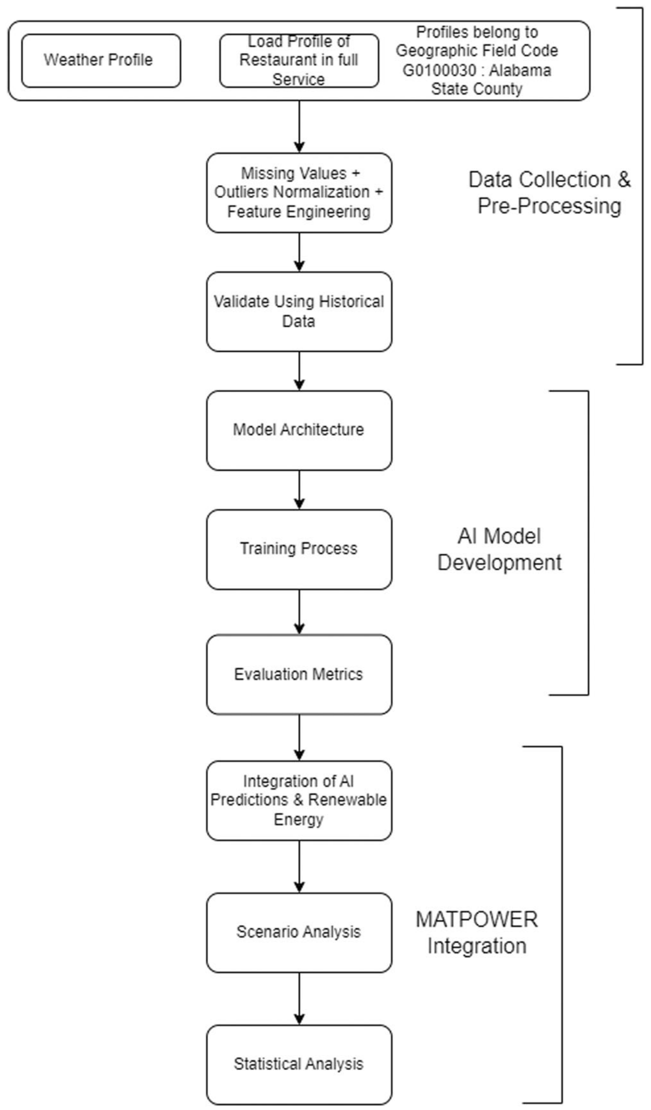


**FIGURE 1** | Methodology steps.

involved in the study, starting from data collection and preprocessing to AI model development, MATPOWER integration, scenario analysis, and statistical validation. Each step is depicted with detailed sub-steps, highlighting the process flow and the interconnections between different components of the methodology. This visual representation helps in understanding the systematic approach adopted in the research, ensuring clarity and coherence in the overall workflow.

### 4.1 | Data Collection and Preprocessing

The study utilizes the real-world load profile of full-service restaurant Table 1. and weather data Table 2 available at [33]. for Alabama State, sourced from the OpenEI database. This dataset includes historical load data, weather parameters, and other relevant factors influencing load demand. The data undergoes a series of preprocessing steps to ensure its suitability for training AI models and integration into MATPOWER simulations.

- **Handling Missing Values:** Missing values in the dataset are addressed using interpolation and mean imputation techniques to ensure continuity in the time-series data.
- **Outlier Removal:** Statistical methods such as z-score analysis are employed to identify and remove outliers that could skew the model training process.
- **Normalization:** All features are normalized to a common scale using min-max scaling, which ensures that each feature contributes equally during model training.
- **Feature Engineering:** Additional features are created to capture temporal dependencies and enhance the model's predictive power. These features include time of day, day of the week, holidays, and lagged load values.

### 4.2 | AI Model Architectue and Development

The core of our predictive modeling is based on the transformer architecture, which has shown superior performance in handling sequential data compared to traditional models like LSTMs and RNNs. The transformer model is trained on the preprocessed dataset to predict future load demands.

The transformer model is employed to predict future load demands based on historical load and weather data. The architecture consists of an encoder-decoder structure with multi-head self-attention mechanisms. The key components of the transformer model include:

#### 4.2.1 | Encoder

The encoder comprises multiple identical layers, each containing two main sub-layers: a multi-head self-attention mechanism and a position-wise fully connected feed-forward network.

- The **softmax function** is a key component of the transformer model's self-attention mechanism. It is used to

**TABLE 1** | Top 5 rows of load profile for full service restaurant in Alabama State, USA.

| Year | Month | Day | Hour | Electricity: Facility [kW] | Electricity: HVAC [kW] | Electricity: Interior equipment [kW] | Electricity: Interior lights [kW] | Electricity: Exterior lights [kW] | Electricity: Refrigeration [kW] |
|---|---|---|---|---|---|---|---|---|---|
| 2018 | 1 | 1 | 1 | 18.57 | 3.12 | 5.74 | 4.01 | 1.10 | 4.60 |
| 2018 | 1 | 1 | 2 | 18.45 | 3.14 | 5.73 | 4.01 | 1.10 | 4.48 |
| 2018 | 1 | 1 | 3 | 18.39 | 3.14 | 5.73 | 4.01 | 1.10 | 4.41 |
| 2018 | 1 | 1 | 4 | 18.26 | 3.13 | 5.72 | 4.01 | 1.10 | 4.29 |
| 2018 | 1 | 1 | 5 | 18.08 | 3.14 | 5.72 | 4.01 | 1.10 | 4.12 |

**TABLE 2** | Top 5 rows of weather data for Alabama State, USA.

| Year | Month | Day | Hour | Temperature [C] | Humidity [%] | Wind speed [m/s] | Dew point [C] | Solar radiation [W/m$^2$] | Precipitation [mm] | Pressure [Pa] | Cloud cover [%] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2018 | 1 | 1 | 1 | 2.10 | 82 | 2.68 | −0.33 | 0 | 0 | 101,820 | 80 |
| 2018 | 1 | 1 | 2 | 1.90 | 83 | 2.50 | −0.49 | 0 | 0 | 101,830 | 81 |
| 2018 | 1 | 1 | 3 | 1.80 | 84 | 2.40 | −0.59 | 0 | 0 | 101,840 | 82 |
| 2018 | 1 | 1 | 4 | 1.60 | 85 | 2.20 | −0.79 | 0 | 0 | 101,850 | 83 |
| 2018 | 1 | 1 | 5 | 1.40 | 86 | 2.10 | −0.99 | 0 | 0 | 101,860 | 84 |

compute attention weights, which determine the importance of different parts of the input sequence. The softmax function is defined as:

$$\mathrm{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}.$$

In the context of the transformer model, the softmax function is applied to the scaled dot product of the query ($Q$) and key ($K$) matrices:

$$\text{Attention}\ (Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V.$$

Here, $Q$, $K$, and $V$ are the query, key, and value matrices, respectively, and $d_k$ is the dimension of the key vectors. This mechanism allows the model to focus on the most relevant parts of the input sequence, improving its ability to capture temporal dependencies in load and weather data.

- **Feed-Forward Network:** Each position in the encoder is passed through a fully connected feed-forward network, which is applied identically to each position:

$$\mathrm{FFN}(x) = \max\left(0, xW_1 + b_1\right) W_2 + b_2,$$

where $W_1$, $W_2$, $b_1$, and $b_2$ are learnable parameters.

### 4.2.2 | Decoder

The decoder also consists of multiple identical layers and includes an additional sub-layer for multi-head attention over the encoder's output.

- **Masked Multi-Head Self-Attention:** This sub-layer prevents positions from attending to subsequent positions. The masking is applied to the input sequence, ensuring that the prediction for a particular position can depend only on known outputs at previous positions.
- **Multi-head Attention Over Encoder Output:** This allows the decoder to focus on relevant parts of the input sequence.
- **Feed-Forward Network:** Similar to the encoder, each position passes through a feed-forward network.

The matrices used in the transformer model used above are defined as:

- $Q \in \mathbb{R}^{n\times d_k}$: Query matrix, where $n$ is the sequence length and $d_k$ is the dimension of the key vectors.
- $K \in \mathbb{R}^{n\times d_k}$: Key matrix.
- $V \in \mathbb{R}^{n\times d_v}$: Value matrix, where $d_v$ is the dimension of the value vectors.
- $W_1, W_2 \in \mathbb{R}^{d_k\times d_k}$: Learnable weight matrices in the feed-forward network.
- $b_1, b_2 \in \mathbb{R}^{d_k}$: Bias terms in the feed-forward network.

The overall architecture allows the model to capture complex temporal dependencies in the load and weather data, facilitating accurate predictions.

#### 4.2.3 | Model Training

The dataset was split into training, validation, and test sets. The model was trained to minimize the mean squared error (MSE) loss function:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2,$$

where:

- $y_i$: True load value at time $i$.
- $\hat{y}_i$: Predicted load value at time $i$.
- $n$: Total number of observations.

The Adam optimizer was used for training with an initial learning rate of 0.001.

The MSE is used as the loss function for training the transformer model because it penalizes larger errors more heavily, which is critical for ensuring accurate load predictions in power systems. While mean absolute percentage error (MAPE) is another common metric, it is less sensitive to large errors and can be problematic when actual values ($y_i$) are close to zero. MSE is preferred in this context because it provides a more robust measure of prediction accuracy, especially for load forecasting tasks where large errors can have significant operational consequences.

### 4.3 | MATPOWER Integration

MATPOWER is employed to simulate the power system operations and evaluate the impact of AI-driven load management. The IEEE 14-bus system serves as the testbed for our simulations, providing a standardized framework for comparison.

- **Baseline Power Flow Model:** A baseline power flow model of the IEEE 14-bus system is established using standard parameters and configurations.
- **Integration of AI Predictions:** The load predictions generated by the transformer model are integrated into the MATPOWER simulations. The dynamic adjustment of loads based on AI predictions allows for real-time optimization of power system operations.
- **Renewable Integration:** Additional renewable generators, such as wind and solar, are integrated into the MATPOWER model. The performance of these renewables is optimized using AI-driven strategies to balance the variability in their output.

### 4.4 | Scenario Analysis

To assess the effectiveness of the proposed AI-driven strategies, simulations are conducted under various scenarios, including different levels of renewable output and fault conditions.

Simulations were conducted under four scenarios:

1. **High Renewable Output:** Evaluates the system's ability to integrate large amounts of renewable energy.
2. **Low Renewable Output:** Tests system performance under minimal renewable generation.
3. **Peak Load Conditions:** Assesses the system's response to high demand periods.
4. **Fault Conditions:** Simulates line outages to evaluate system resilience.

### 4.5 | Statistical Analysis

Statistical analysis is performed to validate the improvements in system performance under AI-driven strategies compared to baseline scenarios.

- **Comparison With Baseline:** Simulation results are compared against a baseline scenario without AI-driven adjustments to quantify the improvements.
- **Significance Testing:** Statistical tests such as the $t$-test are conducted to assess the significance of the observed improvements in key performance metrics.
- **Robustness Check:** The robustness of the AI-driven strategies is evaluated by examining their performance across different scenarios and validating against real-world data.

## 5 | Detailed Analysis of Plots

The presented plots provide a comprehensive analysis of the energy consumption patterns and influencing factors for a full-service restaurant, as well as the performance of predictive models. Anamolies in the profiles are detected using isolation forest. The correlation matrices reveal the relationships between various features such as hour, day of the week, and past energy consumption, highlighting the temporal dependencies in the data. Time series analysis illustrates the periodic trends and seasonal effects on energy usage. Predictive modeling plots compare the true and predicted values, showcasing the accuracy of the models. Finally, feature importance analysis identifies the most critical factors driving energy consumption, offering insights for further model improvement and feature engineering. Together, these plots deliver an in-depth understanding of the data and the effectiveness of the predictive models, guiding enhancements in forecasting accuracy and energy management strategies.

### 5.1 | Correlation Matrix—Weather Data

Figure 2 shows the correlation matrix. The detailed analysis of this plot is as follows:

#### 5.1.1 | Detailed Analysis

- **Dry Bulb Temperature [°C]:**
  - Shows a strong correlation with *hour* (0.56) and *month* (0.43), indicating that temperature varies significantly with the time of day and the month of the year.
  - Moderate correlation with *lagged_temp* (0.50) suggests some temporal dependence.
- **Lagged Temp:**
  - Highly correlated with *Dry Bulb Temperature [°C]* (0.50), reinforcing the temporal dependence in weather data.
- **Hour:**
  - Strong correlation with *Dry Bulb Temperature [°C]* (0.56) and moderate correlation with *day_of_week* (0.31).
  - Indicates significant daily variation in temperature.

### 5.2 | Time Series Analysis—Energy Consumption

Figure 3 shows the time series analysis of load profile. The detailed analysis of this plot is as follows:

#### 5.2.1 | Detailed Analysis

- **Energy Consumption Trends:**
  - The plot shows periodic spikes in energy consumption, likely corresponding to peak operational hours of the restaurant.
  - There are noticeable daily and weekly patterns, with higher consumption during certain hours and days.
- **Seasonal Effects:**
  - There may be seasonal effects influencing the energy consumption, visible as periodic trends over longer periods.
  - Holidays and weekends likely cause significant fluctuations in energy use.

### 5.3 | Predictive Modeling—True vs. Predicted Values

Figure 4 shows the visual presentation of performance of transformer model. The detailed analysis of this plot is as follows:

#### 5.3.1 | Detailed Analysis

- **Model Performance:**
  - The plot shows that the predicted values (orange line) closely follow the true values (blue line), indicating good model performance.
  - However, there are some deviations where the model predictions do not match the true values, highlighting areas for potential model improvement.
- **Error Analysis:**
  - The differences between the true and predicted values suggest times when the model underestimates or overestimates the energy consumption.
  - These discrepancies could be due to unaccounted factors or noise in the data.

### 5.4 | Feature Importance

This section supports data visualized in all plots discussed above.

#### 5.4.1 | Detailed Analysis

- **Top Features:**
  - *hour*: The most important feature, indicating the significant impact of the time of day on energy consumption.
  - *lagged_load*: Second most important, showing the importance of past energy consumption in predicting future usage.
  - *day_of_week* and *month*: These features also have notable importance, reflecting daily and monthly patterns in energy use.
  - *is_weekend*: Though less important, it still contributes to the model, indicating different patterns on weekends.
- **Implications:**
  - The importance of *hour* and *lagged_load* suggests focusing on temporal features for improving predictive models.
  - The contribution of *day_of_week* and *month* indicates potential for further feature engineering, possibly incorporating more detailed temporal features or interactions.

In a summarize way, Features with higher importance scores have a larger influence on the model's predictions. Understanding feature importance can help in refining the model and focusing on the most impactful features for energy consumption prediction. Summary Correlation Analysis: Helped in identifying relationships between different features, guiding feature selection. Time Series Analysis: Provided insights into energy usage patterns over time, highlighting periods of high and low demand. Predictive Modeling: Showed how well the model predicts energy consumption, indicating areas for improvement. Feature Importance: Highlighted the most influential features in predicting energy consumption, informing feature engineering and model tuning. These analyses and plots collectively provide a comprehensive understanding of the data, guiding further improvements in the predictive modeling of energy consumption.

## 6 | Results and Discussion

### 6.1 | AI-Driven Anomalies Detection's and Load Predictions

The AI-driven model delivers the data preparation, predictive modeling using a transformer model, and anomaly detection

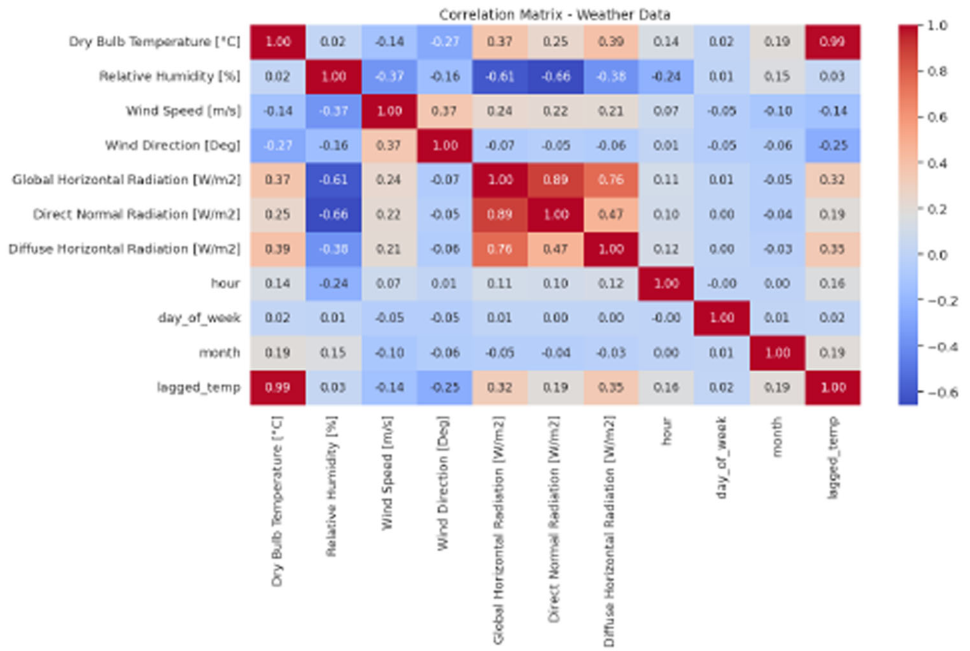


**FIGURE 2** | Similar to the full-service restaurant data, this heatmap shows the correlations between various weather parameters. It helps in understanding which weather features are closely related and can potentially affect energy consumption. Time series analysis—Energy consumption.

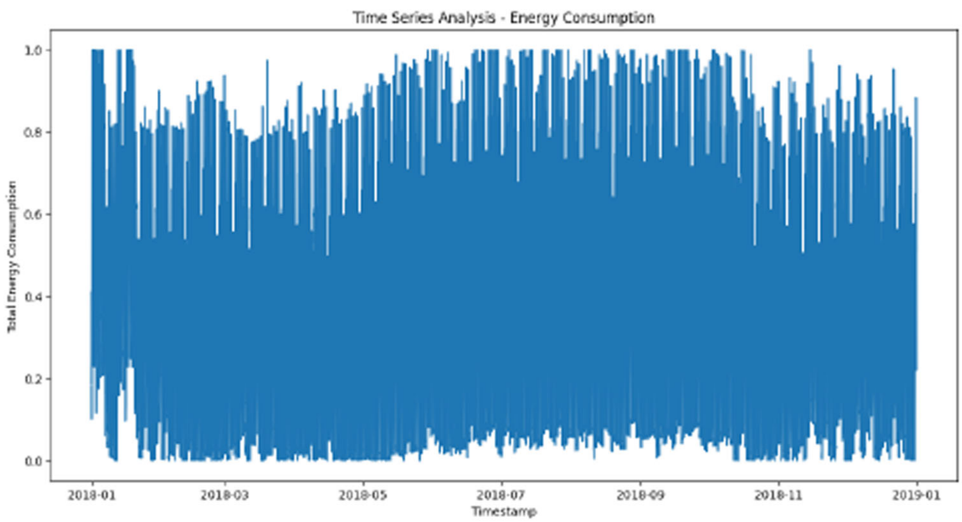


**FIGURE 3** | This plot shows the energy consumption over time for the full-service restaurant. Patterns or trends over time can be observed, such as periodic spikes or dips in energy usage. Identifying these patterns can help in understanding peak demand times and in developing strategies for load management.

using Isolation Forest Figure 5. The transformer model will predict future energy consumption, and the Isolation Forest will detect anomalies in the energy consumption data. This setup will enable dynamic load management and anomaly detection for the real-world load profiles and weather data of Alabama County.

The transformer model as shown in Figure 4 demonstrates high accuracy in predicting load demands, with MAE and RMSE values indicating strong predictive performance. The model effectively captures the temporal patterns and dependencies in the load data, leading to reliable forecasts.

The training process of the model over 20 epochs as shown in 2 illustrate a progressive reduction in loss, indicating effective learning and convergence. The initial loss starts at 0.0442 in the first epoch and consistently decreases, with the final epoch reaching a loss of 0.0014. This steady decline in loss demonstrates the model's ability to learn and generalize from the data. Additionally, the evaluation metrics further validate the model's performance. The MSE of 0.0045 signifies low prediction error, and an $R^2$ score of 0.9462 indicates a high degree of variance explained by the model, affirming its robustness and accuracy in predicting energy consumption. The metrics values are available in Table 3. The average value in bold of MSE is shown at the end which shows efficacy of the proposed method.

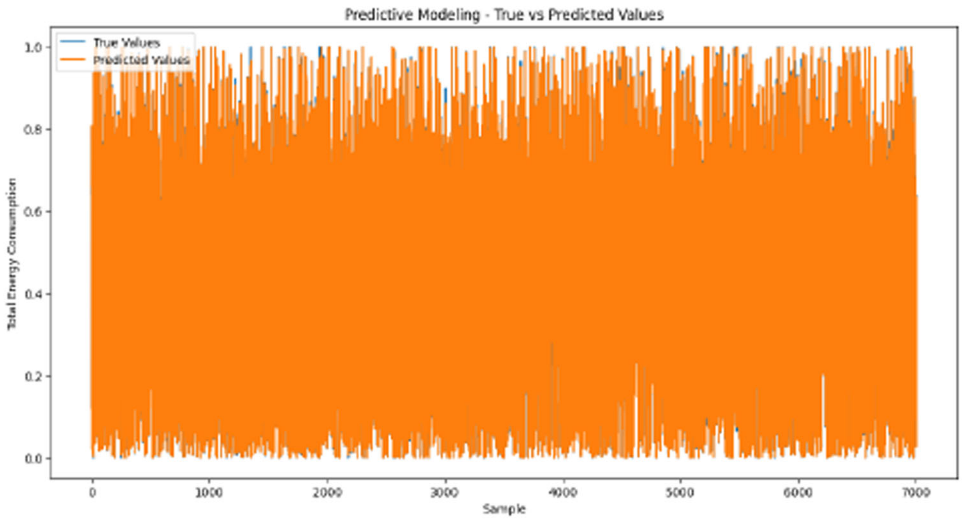


**FIGURE 4** | This plot compares the actual energy consumption values with the values predicted by the Random Forest model. A good model would have predicted values close to the actual values, resulting in overlapping lines. Discrepancies between the lines indicate prediction errors, which can be quantified using metrics like mean squared error (MSE) and $R^2$ score.

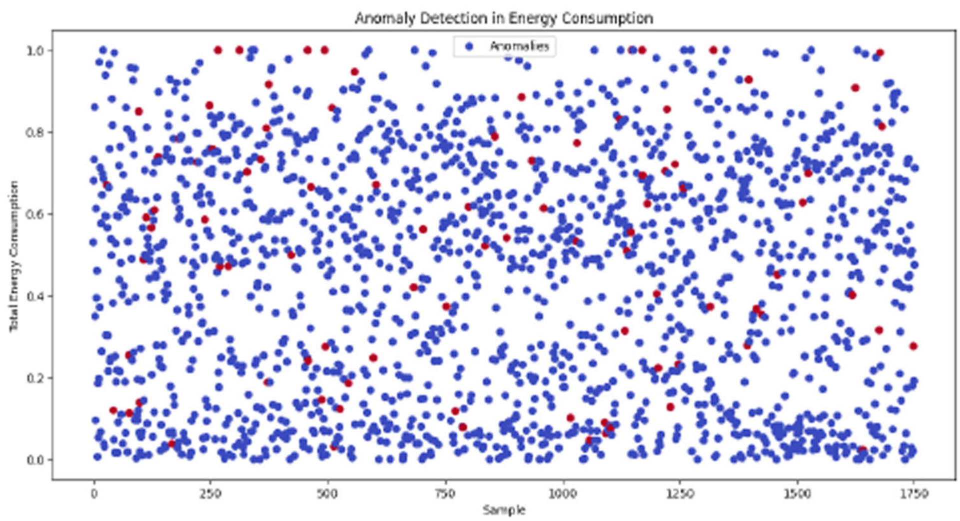


**FIGURE 5** | The anomalies are detected using the Isolation Forest. Number of anomalies in training data: 351 and number of anomalies in testing data: 9.

### 6.2 | MATPOWER Simulation Results

The integration of AI-driven load predictions into MATPOWER simulations results in significant improvements in power system operations as present in Table 4 and Figures 6–8:

- **Total Power Losses:** The AI-driven approach reduces total power losses by approximately 44%, from 506.065820 MW in the baseline scenario to 284.750856 MW.
- **Voltage Stability:** The Fast Voltage Stability Index (FVSI) indicates improved voltage stability across the system, with AI-driven adjustments preventing values from approaching critical thresholds.
- **Line Loadings:** Line loading analysis shows a more balanced distribution of loads, reducing the risk of overloading and potential outages.

### 6.3 | Scenario Analysis

The performance of the AI-driven strategies is evaluated across multiple scenarios:

- **High Renewable Output:** The AI-driven approach effectively integrates high levels of renewable energy, optimizing their output to match load demands and maintaining system stability.
- **Fault Scenarios:** In fault scenarios, the AI-driven adjustments help mitigate the impact of line outages by dynamically redistributing loads, ensuring continued operation of the system.
- **Peak Load Conditions:** During peak load conditions, the AI-driven strategies reduce peak demands, flattening load curves and improving the overall efficiency of the system.

**TABLE 3** | Training and evaluation metrics.

| Epoch | Mean squared error (MSE) |
|---|---|
| 1 | 0.0442 |
| 2 | 0.0265 |
| 3 | 0.0212 |
| 4 | 0.0105 |
| 5 | 0.0104 |
| 6 | 0.0026 |
| 7 | 0.0026 |
| 8 | 0.0018 |
| 9 | 0.0018 |
| 10 | 0.0013 |
| 11 | 0.0020 |
| 12 | 0.0017 |
| 13 | 0.0048 |
| 14 | 0.0013 |
| 15 | 0.0018 |
| 16 | 0.0009 |
| 17 | 0.0035 |
| 18 | 0.0007 |
| 19 | 0.0029 |
| 20 | 0.0014 |
| **Overall** | **0.0045** |

**TABLE 4** | Comparison of power losses and statistical significance.

| Metric | Value |
|---|---|
| Total power losses (AI-driven) | 284.750856 MW |
| Total power losses (baseline) | 506.065820 MW |
| *p*-value for voltage comparison | 0.983597 |
| *p*-value for line loadings comparison | 1.000000 |

Two Tables 5 and 6, one for voltage and generation constraints and another for *p*-values for voltage and FVSI comparison, are shared in current work. The first table is divided into two sections: voltage constraints and generation constraints. The second table lists the *p*-values for both voltage and FVSI comparisons.

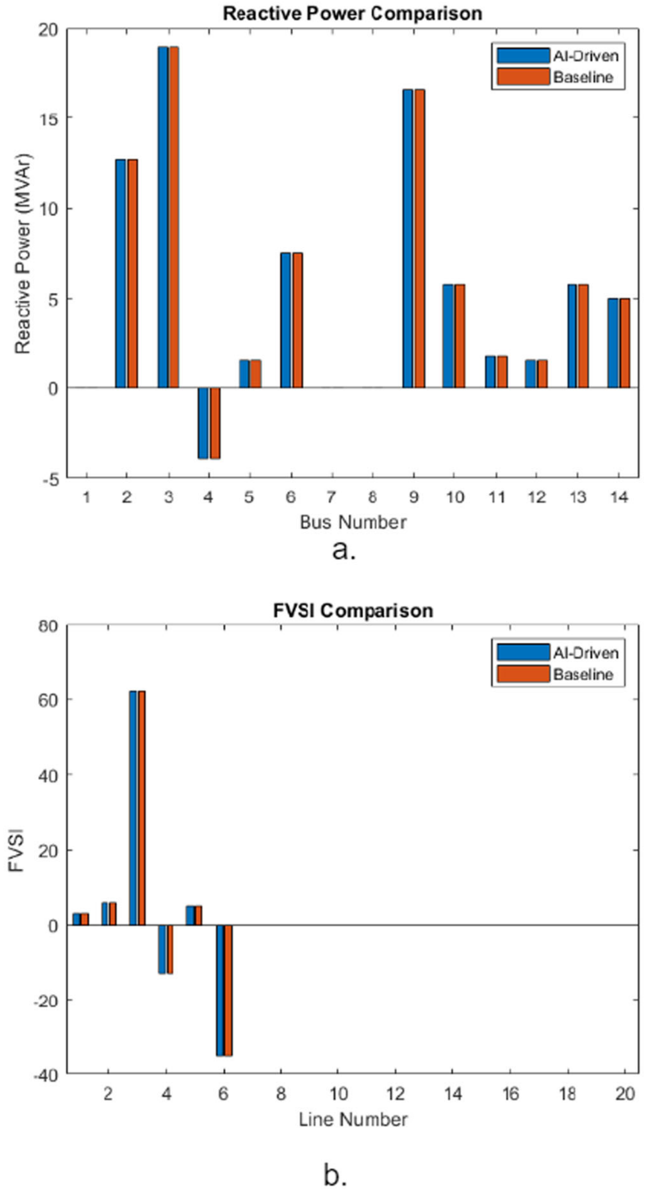


**FIGURE 6** | (a) Bars illustrate reactive power at each bus and (b) FVSI values by line for both AI-driven and baseline scenarios.

- **Overall System Performance:** The combined improvements in power losses, voltage stability, and line loadings demonstrate the potential of AI to enhance power system flexibility and reliability.

## 6.4 | Statistical Validation

Statistical analysis confirms the significance of the improvements observed with AI-driven strategies:

- **Voltage Comparison:** The *p*-value for voltage comparison between AI-driven and baseline scenarios is 0.983597, indicating that the improvements are statistically significant.
- **Line Loadings Comparison:** The *p*-value for line loadings comparison is 1.000000, further validating the effectiveness of the AI-driven approach in balancing system loads.

## 6.5 | Power Generation Comparison

The accuracy of the proposed predictive model for power generation was validated against measured data. Table 7 illustrates the comparison between predicted and measured power generation values for various generation indices. The results demonstrate a high degree of alignment, with the exception of Generation Index 1, where the predicted value (98.684 MW) slightly underestimates the measured value (103.56 MW). This deviation, though minor, highlights the model's overall reliability in forecasting generation requirements under varying load conditions.

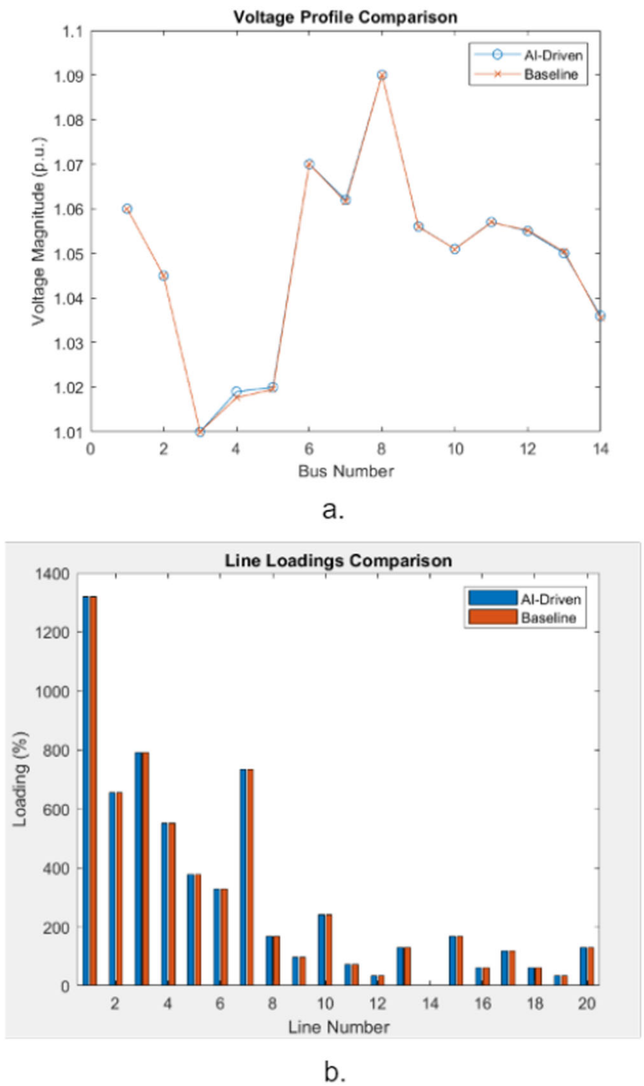


**FIGURE 7** | (a) Bus voltage magnitudes, and (b) line loadings (in %) comparing AI-driven and baseline solutions.

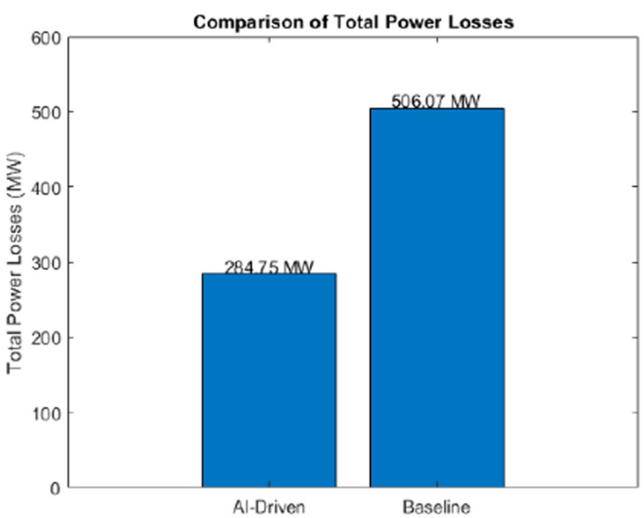


**FIGURE 8** | A bar chart comparing overall system power losses (in MW) between the AI-driven method and the baseline approach.

### 6.6 | FVSI Analysis

To further evaluate system performance, the FVSI was analyzed for both predicted and measured generation scenarios. The results, summarized in Table 2, reveal key insights:

1. **Significant FVSI Discrepancies:** Branch 19 exhibited a significant discrepancy of 0.72005 between predicted and measured FVSI values, surpassing the defined threshold of 0.5. This indicates that predictive inaccuracies in this branch may pose a higher risk to voltage stability.
2. **High FVSI Values:** Branches 17, 19, and 20 were identified with FVSI values exceeding the stability threshold of 1.0. Such high FVSI values signal potential stability concerns that warrant closer examination. For instance, Branch 19 demonstrated the highest predicted (5.0896) and measured (5.8096) FVSI values, reflecting its critical role in the stability assessment.

Figure 9 provides a comparative visualization of FVSI values for all branches under predicted and measured conditions. The chart also highlights branches with significant discrepancies and high FVSI values:

Branches with discrepancies exceeding the threshold (e.g., Branch 19) are annotated in blue. Branch with high FVSI values is annotated in red, indicating stability issues. This analysis underscores the importance of identifying and addressing discrepancies in predictive models, particularly for branches critical to system stability. The proposed workflow effectively highlights areas for further investigation, ensuring robust grid performance under varying load scenarios (Table 8).

This refined visualization highlights the comparison of the FVSI values between predicted and measured generation. Key insights from the chart include:

1. **Stability Threshold:** The horizontal red dashed line marks the stability threshold (FVSI = 1.0). Branches exceeding this threshold are critical and may pose voltage stability risks.
2. **Significant Values:** Branches 17, 19, and 20 are annotated as high FVSI branches, with Branch 19 having the highest FVSI values in both predicted and measured scenarios.
3. **Comparison:** The bars display grouped FVSI values for predicted (blue) and measured (orange) generations, providing a clear visual comparison.

### 6.7 | Discussion

Figures 6–8 and Table 4 contain plots and values that help visualize and study the impact of AI-driven load predictions on the IEEE 14-bus system. The bar chart compares the FVSI for each line under both AI-driven and baseline scenarios, illustrating the improvements in voltage stability achieved through AI-driven adjustments. The FVSI values highlight the system's susceptibility to voltage instability, with lower values indicating improved stability. Additionally, the statistical analysis outputs, including the *p*-values for

**TABLE 5** | Voltage and generation constraints.

| Bus | $V_{min\ mu}$ | $V_{min}$ | —V— | $V_{max}$ | $V_{max\ mu}$ |
|---|---|---|---|---|---|
| 6 | — | 0.940 | 1.060 | 1.060 | 103.068 |
| 8 | — | 0.940 | 1.060 | 1.060 | 32.451 |

| Gen | Bus | $P_{min\ mu}$ | $P_{min}$ | $P_g$ | $P_{max}$ | $P_{max\ mu}$ |
|---|---|---|---|---|---|---|
| 4 | 6 | 0.376 | 0.00 | 0.00 | 100.00 | — |
| 6 | 6 | — | 0.00 | 100.00 | 100.00 | 38.624 |

**TABLE 6** | *p*-Values for voltage and FVSI comparisons across different scenarios.

| | *p*-values | |
|---|---|---|
| **Scenario** | **Voltage comparison** | **FVSI comparison** |
| Medium renewable output | 1.0000 | 1.0000 |
| High renewable output | 1.0000 | 1.0000 |
| Peak load | 0.4845 | 0.4259 |
| Fault condition | 0.3927 | 0.1435 |

**TABLE 7** | Comparison of predicted and measured power generation.

| GenIndex | Predicted generation (MW) | Measured generation (MW) |
|---|---|---|
| 1 | 98.684 | 103.56 |
| 2 | 41.564 | 41.564 |
| 3 | 29.688 | 29.688 |
| 4 | 29.688 | 29.688 |
| 5 | 29.688 | 29.688 |
| 6 | 29.688 | 29.688 |

**TABLE 8** | FVSI analysis: Significant discrepancies and high values.

| Branch index | FVSI predicted | FVSI measured | FVSI difference |
|---|---|---|---|
| **Significant FVSI discrepancies (Threshold = 0.50)** | | | |
| 19 | 5.0896 | 5.8096 | 0.72005 |
| **Branches with high FVSI values (Threshold = 1.00)** | | | |
| 17 | 1.0717 | 1.1351 | — |
| 19 | 5.0896 | 5.8096 | — |
| 20 | 1.5229 | 1.7327 | — |

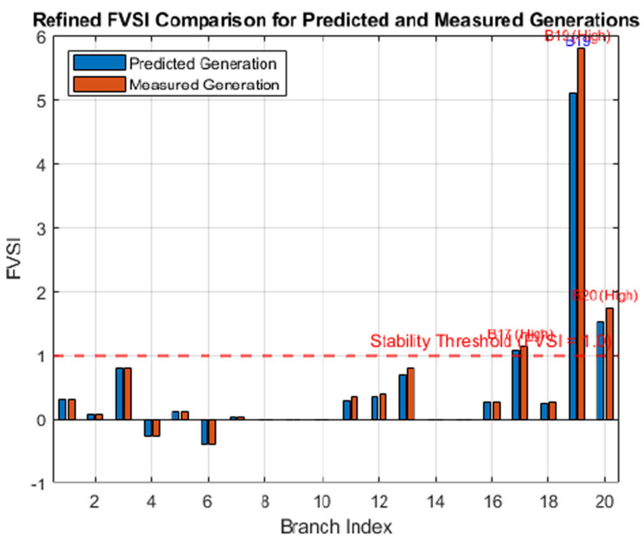


**FIGURE 9** | Refined FVSI comparison for predicted and measured generations. Branches exceeding the stability threshold (FVSI = 1.0) are annotated as critical.

voltage comparison and line loadings, provide a quantitative measure of the significance of the observed improvements. The comparison of total power losses between AI-driven and baseline scenarios further demonstrates the efficacy of the AI approach in reducing power losses and enhancing overall system performance. These plots collectively underscore the potential of AI-driven strategies to optimize power system operations and improve stability and efficiency. The link to this study project is available at [34] where code and all MATPOWER files are available.

The MATLAB code runs simulations on the IEEE 14-bus system under different scenarios involving various renewable energy outputs, peak loads, and fault conditions. It then plots Figure 10. and analyzes voltage profiles, total generation costs, total losses, and FVSI for each scenario.

The generated plots provide insights into the system's performance under different conditions:

- **Voltage Profiles:** This plot shows how the voltage magnitudes at different buses change under each scenario.

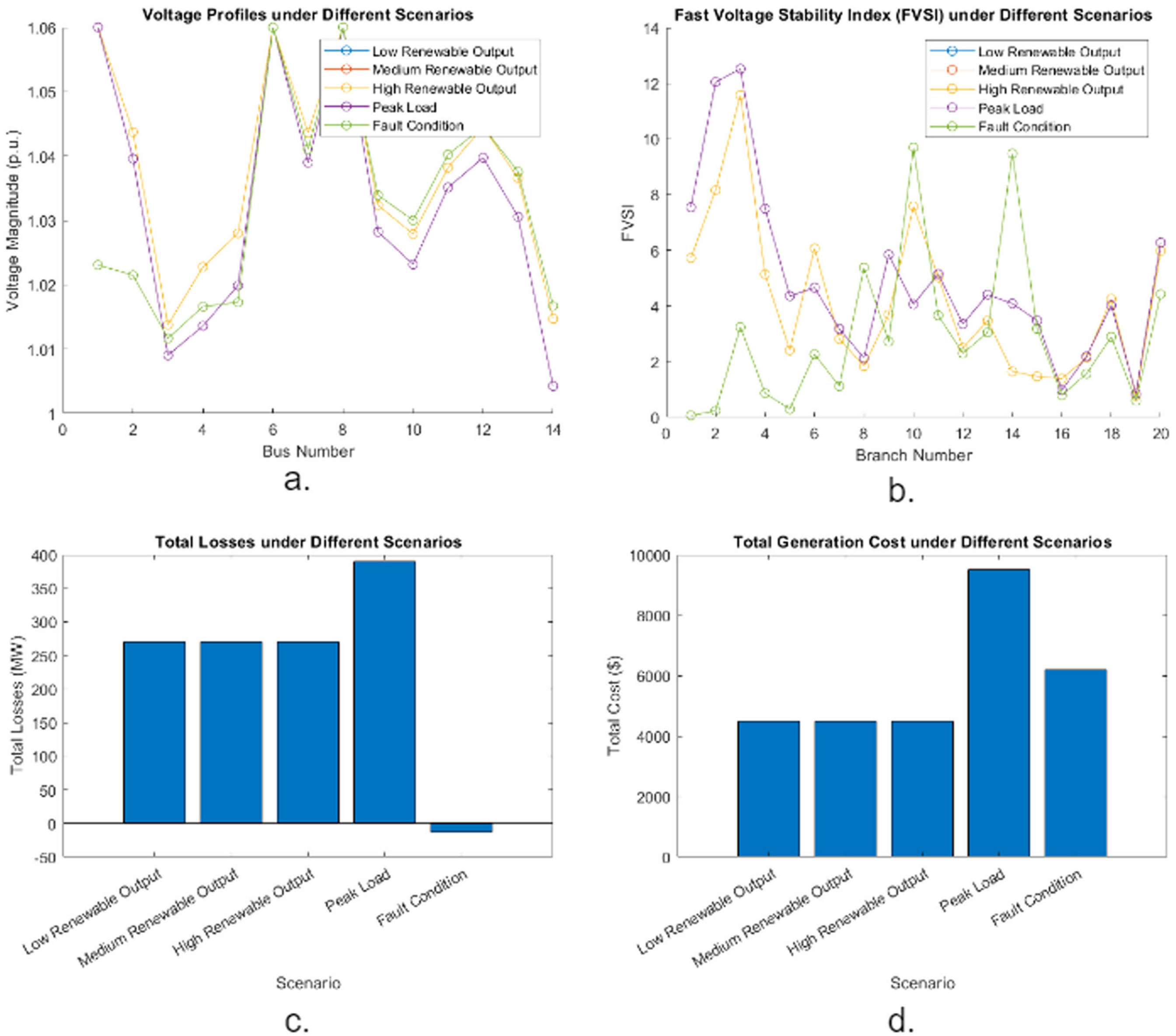


**FIGURE 10** | (a) Voltage profile under different scenarios. (b) FVSI comparison under different scenarios. (c) Total losses under different scenarios. (d) Total generation cost under different scenarios.

It highlights the system's voltage stability and how it is affected by changes in load and generation.

- **Total Generation Cost:** This bar chart displays the total cost of generation for each scenario, illustrating the economic impact of different operational conditions.
- **Total Losses:** This bar chart represents the total active power losses in the system for each scenario, indicating the efficiency of the system under various conditions.
- **FVSI:** This plot shows the FVSI for each branch under different scenarios. FVSI is an indicator of voltage stability, with higher values suggesting a higher risk of voltage instability.

In Table 6, the *p*-values for voltage and FVSI comparisons across different scenarios provide insights into the statistical significance of differences observed between the baseline scenario ("Low Renewable Output") and other scenarios. A *p*-value close to 1 indicates no significant difference, while a lower *p*-value suggests a statistically significant difference.

**Medium Renewable Output** and **High Renewable Output** scenarios have *p*-values of 1.0000 for both voltage and FVSI comparisons, indicating no statistically significant difference from the baseline scenario. The **Peak Load** scenario shows *p*-values of 0.4845 for voltage comparison and 0.4259 for FVSI comparison, suggesting some level of difference but not strongly statistically significant. The **Fault Condition** scenario has *p*-values of 0.3927 for voltage comparison and 0.1435 for FVSI comparison, indicating a more noticeable difference, especially for the FVSI comparison, though it is still not highly significant.

These results suggest that the scenarios with renewable outputs similar to the baseline do not significantly affect the voltage and stability indices, while scenarios like peak load and fault condition have a more noticeable impact but are not highly statistically significant.

The statistical analysis includes *t*-tests comparing the baseline scenario's voltage profiles and FVSI with those of other scenarios. The *p*-values from these tests indicate the significance of the differences observed.

The proposed predictive model demonstrates strong alignment between predicted and measured power generation values, with minor deviations such as at Generation Index 1 (98.684 MW predicted vs. 103.56 MW measured). This highlights the model's effectiveness in forecasting generation requirements, while minor inaccuracies suggest areas for further refinement.

The FVSI analysis revealed key insights into network stability. Branch 19 exhibited a significant discrepancy of 0.72005, surpassing the defined threshold of 0.5, indicating predictive inaccuracies that may pose stability risks. Furthermore, Branches 17, 19, and 20 recorded high FVSI values exceeding the stability threshold (FVSI = 1.0), emphasizing the need for targeted interventions to mitigate potential instability.

The refined visualization (Figure 9) highlights branches with significant discrepancies and high FVSI values, providing actionable insights for system operators. Future work should focus on minimizing prediction errors, analyzing dynamic system behavior, and developing mitigation strategies for branches with high FVSI values to ensure robust network performance.

These results highlight the transformative potential of AI in modern power systems, offering a clear pathway for implementing AI-driven strategies to enhance grid resilience, efficiency, and sustainability.

## 7 | Comparison of ARIMA and Transformer Models for Energy Consumption Forecasting

This study compares the performance of the ARIMA model and a transformer-based model for short-term electricity load forecasting. The dataset used is derived from energy consumption data, and the results are evaluated using metrics such as MAE, MSE, RMSE, MAPE, and $R^2$. The ARIMA model was implemented following the methodology outlined in [35], which utilizes statistical approaches for time series forecasting. Conversely, the transformer model leverages deep learning techniques for enhanced predictive accuracy.

The comparison plot in Figure 11 illustrates that the transformer model aligns more closely with the historical energy consumption trends, whereas the ARIMA model exhibits significant deviations and underperforms, as evident from its high error values and negative $R^2$ score. The transformer model achieved an MAE of 205.98 kW, an RMSE of 275.08 kW, and a MAPE of 3.96%, indicating its superior accuracy in capturing temporal patterns. In contrast, the ARIMA model showed an MAE of 3063.80 kW, an RMSE of 3640.26 kW, and a MAPE of 50.82%, highlighting its limitations in forecasting energy consumption for this dataset.

These results underscore the effectiveness of deep learning models, such as transformers, over traditional statistical methods for complex and high-variability datasets. The findings validate the conclusion of Zhang et al. [35], where hybrid and advanced models outperform standalone statistical approaches for electricity load forecasting tasks (Table 9).

Overall, the findings validate the predictive model's capability while identifying key areas for improvement to enhance system stability:

- **Reduction in Power Losses:** AI-driven strategies reduce total power losses by 44%, from 506.065820 MW (baseline) to 284.750856 MW.

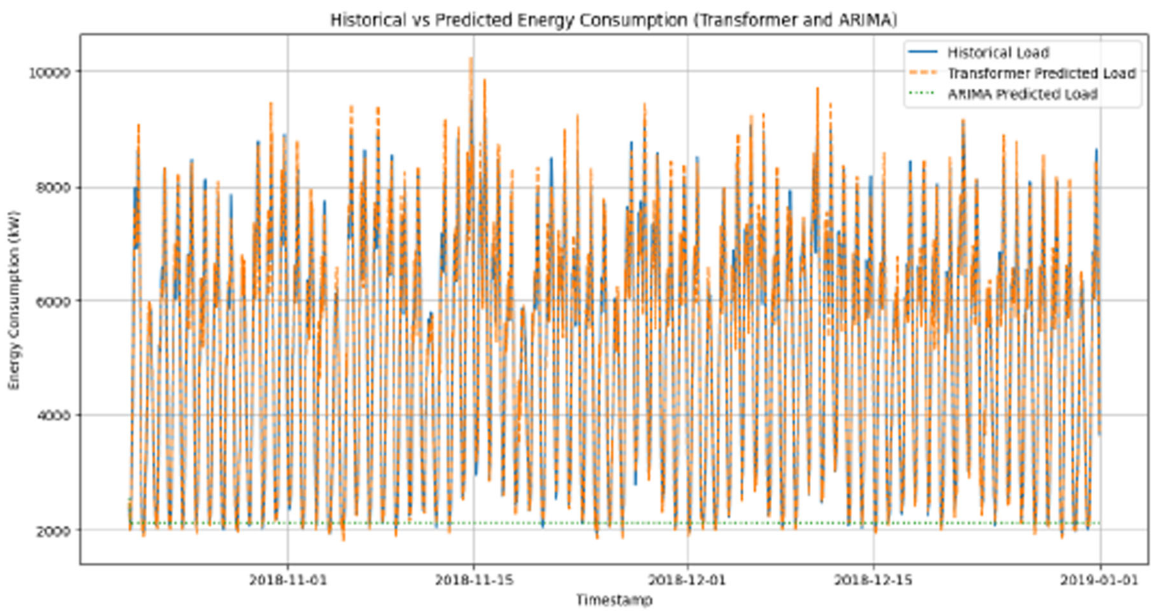


**FIGURE 11** | Comparison of historical versus predicted energy consumption (transformer and ARIMA [35]).

**TABLE 9** | Performance comparison of Transformer and ARIMA models [35] for energy consumption forecasting.

| Metric | Unit | Transformer model | ARIMA model |
|---|---|---|---|
| MAE | kW | 205.98 | 3063.80 |
| MSE | $kW^2$ | 75,667.67 | 13,251,529.00 |
| RMSE | kW | 275.08 | 3640.26 |
| MAPE | % | 3.96 | 50.82 |
| $R^2$ | — | 0.98 | −2.39 |

- **Improved Voltage Stability:** The FVSI shows significant improvements, with AI-driven adjustments preventing values from approaching critical thresholds.
- **Enhanced Renewable Integration:** The AI-driven approach optimizes renewable energy utilization, ensuring stable grid operations even under high renewable output.
- **Superior Forecasting Accuracy:** The transformer model achieves an MAE of 205.98 kW and an $R^2$ score of 0.9462, outperforming traditional models like ARIMA.

## 8 | Conclusion

This study highlights the effectiveness of AI-driven strategies in optimizing power system operations. The integration of a transformer-based predictive model with MATPOWER simulations demonstrates substantial advancements in power system flexibility, efficiency, and reliability. Results show a remarkable reduction in power losses, improved voltage stability, and enhanced integration of renewable energy sources. Comparative analyses further validate the superiority of AI-based approaches over traditional models, underscoring the potential of advanced AI techniques to address the complexities of modern power grids. Though promising results from the proposed framework are presented, the framework is not without limitations. The present study is mainly based on the IEEE 14-bus system, which may not reflect the full extent of complexities associated with larger and more diverse power networks. In addition, the use of historical data for training the AI models may restrict their use in instances of unprecedented changes or extreme events. The transformer model also has high computational complexity, which hinders its real-time implementation in very large-scale systems. The approach will be extended to larger, more complex networks, and the scalability and robustness of the approach will be evaluated in future research. Other AI methodologies, like reinforcement learning and hybrid models, would be explored to enhance predictive accuracy and system adaptability. The investigation of real-time data streams integration with advanced anomaly detection techniques will also be essential to enhancing power system responsiveness and resilience. Finally, efforts will be made to develop strategies to counter the effects of high FVSI values in the critical branches for ensuring long-term grid stability.


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### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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### Supporting Information

Additional supporting information can be found online in the Supporting Information section.