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Research Article

Data-Driven Load Forecasting and Power Flow Optimization Using Deep LSTM Networks

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Abstract

In light of the rapidly increasing global demand for energy, accurately forecasting short-term electricity consumption has become a critical yet challenging task for modern power system operation and planning, as traditional methods often struggle to handle the variability and uncertainty of load demand. To address these limitations, this study proposes an integrated and data-driven framework that combines an Alternating Current Optimal Power Flow (ACOPF) model with a Long Short-Term Memory (LSTM) recurrent neural network in order to simultaneously enhance forecasting accuracy and operational efficiency. The LSTM model, trained on historical load data, is used to generate reliable 24-hour ahead electricity demand forecasts, which are then dynamically incorporated into the MATPOWER simulation environment using the IEEE 30-bus test system. The results demonstrate that the proposed approach achieves a high level of predictive performance, with a root mean square error (RMSE) of 0.3794, indicating its effectiveness in capturing temporal load patterns. More importantly, the integration of these forecasts into the ACOPF framework enables more proactive and informed decision-making in power system operations, leading to a significant improvement in economic dispatch by reducing the hourly generation cost from $576.89/h under conventional approaches to $490.91/h, corresponding to an approximate cost reduction of 14.9%. Overall, this study highlights the strong synergy between deep learning techniques and optimization models for smart grid management, showing that the proposed framework not only improves forecasting precision but also enhances system efficiency, reduces operational costs, and supports more reliable, flexible, and cost-effective power system operations.

Keywords

Deep Learning, LSTM, Optimal Power Flow (OPF), MATPOWER, IEEE 30-bus, Forecasting

1. Introduction

Modern power grid management faces growing challenges related to rising energy demand, the liberalization of electricity markets, and the large-scale integration of intermittent renewable energy sources [28]. In this context, short-term load forecasting (STLF) plays a fundamental role in ensuring operational reliability, grid stability, and cost-effective planning of electricity generation [1]. Indeed, even a relatively small error in demand forecasting can lead to significant operational

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costs, poor generator dispatch planning, or a deterioration in the overall performance of the power system.

Traditionally, the optimization of power grid operations is performed using Optimal Power Flow (OPF), which aims to determine the optimal dispatching of generators while adhering to the system's technical constraints. Conventional OPF methods generally rely on deterministic models using fixed loads or linear demand estimates [5]. However, the highly nonlinear, dynamic, and stochastic nature of modern electricity demand limits the performance of these traditional approaches, particularly in smart grids where load variations can be rapid and unpredictable [29].

With recent advances in artificial intelligence, deep learning techniques have demonstrated considerable potential for analyzing energy time series [30]. Among these techniques, Long Short-Term Memory (LSTM) neural networks have proven particularly effective for forecasting electricity demand. Thanks to their advanced recurrent architecture, LSTM networks are capable of capturing the long-term temporal dependencies present in historical electricity consumption data. Unlike traditional neural networks, LSTMs also overcome the vanishing gradient problem, which significantly improves the accuracy of models for time series forecasting tasks [3, 4].

In this context, several recent studies have explored the use of deep learning models to improve the accuracy of load forecasts [31]. However, only a limited number of studies have actually integrated these forecasts into a power system optimization framework, such as the calculation of optimal power flow [32]. Yet, the direct integration of forecast results into optimization algorithms could significantly improve the economic and operational performance of modern power grids [33].

In this work, we propose an integrated approach that combines load forecasting based on a Deep LSTM network with AC Optimal Power Flow (ACOPF) optimization. The forecasting model is trained using historical electricity load data to predict hourly demand for the next 24 hours. These forecasts are then used to dynamically adjust the system load in the OPF calculation.

To evaluate the effectiveness of the proposed approach, simulations are performed using the MATPOWER platform, which is widely used for the analysis and optimization of power systems [2]. The test system considered is the IEEE 30-bus network, which serves as a classic benchmark for studying optimization problems in power systems [34].

The experimental results show that integrating LSTM forecasts into the optimization process improves generator dispatch planning and significantly reduces the operational costs of the power system.

The main contributions of this work can be summarized as follows:

1) Development of a Deep LSTM model for short-term (24-hour) load forecasting.
2) Direct integration of load forecasts into an AC Optimal Power Flow optimization framework.
3) Evaluation of the proposed approach on the IEEE 30-bus test system using the MATPOWER environment.
4) Analysis of the economic impact of load forecasting on reducing power generation costs in the power system.

The remainder of this paper is organized as follows. Section II presents the Deep LSTM-based forecasting model and the data preparation process. Section III describes the mathematical formulation of the optimal power flow problem applied to the IEEE 30-bus system. Section IV presents the simulation results and the analysis of the system's economic performance. Finally, Section V concludes the paper and proposes several avenues for future research.

2. Literature Review

2.1. The Problem of Optimal Power Flow

The problem with AC OPF is to minimize the total cost of production [15, 35]:

$$min \sum_{i\in \mathcal{G}} C_i \left(P_{g,i}\right) \tag{1}$$

Subject:

1) AC power flow equations
2) Generator limits
3) Voltage amplitude limits
4) Thermal limits of power lines

Where P_{gi} denotes the active power delivered by generator i.

The problem of optimal power flow aims to minimize the total cost of generation in an electrical power system. When considering only the objective function, this is an unconstrained optimization problem. When using power flow equations, this is an optimization problem with equality constraints [13, 36, 37]. When including power limits, this is an optimization problem with both equality and inequality constraints. [16, 17, 20, 24, 25].

min F(x) (objective function)

However,

g_i (x) = 0; i = 1, 2, …, n (equality constraints)

And,

h_j (x) ≤ 0; j = 1, 2, …, m (inequality constraints)

Objective function:

This function takes into account the need to minimize the total cost of active power generation [21-23, 35]. It is assumed that the individual cost of each generation plant depends solely on active power generation [14, 18-20, 22].

$$F = \sum_{i=1}^{ng} f_i = \sum_{i=1}^{ng} C_i = \sum_{i=1}^{ng} \alpha_i + \beta_i P_{Gi} + \gamma_i {P_{Gi}}^2$$

2.2. IEEE 30-Bus Test System

The 30-node IEEE network serves as a benchmark; it includes multiple generators, transmission constraints, and nonlinear power flow characteristics.

The study was conducted on the standard 30-node IEEE network, which is widely used as a test case for evaluating power flow optimization algorithms. The data file includes several matrices representing the various components of the power grid, which are necessary for formulating the OPF problem [26, 27].

The main data structures extracted are described below:

Matpower Case (mpc): This is the main structure containing all the network information, in accordance with the Matpower format.

mpc.bus: This matrix describes the characteristics of each node (bus) in the network. Each row corresponds to a node and includes:

1) The bus type (1 = load, 2 = PV, 3 = slack) [38]
2) Active and reactive demand (Pd, Qd),
3) Voltage limits (Vmin, Vmax),
4) The phase angle and magnitude of the voltage (θ, V) [38]

mpc.gen: This matrix contains data relating to generators, including:

1) The injection node,
2) The active and reactive power generated (Pg, Qg),
3) The upper and lower limits (Pmax, Pmin, Qmax, Qmin),
4) Terminal voltage.

mpc.branch: This matrix details the characteristics of the transmission lines, including:

1) Origin and destination nodes,
2) Impedance (resistance R, reactance X) and susceptance,
3) Maximum thermal capacity (rateA).

mpc.gencost: This matrix contains the coefficients of the quadratic cost functions associated with each generator. It is used in the objective function to minimize the total cost of production.

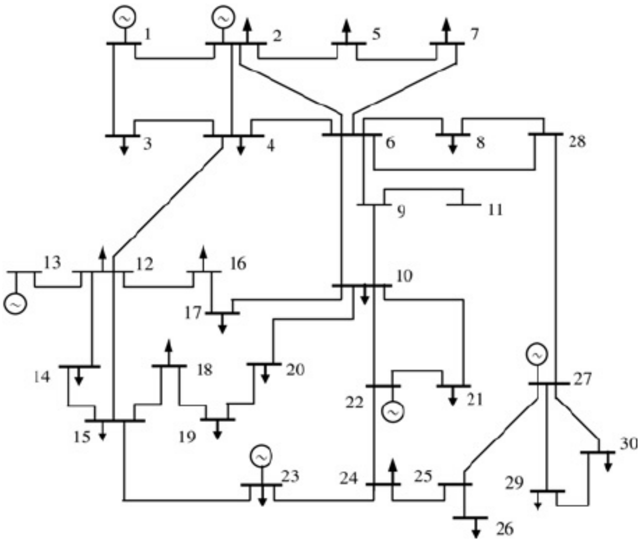


Figure 1. *IEEE 30 bus.*

This data is used as input for solving the OPF problem, where the main objective is to minimize generation costs while respecting the physical and operational constraints of the power grid (power balance, voltage limits, line capacity, etc.). The file also includes simulation results, such as power distribution, line losses, and the final state of each bus after optimization [27].

3. Theoretical and Methodological Context

Short-term load forecasting is an essential component of the operational management of modern power systems [39]. An accurate estimate of demand improves generator dispatch planning, reduces operating costs, and increases the reliability of the power grid [40]. Among the various approaches proposed in the literature, deep learning-based methods have demonstrated remarkable performance in modeling complex energy time series [10, 11].

In this work, a forecasting model based on a Long Short-Term Memory (LSTM) recurrent neural network is developed to predict hourly electricity demand for the next 24 hours.

3.1. Description of the Dataset

The forecasting model is developed using the AEP Hourly Load Dataset, which provides hourly electricity demand measurements in megawatts. In this study, 90 days of data (2160 observations) are used, offering sufficient temporal resolution to capture daily load patterns while maintaining computational efficiency. The dataset is split into 80% for training and 20% for testing to ensure proper generalization. Prior to training, the data are standardized to improve convergence and numerical stability. To model temporal dependencies, a sliding window approach is adopted, where the previous 24 hours are used to predict the next 24 hours, enabling effective multi-step forecasting of daily load cycles. The proposed deep learning model consists of a two-layer LSTM architecture (128 and 64 units) with dropout regularization, followed by fully connected layers. The network is trained using the Adam optimizer with 60 epochs, a batch size of 32, and a learning rate of 0.001. Model performance is evaluated using the RMSE metric, yielding a value of 0.3794, which indicates good forecasting accuracy. The predicted 24-hour load profile is subsequently integrated into the AC optimal power flow framework to assess its impact on generation cost optimization [10, 11, 41-43].

3.2. Deep LSTM Network Architecture

The network comprises two stacked LSTM layers (128 and 64 units) with dropout (0.2), followed by a fully connected layer and a ReLU activation.

3.3. Model Training Process

The model is trained using the Adam (Adaptive Moment Estimation) optimization algorithm, which is widely used in deep neural networks due to its ability to accelerate convergence and stabilize learning [11]. The main training parameters are as follows:

Table 1. *Training Parameters.*

Parameter	Value
Optimizer	Adam
Number of epochs	60
Mini-batch size	32
Initial learning rate	0.001

During training, the network adjusts its parameters to minimize the error between the predicted values and the actual load values.

3.4. Evaluation of Forecasting Performance

The model's accuracy is evaluated using the Root Mean Square Error (RMSE) metric, which is widely used in studies of electricity load forecasting [11].

The experimental results obtained in this study show that the proposed model achieves a root mean square error (RMSE) of 0.3794, indicating good generalization ability for short-term electricity load forecasting.

The forecasts obtained for the next 24 hours are then used as input in the AC Optimal Power Flow optimization model to analyze their impact on the power system's generation costs.

4. Results

To evaluate the performance of the proposed approach, several simulations were conducted by combining load forecasting based on a Deep LSTM network with an AC Optimal Power Flow (ACOPF) optimization model. The experiments were carried out in the MATLAB environment, using the MATPOWER platform, which is widely used for the analysis and optimization of power systems [9].

The test system used is the IEEE 30-bus network, which serves as a classic benchmark for studying optimization problems in power systems [6].

4.1. Historical Load

This figure shows the historical electrical load used to train the model.

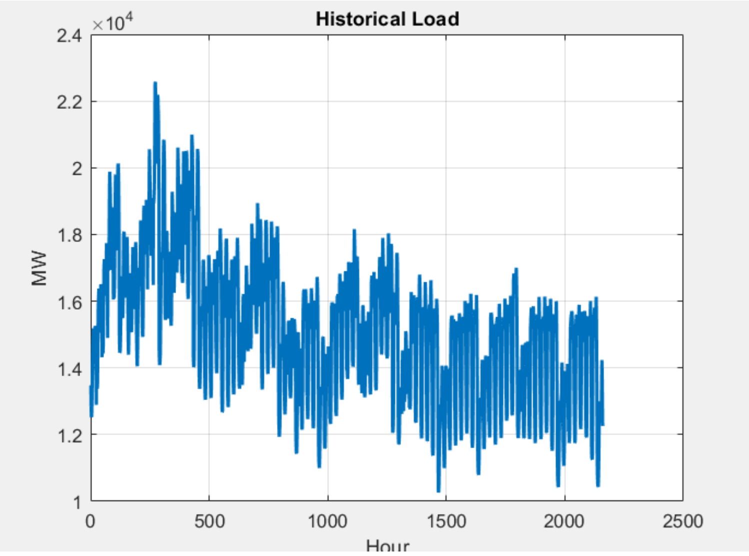


Figure 2. *Historical Electricity Load.*

The figure shows the time series of electricity demand over approximately 2,200 hours. The load varies approximately between:

1) 10 000 MW
2) 23 000 MW

Several important characteristics can be observed:

4.1.1. Load Variability

Demand exhibits:

1) Significant short-term fluctuations
2) Stochastic variability

This corresponds to the actual behavior of power grids.

4.1.2. Presence of Cycles

The following are observed:

1) Daily cycles
2) Seasonal or weekly variations

These patterns are typical of consumption profiles.

4.1.3. Importance for Forecasting

The high variability indicates that:

Load forecasting is necessary to improve OPF optimization.

Without forecasting:

1) The system must manage uncertainty
2) Which can increase operating costs

The historical load profile exhibits significant stochastic fluctuations, ranging from approximately 10,000 MW to 23,000 MW over the observed horizon. Such variability underscores the need for accurate short-term load forecasts to enable optimal energy flow calculations.

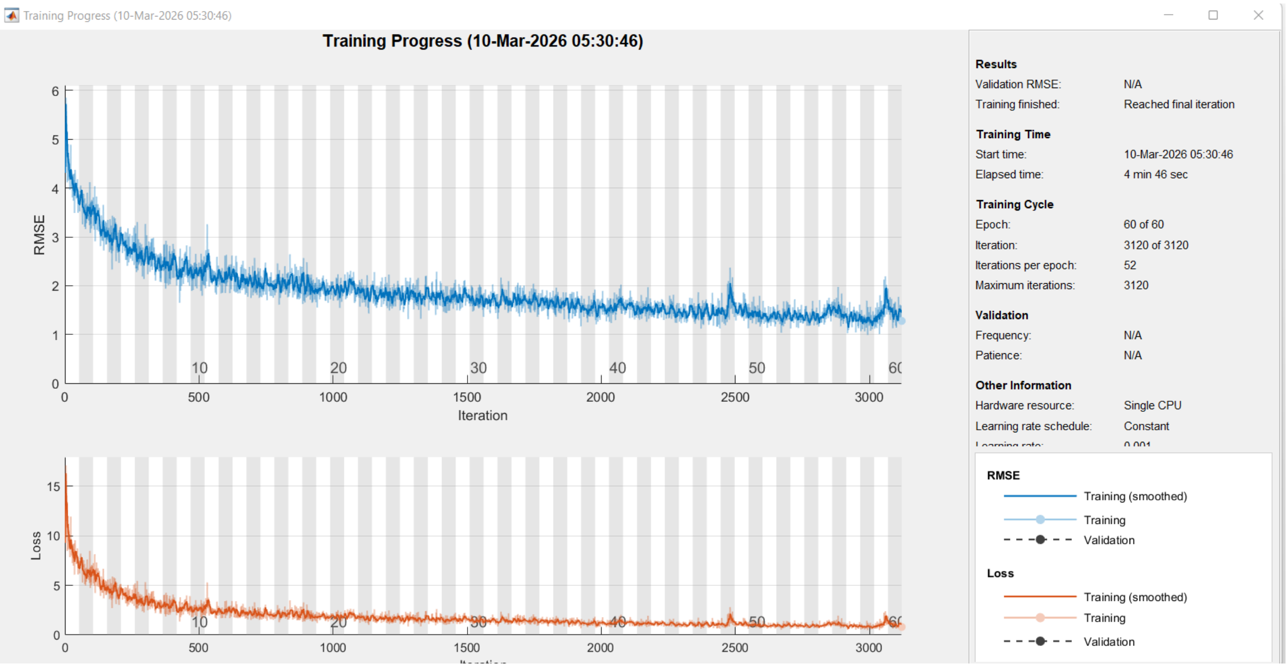
4.2. Training the LSTM Model

LSTM Forecast RMSE = 0.3794

The figure below shows the training of the LSTM model.

Two indicators are displayed:

1) RMSE
2) Loss



Results
Validation RMSE: N/A
Training finished: Reached final iteration

Training Time
Start time: 10-Mar-2026 05:30:46
Elapsed time: 4 min 46 sec

Training Cycle
Epoch: 60 of 60
Iteration: 3120 of 3120
Iterations per epoch: 52
Maximum iterations: 3120

Validation
Frequency: N/A
Patience: N/A

Other Information
Hardware resource: Single CPU
Learning rate schedule: Constant
Learning rate: 0.001

Figure 3. Training Progress.

The training curve shows a steady decrease in RMSE, confirming effective learning of temporal dependencies by the LSTM model. The rapid convergence during early epochs indicates efficient parameter optimization, while the stabilization phase suggests that the model has reached a near-optimal solution. However, the absence of a validation curve prevents a complete assessment of generalization capability. Despite this limitation, the low RMSE value aligns with the observed reduction in OPF cost, demonstrating the effectiveness of the proposed approach.

This means that:

1) The LSTM effectively captures temporal dynamics
2) The model can be used for load forecasting.

4.3. Performance of the LSTM Load Forecasting Model

The first step is to evaluate the Deep LSTM model's ability to predict electricity demand for the next 24 hours. The model is trained using historical electricity load data from the AEP Hourly Load dataset, as described in the previous section.

Forecast accuracy is measured using the Root Mean Square Error (RMSE) metric, commonly used in energy forecasting studies [11].

The results show that the model achieves a forecast error of:

$$RMSE=0.3794$$

This low RMSE value indicates that the LSTM model is capable of effectively capturing the temporal dependencies present in the electricity consumption data.

Figure 4 illustrates the load forecast obtained for the next 24 hours.

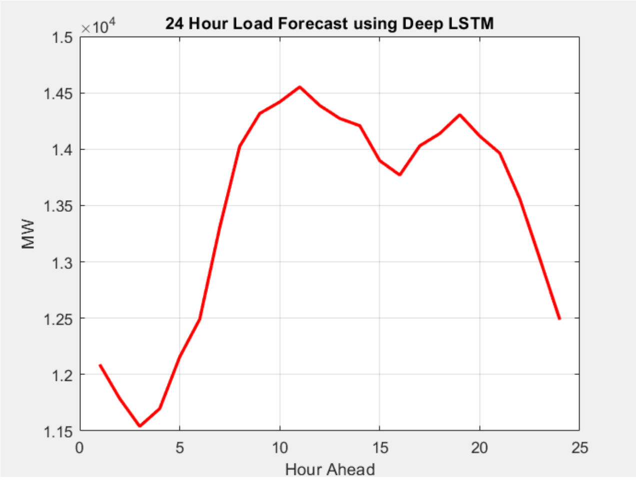


Figure 4. 24 Hours Load Forecast.

It can be observed that the load exhibits dynamic behavior typical of electrical systems, characterized by a gradual increase during the day followed by a decrease during periods of low consumption. This type of daily variation is well captured by the LSTM model, confirming its ability to model complex energy time series [10].

4.4. Analysis of Costs Associated with Optimal Power Flow

Once the future load is estimated, the resulting forecasts are integrated into the AC Optimal Power Flow model to determine the optimal dispatching of generators for each hour of the day.

First, a standard AC Optimal Power Flow is solved using the average system load:

$$C_{classical} = 576.89 \text{ \$/h}$$

Next, the load predicted by the LSTM model is used to dynamically adjust the system demand for each hour. The OPF is then recalculated for each hourly period.

The resulting average cost is:

$$C_{LSTM-OPF} = 490.91 \text{ \$/h}$$

These results show that integrating load forecasts into the optimization process significantly reduces the operational cost of the power system.

Figure 5 shows the hourly evolution of the OPF cost calculated using LSTM forecasts.

It can be observed that variations in generation costs directly follow fluctuations in the forecasted load. Periods of high demand lead to an increase in generation costs, while periods of low demand result in a reduction in operating costs.

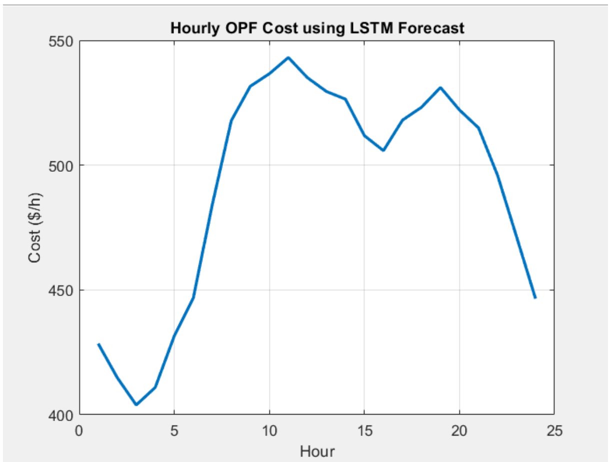


Figure 5. Hourly OPF cost using LSTM forecasts.

4.5. Economic Impact of the Proposed Approach

To assess the economic impact of the proposed method, a direct comparison is made between the cost obtained using the conventional OPF and the cost obtained by integrating the LSTM forecast.

The results are summarized in the following table:

Table 2. Generation cost results.

Method	Generation Cost ($/h)
Classical OPF	576.89
LSTM-based OPF	490.91

The relative reduction in generation cost is calculated as follows:

$$Cost \text{ Reduction } (\%) = \frac{C_{classical}-C_{LSTM-OPF}}{C_{classical}} \times 100$$

Substituting the values:

$$Cost \text{ Reduction } = \frac{576.89-490.91}{576.89} \times 100$$

$$Cost \text{ Reduction } \approx 14.9\%$$

This significant reduction demonstrates that the use of deep learning-based load forecasting can considerably improve the economic planning of generator dispatch.

These results also confirm the findings reported in several recent studies, which indicate that integrating deep learning methods into energy management systems can improve the operational efficiency of modern power grids [7, 8].

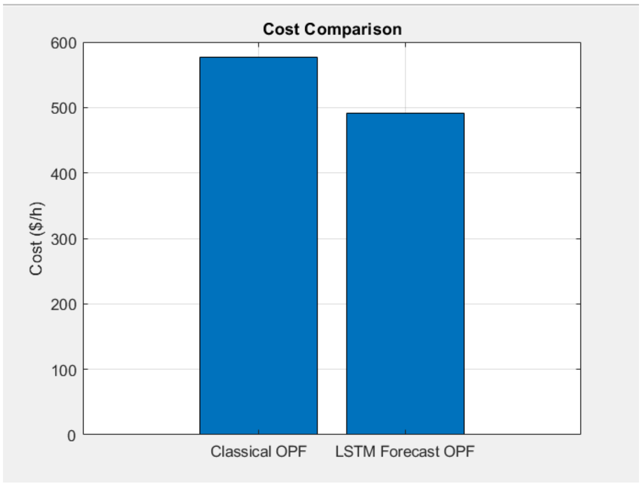


Figure 6. Cost comparaison.

4.6. Analysis of Generator Commissioning

Power flow optimization also makes it possible to determine the active power generated by each generator in the system.

Figure 7 illustrates the distribution of power generation among the various generators in the IEEE 30-bus network in the case of conventional OPF.

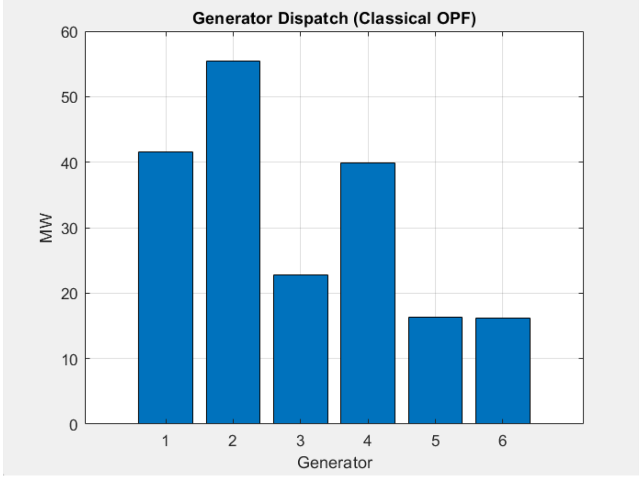


Figure 7. Generator Dispatch.

It is observed that the power generated varies from one generator to another depending on their economic and technical characteristics. Generators with lower marginal costs are generally given priority, in accordance with the principles of economic dispatch optimization [12].

5. Discussion

The results clearly demonstrate the value of integrating AI-based forecasting models into power system optimization tools. The use of a Deep LSTM model effectively captures temporal variations in electricity demand, while integrating these forecasts into the ACOPF model improves generator dispatch planning and reduces generation costs.

However, certain limitations should be noted. First, the study is conducted on a standard test system (IEEE 30-bus), which does not fully reflect the complexity of real-world power grids. Second, the uncertainties associated with load forecasts are not explicitly accounted for in the optimization model.

Future work could thus explore the integration of robust or stochastic optimization methods to account for the uncertainty in load forecasts and renewable energy sources [7].

6. Conclusion

This paper presents a data-driven approach for electricity load forecasting and power flow optimization using deep LSTM (Long Short-Term Memory) networks. The proposed method leverages the ability of LSTM models to capture temporal dependencies in time series of load data, thereby enabling accurate short-term load forecasting. These forecasts can contribute to more efficient operation and planning of power grids.

The results demonstrate that the LSTM-based model offers reliable forecasting performance and can help improve decision-making in power grid operations. By integrating data-driven forecasting techniques with power flow analysis, the proposed approach offers a promising framework for improving the efficiency and reliability of modern power grids.

Future work will focus on integrating additional influencing factors, such as meteorological variables, and on validating the approach on larger-scale power grids to further confirm its scalability and robustness.

Abbreviations

STLF	Short-term Load Forecasting
ACOPF	Alternating Current Optimal Power Flow
AC	Alternating Current
IEEE	Institute of Electrical and Electronics Engineers
AEP	American Electric Power
LSTM	Long Short-Term Memory
RelU	Rectified Linear Unit
ADAM	Adaptive Moment Estimation
RMSE	Root Mean Square Error

Author Contributions

Randriamora Edmond: Conceptualization, Investigation, Methodology, Resources, Writing – original draft, Writing – review & editing

Rasolofonirina Tokiniaina Francky: Data curation, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing

Randriamaroson Mahandrisoa Rivo: Conceptualization, Project administration, Resources, Supervision, Validation, Writing – review & editing

Conflicts of Interest

The authors declare no competing interests.

Appendix

Pseudocode

```
Start
    Initialize MATPOWER
    Define electrical constants
    Configure OPF options
    Read CSV file
    Extract actual load (MW)
    Select 90 days (2160 hours)
    Calculate mean $\mu$
    Calculate standard deviation $\sigma$
    Normalize the data:
        $data\_norm = (data - \mu) / \sigma$
    For i = 1 to N:
        X[i] = 24-hour sequence (input)
        Y[i] = forecast for the next 24 hours (output)
    End For
    Split data:
        80% → training
        20% → testing
    Define network:
        Input layer
        LSTM (128 neurons)
        Dropout
        LSTM (64 neurons)
        Dense layer + ReLU
        Output layer (24 values)
    Configure parameters:
        Optimizer = Adam
        Epochs = 60
        Batch = 32
    Train the network
    Take the last 24 values
    Predict the next 24 hours
    Normalize the results
    Predict on test data
    Calculate RMSE:
        $RMSE = \sqrt{\text{mean of squared errors}}$
    Load the IEEE 30-bus system
    Run OPF with average load
    Obtain conventional cost
    For each hour h = 1 to 24, do the following:
        Calculate factor $\alpha$:
            $\alpha = predicted\_load / average\_load$
        Adjust network loads:
            $PD = base\_PD \times \alpha$
            $QD = base\_QD \times \alpha$
        Run OPF
        Store hourly cost
    End For
    Calculate average LSTM-OPF cost
    Compare:
        Conventional cost
        LSTM-OPF cost
Plot:
        Historical load
        LSTM forecast
        OPF hourly cost
        Cost comparison
End [44]
```

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