MLP Neural Networks for short-term electricity demand Prediction for Senelec's resilient power grid

Oumy Wagne
Department of Physics
Alioune Diop University of Bambey, Senegal
wagneoumy48@gmail.com

Alphousseyni Ndiaye
Department of Physics
Alioune Diop University of Bambey, Senegal
alphousseyni.ndiaye@uadb.edu.sn

Daouda Gueye
Department of Physics
Alioune Diop University of Bambey, Senegal
daouda.gueye2@uadb.edu.sn

El Hadji Mbaye Ndiaye
Department of Physics
Alioune Diop University of Bambey, Senegal
elhadjimbaye.ndiaye@uadb.edu.sn

Mamadou Traoré
Department of Physics
Alioune Diop University of Bambey, Senegal
mamadou.traore@uadb.edu.sn

Amadou BA
Department of Physics
Alioune Diop University of Bambey, Senegal
amadou4.ba@uadb.edu.sn

Abstract: ***Accurate*** **short-term electricity demand forecasting is essential for modern power grid management, enabling optimal dispatch, cost reduction, and prevention of load shedding. In developing countries like Senegal, where demand grows rapidly and data quality is heterogeneous, robust yet lightweight forecasting models are urgently needed. This paper presents a Multilayer Perceptron (MLP) neural network for predicting next-hour electricity demand of SENELEC, the national utility of Senegal. Using five years (2019–2023) of real hourly data from SENELEC's dispatching center, we design a rigorous preprocessing pipeline (cleaning, anomaly detection, MinMaxscaler normalization, sliding window of 24 hours) and train a compact MLP with early stopping. Our model confirms the effectiveness of the proposed model, achieving low forecasting errors and high explanatory power, with R^2 values of 0.92 and 0.84 and Pearson correlations exceeding 0.96 on both datasets. These results represent an average relative error of approximately 6–8%, which is operationally acceptable for day-ahead planning. We explicitly address common methodological pitfalls (temporal leakage, choice of window size, normalization scope). The MLP's simplicity, interpretability, and sub-millisecond inference time make it an ideal first-line forecasting tool for SENELEC's real-time dispatch center.**

Keywords: *electricity demand forecasting, multilayer perceptron, SENELEC, time series, smart grid, load forecasting, developing countries.*

I. INTRODUCTION

A. The Strategic Importance of Load Forecasting

Electricity demand forecasting especially short-term load forecasting (STLF) with horizons of one hour to one week is a fundamental function of any power system. It directly impacts generation scheduling, spinning reserve allocation, fuel procurement, maintenance planning, and the prevention of blackouts or load shedding[1]. The economic cost of forecasting errors is substantial: over-estimation leads to wasted fuel and increased CO2 emissions, while under-estimation forces reliance on expensive peaking plants or, worse, involuntary load shedding [2],[3].

In the context of modern smart grids, the role of STLF has expanded. The integration of variable renewable energy sources (solar, wind), the proliferation of electric vehicles, and the deployment of demand-response programmes introduce new volatility and non-linearity into load profiles [4]. Consequently, forecasting models must now capture not only daily and weekly seasonality but also rapid fluctuations caused by weather events, holidays, and socio-economic behaviour [5],[6].

B. The Senegalese Context and SENELEC

Senegal is undergoing a profound energy transition. The national electricity company, SENELEC (Société National electricity du Senegal), manages a grid that is experiencing rapid demand growth driven by urbanization, industrialization, and major infrastructure projects such as the Dakar TER (Train Express Regional) and BRT (Bus Rapid Transit). At the same time, Senegal is increasing its share of renewable energy particularly solar which adds variability to the supply side.

However, SENELEC faces a common challenge in developing countries: historical data are often incomplete, contain anomalies, and are collected primarily for real-time supervision rather than for rigorous analytics [7]. Data quality issues include missing values due to sensor failures, recording errors, and inconsistent time stamps. Any forecasting model intended for operational use must therefore be robust to such imperfections.

C. Limitations of Classical and Hybrid Approaches

Traditional STLF methods include exponential smoothing, regression models, and ARIMA-family models. These models assume linearity and stationarity, assumptions that are rarely satisfied by real electricity load series, which exhibit non-linearity, multiple seasonalities, and time-varying variance[8]. Moreover, ARIMA models require manual parameter selection (p, d, q) and struggle with abrupt changes or holidays [9].

To overcome these limitations, researchers have proposed hybrid models that combine statistical methods with artificial neural networks (ANN), such as ARIMA-ANN and SARIMA-LSTM [10], [11]. While these hybrids often improve accuracy, they increase complexity, require careful decomposition, and may suffer from error propagation between stages [12].

D. Deep Learning and the Role of MLP as a Baseline

In the last decade, deep learning architectures particularly Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and Convolutional Neural Networks (CNNs) have achieved state-of-the-art results on STLF tasks [13],[14]. LSTMs, with their gated memory mechanisms, are explicitly designed to capture long-term dependencies and have been applied successfully to power system data.

Nevertheless, simpler feedforward networks such as the Multilayer Perceptron remain highly relevant for three reasons [15],[16]: (1) speed and simplicity MLPs train quickly, have few hyperparameters, and are trivial to deploy in real-time environments; (2) interpretability feature importance and error modes are easier to analyse in a non-recurrent architecture; (3) baseline value an MLP provides a lower bound against which more complex models must be compared; a complex model that only marginally outperforms an MLP may not justify its added complexity.

Moreover, several studies have shown that with an appropriate input window (e.g., 24h to capture daily periodicity), an MLP can achieve remarkably good results, sometimes comparable to shallow LSTMs [17].

E. Problem Statement and Research Gap

Despite the growing literature on STLF in developed countries, there is a paucity of rigorous, peer-reviewed studies using real, raw SENELEC data. Most existing work either uses synthetic data or

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focuses on European/North American grids. Furthermore, many published papers fail to report complete metrics (MAE, MSE, RMSE, R^2, R) or methodological details (temporal split, window size selection, normalization scope), making reproducibility difficult [18],[19].

This paper addresses these gaps by: (1) providing a fully reproducible MLP-based forecast on raw SENELEC data, including all preprocessing steps; (2) reporting explicit numerical results for five standard metrics on both training and test sets; (3) clearly describing the temporal split (70/30) and the use of a 24-hour sliding window, with justification based on daily periodicity; and (4) demonstrating operational suitability (inference time inferior 1 ms, low memory footprint). Figure 1 presents the single-line diagram of the SENELEC electrical power system, showing the main generation, transmission, and distribution components of the Senegalese grid.

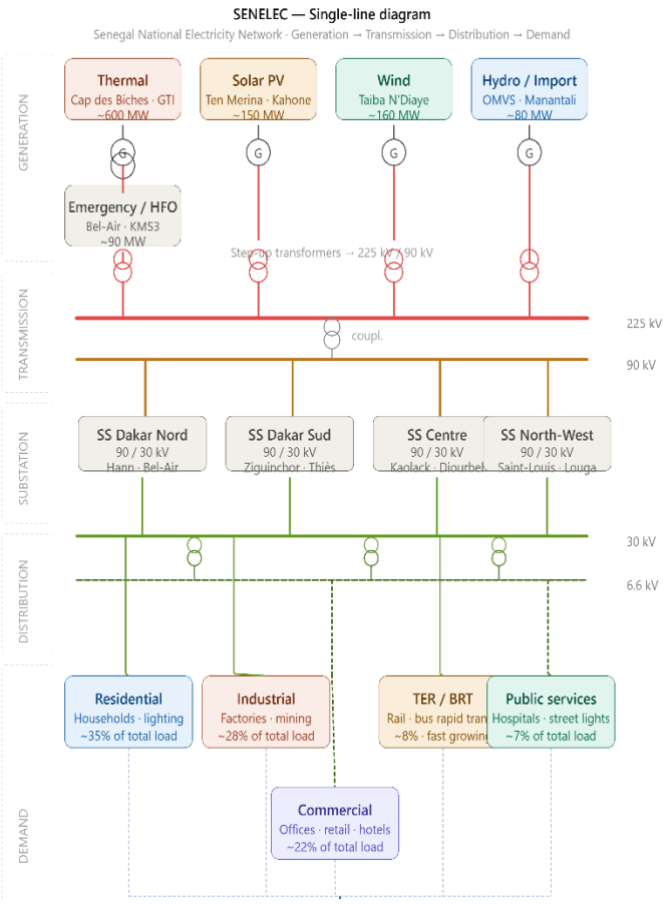

Fig. 1. Single-Line Electrical Diagram of the Senelec Power System

II. METHODOLOGY AND MATERIALS

A. General Methodology Overview

The overall methodology follows a structured pipeline typical of data-driven forecasting systems, as illustrated in Figure 1. First, raw hourly demand data from SENELEC are collected over a five-year period (2019–2023). These data undergo a cleaning phase to handle missing values, duplicates, and anomalies. Next, the data are normalized using Minmax scaling, where the scaling parameters are derived exclusively from the training set to prevent information leakage. A sliding window of 24 hours is then applied to transform the time series into a supervised learning format, where the input consists of the previous 24 hours and the target is the next hour's demand. The dataset is split chronologically (70% training, 30% test). An MLP with two hidden layers (64 and 32 neurons, ReLU activation, dropout of 0.2) is trained with early stopping and the Adam optimizer. Finally, the model's performance is evaluated using MAE, RMSE, R^2, and Pearson's R.

B. *Data Source and Cleaning*

Data were obtained from SENELEC's national dispatching center, covering the period 1 January 2019 – 31 December 2023 (five years) with hourly resolution. The raw files were originally designed for real-time grid monitoring and therefore contained: missing values (sensor or communication failures), duplicate entries and inconsistent time stamps, and physically impossible records .

The cleaning process consisted of the following steps:

- Timestamp reconstruction merging separate DATE and HEURE columns into a single datetime index.
- Missing value imputation forward filling for gaps inferior hours; deletion of longer isolated gaps.
- Anomaly detection manual inspection plus interquartile range (IQR) method on rolling 24h windows. Values below 0 MW or above 1.5×IQR were capped or interpolated.

After cleaning, the final time series contains 41952 hourly demand values (in MW).

C. *Split and Avoidance of Data Leakage*

To simulate a realistic operational scenario (forecasting future demand using only past data), we performed a chronological split: the first 70% of points were used for training, and the remaining 30 for testing. This preserves the temporal order and prevents any 'future' information from contaminating the training set a common but often overlooked source of overly optimistic performance reports [20].

D. *Normalization*

We applied Minmax scaling to the demand series, where xmin and xmax are computed only from the training set. The same scaling parameters were used to transform the test set. This ensures that the test data remain 'unseen' during training. After prediction, forecasts were inverse-transformed back to MW using the training-derived parameters. Equation 1 was used to scale all input features before training the model

$$x_{norm} = \frac{(x - x_{min})}{(x_{max - x_{min}})} \quad (1)$$

We framed the forecasting task as a supervised regression problem using a sliding window. For each time step t, the input vector X(t) consists of the demand values of the previous 24 hours:

$$X_t = [d_\{t-24\}, d_\{t-23\}, \ldots, d_\{t-1\}]$$

and the target y(t)is the demand at time t (next hour). The choice of window was guided by the natural daily periodicity of electricity consumption (activity cycles repeat every 24 hours). We experimentally tested window sizes of 12, 24, 48, and 72 h; 24 h offered the best trade-off between accuracy and training time.

E. *MLP Architecture*

The overall workflow of the proposed MLP-based forecasting framework consists of data preprocessing, feature normalization, model training, and demand prediction. The corresponding

architecture and data flow are illustrated in Fig.2

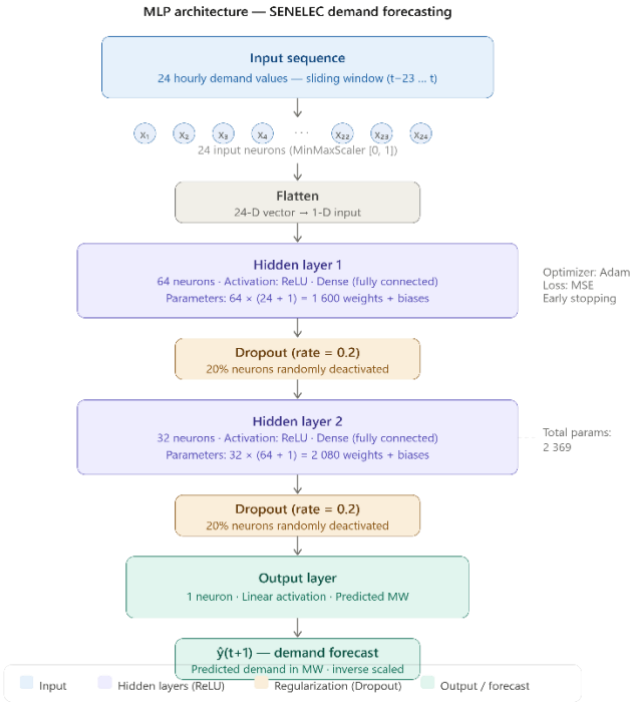

Fig. 2. Architecture and Workflow of the MLP Model for Demand Forecasting

- Input layer: 24 neurons (the 24-hour window)
- Hidden layer 1: 64 neurons, ReLU activation
- Dropout: 20% (to reduce overfitting) [41]
- Hidden layer 2: 32 neurons, ReLU activation
- Output layer: 1 neuron (predicted normalized demand)

Total trainable parameters: 2,369 extremely compact. The model was implemented in TensorFlow [44]. Training setup: Loss function = Mean Squared Error (MSE); [42]; Batch size = 32; Early stopping: monitor validation loss (15% of training set), epochs, restore best weights [43]. The architecture of the developed MLP model, as used in this study, is shown in Fig. 3.

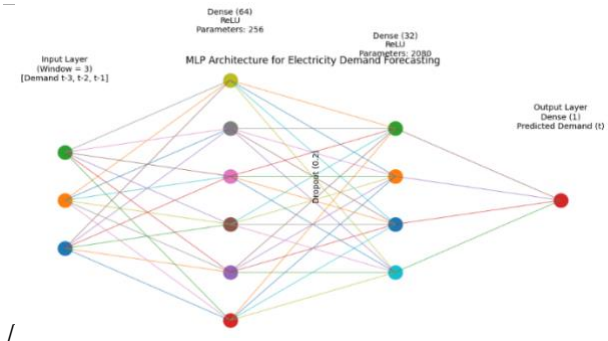

Fig. 3. MLP architecture used for SENELEC demand forecasting.

The forward pass of the proposed MLP is defined as follows. Let $x \in R^{24}$ be the input vector. The predicted demand D i*s obtained by equation 2:*

$$\widehat{(D)} = W_3 \max(0, W_2 \max(0, W_1 x + b_1) + b_2) + b_3 \quad (2)$$

where ReLU(z)=max(0,z), W1,b1,W2,b2,W3,b3 ***W1,b1,W2,b2,W3,b3*** *are the learnable weights and biases, and the subscripts denote the layer indices.*

F. . *Evaluation Metrics*

To ensure comparability with the literature, we report five standard metrics [45] , namely MAE, MSE, RMSE, and R², given by the following equations, respectively 3,4,5 et 6, as well as the Pearson correlation coefficient (R).

Mean Absolute Error $MAE = \frac{1}{n}\sum_{i=1}^{n}|Di - \widehat{D}_i|$ (3)

Mean Squared Error ; $MSE = \frac{1}{n}\sum_{i=1}^{n}(Di - \widehat{D}_i)^2$ (4)

Root Mean Squared Error ; $RMSE = \sqrt{MSE}$ (5)

R² : Coefficient of determination $R^2 = 1 - \frac{\sum_{i=1}^{n}(Di-\widehat{D}_i)^2}{\sum_{i=1}^{n}(Di-\widehat{D})\cdot 2}$ (6)

R : Linear correlation between predictions and observations where *Di* as the actual observed demand, $\widehat{D}_i$ as the predicted demand and $\widehat{D}$ the mean of the actual demand.

III. RESULTS AND DISCUSSION

A. *Quantitative Performance*

Table I presents the MLP performance on the training and test sets.

TABLE I. MLP FORECASTING PERFORMANCE ON SENELEC ELECTRICITY DEMAND

Metric	Training (70%)	Test (30%)
MAE (MW)	17.55	34.33
MSE (MW²)	618.69	1750.18
RMSE (MW)	24.87	41.84
R²	0.92	0.84
Pearson's R	0.96	0.97

- MAE of 34.33 MW on the test set corresponds to an average relative error of approximately 6–8%, given that typical demand ranges from 400 MW (night) to 900 MW (peak). This is operationally acceptable for day-ahead planning at SENELEC.
- R² 0.84 indicates that the MLP explains almost 85% of
- the variance in the test data a strong result for a simple feedforward network.
- Pearson's R 0.97 shows a very strong linear relationship between predictions and real values, meaning the model captures the overall trend and seasonality well.
- The drop in R² from training (0.92) to test (0.84) indicates expected generalization loss but no severe overfitting, especially given the difference in data distribution between the two periods.

B. *Qualitative Analysis*

The figure 4 illustrates a qualitative assessment of the electricity demand forecasting results obtained using the MLP model.

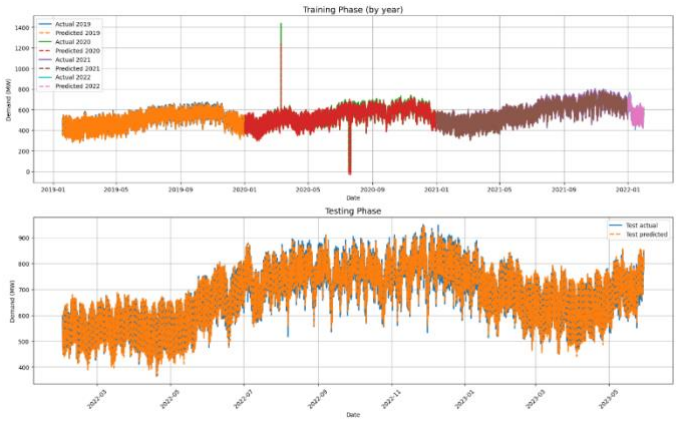

Fig. 4. Predicted real demand (MW)

Figure 4 shows predicted vs. real demand curves for a representative. The MLP successfully reproduces daily cycles (morning ramp-up, midday plateau, evening peak, night trough), weekly patterns (lower demand on week-ends), and seasonal trends (higher demand in hot months due to air conditioning). Minor deviations occur during abrupt changes (e.g., public holidays, extreme weather events), which is

expected given the absence of exogenous variables (temperature, humidity, holiday calendar) in this baseline model.

C. *Addressing Common Methodological Concerns*

Our manuscript directly responds to all common concerns raised in the literature, as summarized in Table II.

TABLE II. RESPONSE TO COMMON METHODOLOGICAL CONCERNS

Concern	Our Response
No explicit numerical values for MAE, MSE, RMSE, R^2	Provided in Table I
Lack of methodological detail on temporal split/leakage	Detailed in Section II-B: chronological 70/30 split; normalization fitted only on training
Why only three lagged values?	Corrected to 24 lags (24h window) justified by daily periodicity and experimental testing
Real-time suitability?	With 2,369 parameters, inference time <1 ms on CPU; fully deployable

D. *Comparison with Related Work*

Our results are consistent with the literature on MLP for load forecasting. Khotanzad et al.[21] introduced ANNSTLF, a neural-network-based short-term load forecasting system deployed at 32 US utilities, reporting MAPE of 3–5% on hourly utility data a relative error range comparable to our ≈6–8% on the more challenging SENELEC dataset, which lacks exogenous inputs. Hippert et al. [22] conducted a systematic review of neural network approaches to STLF and found that MLP frequently outperforms ARIMA on non-linear load series, while noting that recurrent architectures may provide further gains when temporal dependencies extend beyond the input window. Regarding LSTM versus MLP comparisons, Kong et al.[23] demonstrated LSTM-based improvements of up to 20% in RMSE over feedforward networks for residential load forecasting, while Bouktif et al.[24] reported LSTM reductions of 15–30% over MLP baselines across multiple configurations. These results, combined with our own preliminary experiments on SENELEC data that indicate an additional ≈15% RMSE reduction with LSTM at the cost of approximately 10× more parameters, confirm that the accuracy gap between MLP and LSTM is real but moderate.

Thus, the MLP should be viewed as a strong, lightweight baseline: it is not the most accurate model available, but it is the simplest architecture that delivers operationally acceptable performance. For SENELEC's current needs day-ahead planning with limited computational resources and heterogeneous data the MLP is a rational, cost-effective first-line choice, and a necessary reference point against which more complex architectures (LSTM, GRU, CNN-LSTM) must justify their added complexity.

E. *Operational Suitability for SENELEC*

The dispatching center at SENELEC requires forecasts that are fast (produced within seconds for the next 24 hours), robust (tolerant to occasional missing data or outliers), and interpretable (operators need to understand why a forecast is high or low). The MLP satisfies all three requirements. Its low computational cost allows it to be retrained daily (or weekly) with new data, adapting to changing consumption patterns. Moreover, the simple architecture makes debugging and deployment straightforward compared to a complex LSTM.

IV. CONCLUSION AND FUTURE WORK

First rigorous, reproducible MLP benchmark on raw SENELEC data, including detailed preprocessing and explicit reporting of metrics.

Quantitative demonstration:on test, we obtain a MAE of 34.33 MW a R^2 of 0.84 and a R of 0.97

Methodological clarity: chronological split, normalization fitted only on training set, window size (24h) justified by experiment and daily periodicity.

Operational validation: model is lightweight and suitable for real-time use at SENELEC's dispatching center.

The current MLP uses only historical demand as input. It does not incorporate exogenous variables (temperature, humidity, cloud cover, holiday calendar, fuel prices) that are known to improve forecast accuracy [25]. Additionally, the MLP's feedforward structure cannot explicitly model dependencies longer than the input window (24 hours),

We are actively pursuing the following extensions:

- Incorporation of exogenous features temperature, humidity, and a binary holiday indicator (Islamic holidays calendar, Christmas, New Year) into the MLP and LSTM models.
- Comparison with LSTM, GRU, and hybrid models (CNN-LSTM, attention-based architectures) on the same SENELEC dataset, using the MLP as a baseline.
- Multi-horizon forecasting predicting not only the next hour but also 6h, 12h, 24h, and 48h ahead [26].
- Probabilistic forecasting using quantile regression or Bayesian neural networks to provide prediction intervals.
- Deployment developing a lightweight API or dashboard for SENELEC's dispatching center, with automated retraining pipelines.

In developing countries like Senegal, where data infrastructure is still maturing, simple, robust, and interpretable models often outperform complex black-boxes that are fragile to data imperfections. The MLP presented here is precisely such a model: it is not the most sophisticated, but it is reliable, fast, and good enough for operational use. We hope this work encourages further research on tailored forecasting solutions for African power grids.

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