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SHORT-TERM ELECTRICITY DEMAND FORECASTING IN SRI LANKA USING STATISTICAL AND DEEP LEARNING MODELS

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ABSTRACT

Electricity plays a critical role in energy sustainability. Accurate electricity demand forecasting supports achieving energy sustainability in Sri Lanka by enabling more effective planning and management of both renewable and non-renewable energy sources, which are required to generate the electricity. Thus, this study determines the best statistical and deep learning models for short-term electricity demand forecasting using a 4-year time series dataset, provided by the Ceylon Electricity Board of Sri Lanka (Jan 2020–Mar 2024). Initially, the Linear Regression, Polynomial Regression, and Fast Fourier Transform methods used to develop a baseline model by comparing the error rates of their predictions across different sequence lengths. Subsequently, the study proposes the use of Multilayer Perceptron and Long Short-Term Memory (LSTM) as deep learning methods to develop better predictive models for next-day electricity demand. The prediction accuracy of these two models was assessed using key performance metrics, including Mean Absolute Percentage Error, Mean Absolute Error, and Root Mean Square Error. Finally, the performance metrics of each deep learning model were compared against those of the baseline model. The findings show that the LSTM method is very effective for predicting electricity demand. It works well with the dataset and gives the lowest error values for all performance metrics. The final demand forecasting model contributes to smarter grid development, enhances renewable energy integration, and supports energy sustainability by enabling a more energy-efficient future.

Keywords: *Deep Learning; Demand Forecasting; Electricity; Energy Sustainability; Renewable Energy.*

1. INTRODUCTION

Energy sustainability is one of the Sustainable Development Goals (SDGs) (SDG 7), due to the broad and growing nature of energy use, the numerous environmental impacts associated with energy systems, and the significance of energy in living standards and economic development (Kufeoglu, 2022). Many countries, regions, and cities are

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working toward energy sustainability by reassessing their energy consumption, which at present is below the required threshold (Kufeoglu, 2022). Sustainability consists of environmental, economic, and social dimensions, all of which are closely connected to energy (Kabeyi & Olanrewaju, 2023). This connection makes energy sustainability a crucial part of overall sustainability (Konara & Tokai, 2022). Extracting energy resources from the environment and releasing the energy waste back to the environment (Kabeyi & Olanrewaju, 2023) is one good example of the aforementioned connection. Since energy is essential for most activities, achieving energy sustainability is key to reaching broader sustainability goals.

Electricity, produced from various energy sources such as thermal, nuclear, and renewables, is fundamental to modern life and technology. Figure 1 illustrates seven common sources used for electricity generation. Accurate forecasting of electricity demand is essential for energy sustainability, as it helps estimate future power needs from both renewable and non-renewable sources. Such predictions support efficient system operation, strategic planning, and decisions related to infrastructure, maintenance, and management (Zhang et al., 2018). Furthermore, an accurate electricity forecasting model can assist in various aspects, such as ensuring the efficient operation of daily activities, strategic planning of power systems, and addressing areas like management, maintenance, and infrastructure expansion.

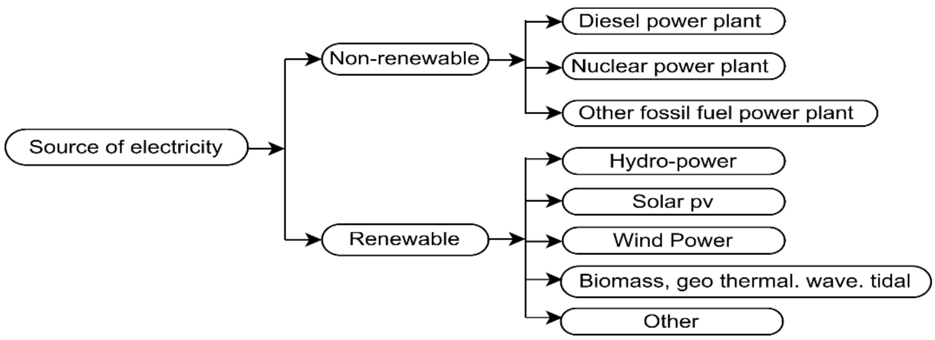

Figure 1: Common energy sources generate electricity

A key goal of electricity forecasting is to ensure an adequate and efficient electricity supply that meets future demand. Electricity forecasting (Also known as "Electricity load forecasting"), which outputs predicted the total electricity demand for the corresponding duration, is classified into short-term (hours to a week), medium-term (weeks to a year), and long-term (over a year) (Somarathne et al., 2022). Short Term Load Forecasting (STLF) aids in electricity distribution and maintenance, handling short-term management and preventing short-term shortages, Mid-Term Load Forecasting (MTLF) supports power planning and market stability, while Long-Term Load Forecasting (LTLF) focuses on long-term infrastructure and technological growth (Shiwakoti et al., 2023). Among the aforementioned three forecasts, SLTF captures the impact of human behaviour on electricity consumption over various time frames, including hourly, daily, weekly, and monthly. Thus, SLTF is crucial in the energy sector, as accurate predictions of future electricity demand are necessary to ensure the reliable and efficient functioning of power systems (Zhang et al., 2018) as well as determine the requirements and help manage the balancing of renewable and non-renewable energy sources, which is part of energy sustainability.

As a developing country, Sri Lanka is no stranger to blackouts and power cuts, with the energy sector struggling for decades due to twin crises: a capacity crisis and a financial crisis. One of the main causes of these blackouts is the decline in rainfall, a recurring issue each year when rainfall is below average. According to the Dailymirror (2022)Sri Lanka experienced its worst power cuts in March and September 2022 due to the country's failure to secure sufficient coal stocks for thermal power generation. However, it was severely impacted by inadequate hydro power generation due to below-average rainfall in 2022 (Dailymirror, 2022). This indicates that having an accurate STLF model to forecast electricity demand at least one day in advance has become crucial for maintaining the supply-demand balance in Sri Lanka. STLF models typically generate point forecasts for future load values, but there is an increasing demand for models that can provide probabilistic forecasts, such as those based on quantile regression (Chen & Ran, 2019). Probabilistic forecasting, unlike deterministic forecasting (point forecasting), acknowledges uncertainty by providing a range of possible outcomes with assigned probabilities, rather than a single point forecast. Two recent studies related to STLF in Sri Lanka have been conducted by Somarathne et al. (2022) and Abeysingha et al. (2021). Both studies used a maximum of 48 data points per day, representing half-hourly electricity demand for forecasting. However, the aforementioned studies did not mention any hyperparameter tuning during the training of their models. The performance of the model is based on the training dataset and its related hyperparameters. As a result, improving data points, selecting the appropriate model, and tuning related model hyperparameters such as input sequence length for predicting the output, network architecture, etc., can significantly enhance the accuracy of STLF.

To address this gap, this study focuses on short-term electricity demand forecasting using a quarter-hourly (15-minutes) recorded demand dataset from Sri Lanka, providing more accurate STLF predictions. The study utilizes an extensive dataset spanning approximately four years (January 1, 2020, to March 31, 2024). As deep learning has shown its capability to capture more complex patterns, the aim of this study is to determine the most effective deep learning model to predict next-day electricity demand by comparing its accuracy with statistical models. Furthermore, this study considers fine-tuning two important hyperparameter, namely, sequence length in order to optimize the model's predictive performance during the training phase.

Below objectives are covered in this study to achieve the aim of this study:

- To analyse and understand electricity demand patterns in the Ceylon Electricity Board (CEB) dataset from 2020 to 2024.
- To identify key temporal trends and factors influencing energy demand for improved forecasting accuracy.
- To evaluate and compare the predictive performance of different modelling approaches in order to determine the most effective model for future energy demand forecasting.

2. LITERATURE REVIEW

Statistical STLF models use past data like electricity load, weather, and calendar information. Statistical approaches encompass a variety of regression models, including linear regression, multiple regression, stepwise regression, logistic regression, and polynomial regression (Sudan, 2024). Additionally, methods such as Moving Average

(MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Autoregressive Integrative Moving Average Exogenous (ARIMAX), and Seasonal Autoregressive Integrated Moving Average (SARIMA) are well-known in the field of statistical prediction (Yadav, 2024). The models based on the aforementioned methods work well for patterns with statistical cycles in predictions, but they are less accurate for real-time load forecasting that includes non-cyclical data with dynamic fluctuations. They also struggle to handle the complex and non-linear nature of load consumption (Zuo et al., 2023). To address the limitations of statistical models in capturing the non-linear and complex patterns in electricity consumption, Artificial Intelligence (AI) techniques have been introduced. These AI techniques include Machine Learning (ML) and Deep Learning (DL) methods, which improve the accuracy of short-term electricity demand forecasting.

DL is a subset of ML that emerged to address more complex patterns in input data. Deep Neural Networks (DNNs) is a method in DL. It is based on artificial neural networks (ANNs), particularly a type known as Feedforward Neural Networks (FNNs), which process information in a unidirectional flow without any feedback loops. DNNs are neural network architectures that consist of multiple layers of ANNs. Multilayer Perceptron (MLP) is one of the simplest DL models, built on the structure of FNN using Backpropagation to learn patterns through hidden layers. Another important type of DNN is the Recurrent Neural Network (RNN), which processes information using feedback loops, allowing the network to retain information from previous inputs. This makes RNNs particularly well-suited for capturing patterns in sequential data. RNN-based architectures are commonly applied in tasks such as text processing, speech recognition, and video analysis. Variants like standard RNNs, Long Short-Term Memory networks (LSTMs), and Gated Recurrent Units (GRUs) have been developed to capture patterns better. LSTM, introduced by Hochreiter and Schmidhuber (1997) was designed to address limitations in RNNs, such as forgetting past data and the issues of vanishing and exploding gradients. GRUs were later developed as a simpler alternative to LSTMs, with fewer parameters but comparable performance (Rivas et al., 2025). LSTM makes it uniquely powerful for sequential data (Malashin et al., 2024), outperforming DNNs (no memory), RNNs (short-term memory), and even GRUs (less precise control).

Both statistical and deep learning models can be effective for learning patterns in time-based data, such as electricity demand. Another aspect of the SLTF models is high dependency on the calendar parameters such as year, month, day of the week, and hour, along with seasonal factors like holidays and special days. These are classified as deterministic variables. Weekday demand is generally higher and more stable due to industrial activities, while weekends and holidays experience lower consumption. To account for these variations, dummy variables are assigned to differentiate between weekdays, weekends, and holidays in predictive models (Ramanathan et al., 1997). In addition to the aforementioned areas, SLTF models can be further fine-tuned using the hyperparameters. A hyperparameter is a parameter whose value is set before the learning process begins, and these values influence the learning process itself (Abeysingha et al., 2021). A hyperparameter can be a sequence length, number of layers, etc., which directly influences the speed and performance of the learning process when training SLTF models.

3. RESEARCH METHODOLOGY

This section provides a visualization of the electricity demand dataset, outlines the methods used to develop the forecast models, and provides a detailed explanation of the proposed electricity demand forecasting model.

3.1 ELECTRICITY DEMAND DATASET

The dataset, sourced from the CEB, contains electricity demand records spanning four years and three months, from January 1, 2020, to March 31, 2024. Figure 2 shows the overall electricity demand profile over four years and three months, illustrating the use of a 365-day rolling moving average to smooth annual trends. The blue line represents the actual recorded energy demand. The data is plotted every 15 minutes (a total of 96 data points per day), representing fluctuations throughout the day. The green line, representing the day-mean, an average of the 96 daily values, highlights seasonal (daily) trends by minimizing short-term day-to-day variations.

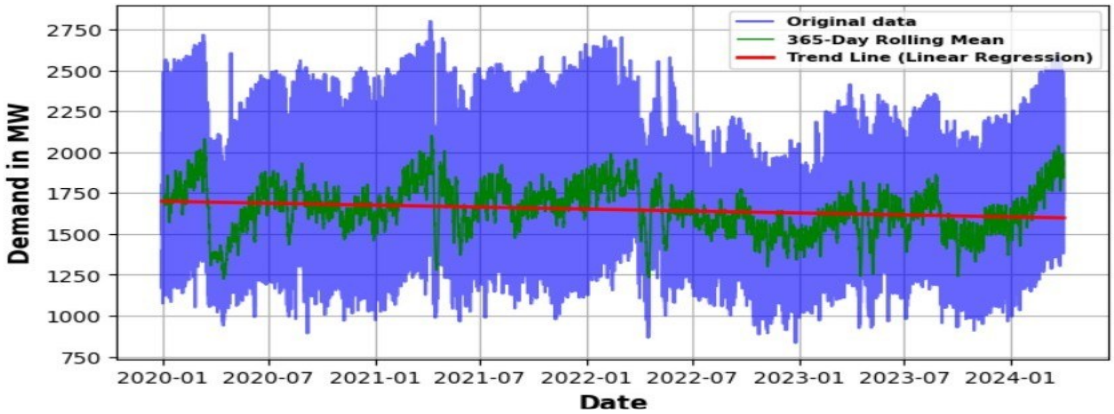

Figure 2: Four years and three months overall demand profile

The red line illustrates the linear regression trend, based on daily mean indicating the overall direction of energy demand over the 4 years period. Notably, from July 2022 to January 2024, a declining trend of demand is observed, primarily due to prolonged power cuts and political instability in Sri Lanka. During this period, the country faced an economic crisis, fuel shortages, and disruptions in electricity generation, all of which contributed to reduce energy consumption.

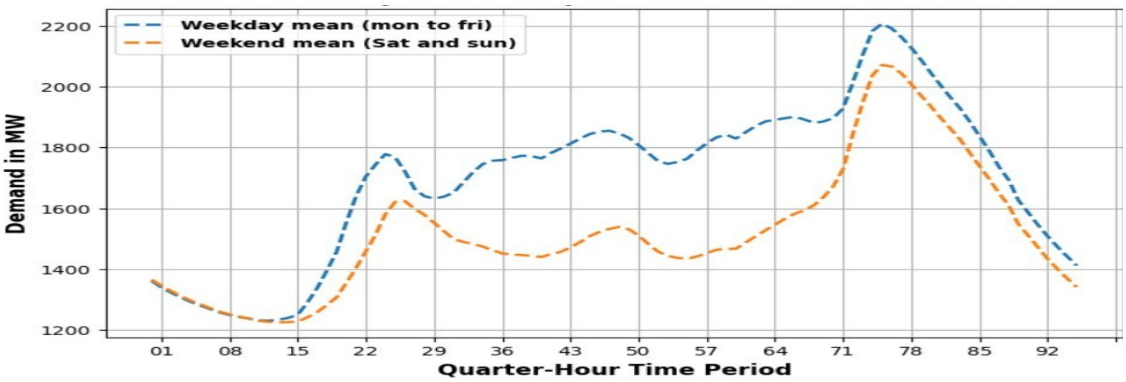

Figure 3: Average demand profile for weekday and weekend patterns

On weekends, residential electricity demand exhibits unpredictable fluctuations due to varying human activities, posing challenges for accurate forecasting. In contrast, weekdays demonstrate more stable demand patterns, particularly during midday and evening hours. Despite these variations, electricity consumption during late-night and early-morning hours remains relatively consistent across both weekdays and weekends, as illustrated in Figure 3. The details in Figure 3 infer the demand fluctuations, peak usage periods, and potential differences in energy consumption trends between regular working days and weekends.

3.2 MODELS

This subsection outlines the methods employed in the study to develop an effective deep learning framework for predicting next-day electricity demand. It begins with a brief overview of three statistical methods, followed by detailed descriptions of two selected deep learning methods, including an explanation of their underlying operating principles. The statistical methods, includes Linear regression, Polynomial regression, and Fast Fourier Transform. These methods help in analysing the trends and seasonality in the electricity demand data. The deep learning methods includes Multilayer Perceptron and Long Short-Term Memory which are known for their ability to capture complex patterns and long-term dependencies in time-series data, making them highly effective for accurate forecasting.

3.2.1 Fast Fourier Transform (FFT)

In frequency analysis, the FFT is employed to identify common frequency components between two time series. As an optimized form of the discrete Fourier transform, FFT detects periodic patterns and their relative strengths within the data. It decomposes input signals into smaller frequency components, making it easier to recognize similarities in the frequency domain. The Fourier transform, a mathematical approach, converts time-domain signals into their frequency-domain equivalents, representing complex signals as a sum of simpler harmonic frequencies (Yemets et al., 2025).

3.2.2 Linear Regression (LR)

Regression analysis is a key statistical method for understanding the relationship between a dependent variable and independent variables. Widely used across scientific fields, it is especially valuable in business and economics for identifying causal links. This method involves modelling relationships and estimating parameters to develop a predictive equation. Simple linear regression focuses on how one independent variable influences a dependent variable, aiding in trend analysis and prediction (Patil & Patil, 2021). The formula for linear regression is as follows (see *Equation 1*),

$y=\beta_0 + \beta_1 x + \varepsilon$ *(Equation 1)*

3.2.3 Polynomial Regression (PR)

Polynomial regression is a form of regression analysis that uses an nth degree polynomial to model the relationship between dependent and independent variables. It is a specific variation of Multiple Linear Regression (MLR) where the polynomial equation captures the curved interactions between these variables (Patil & Patil, 2021). The number of degrees represents the curve’s flexibility. It is useful when the data has a non-linear relationship but can be approximated by polynomial function. The model of polynomial is given below (see *Equation 2*):

$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_h x^h + \varepsilon$ *(Equation 2)*

3.2.4 Multilayer Perceptron (MLP)

A multilayer perceptron represents a type of artificial neural network that incorporates several layers of interconnected units, often referred to as perceptron or neurons. Commonly utilized in supervised learning scenarios, such as classification and regression tasks, an MLP is visually depicted in Figure 4 and is composed of the following key components.

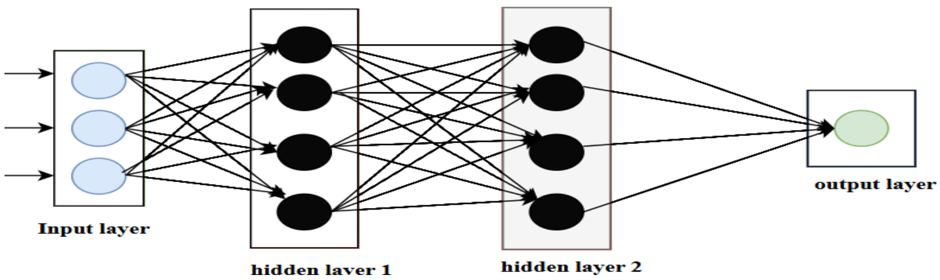

Figure 4: Multilayer perception model

The input layer receives the data, with each node representing a feature of input. Hidden layers process the data through neurons that learn complex patterns, and the number of layers and neurons influences the model's learning capacity. The output layer generates predictions based on the problem, with the number of nodes matching the output categories. Neurons process inputs using an activation function (see Equation 3) that can introduce non-linearity. Weights and biases control the strength of neuron connections and adjust during training to minimize prediction errors (Sakhtiyani et al., 2022). The model is trained through backpropagation, adjusting weights and biases iteratively to reduce the loss function, which measures performance.

$a_j = f\left(\sum\left(w_{ij} * x_i\right) + b_j\right)$ *(Equation 3)*

3.2.5 Long Short-Term Memory (LSTM)

The Long Short-Term Memory network is a widely used deep neural network that features specialized components known as memory blocks within its recurrent hidden layer. Each memory block is equipped with an input gate, which regulates the flow of input activations into the memory cell, and an output gate, which manages the flow of cell activations to the rest of the network (Shiwakoti et al., 2024). LSTM networks map an input sequence ($x_1, x_2 \ldots\ldots x_n$) and output sequence ($y_1, y_2, \ldots\ldots y_n$).

3.3 HYPERPARAMETERS

This study focuses on selecting the best model and corresponding hyperparameters for predicting next-day power consumption. A suitable model is one that accurately captures data patterns, avoids both overfitting and underfitting, and keeps the model structure simple and efficient. The sequence length refers to the number of previous days used as input to the model in order to predict the next day's electricity consumption. It is a key hyperparameter in this study because selecting the right sequence length is important for capturing patterns, seasonal trends, and variations in the data. If the sequence length is too short, the model may miss important long-term dependencies, reducing prediction accuracy. On the other hand, if it is too long, it can introduce noise and increase model complexity. Therefore, optimizing sequence length helps the model effectively learn time-based patterns, which improves both accuracy and efficiency.

3.4 PROPOSED MODEL

The proposed workflow, illustrated in Figure 5, includes five key stages: (1) data preprocessing (handling outliers, separating training and testing data, and constructing a normalization model from the training set), (2) preparing sequences based on varying sequence lengths, (3) model training, (4) renormalising the predicted results, and (5) performance evaluation. Data preprocessing is essential for building an accurate forecasting model. It includes handling outliers and missing values using forward-filling, splitting data into training and testing sets, and applying min-max normalization based on the training data. Normalization is later reversed for interpretation. These steps ensure data consistency, fair evaluation, and improved model accuracy.

The original 15-minute interval electricity demand data are aggregated into daily electricity demand. The training set includes data from January 1, 2020, to December 31, 2022, while the testing set comprises data from January 1, 2023, to March 31, 2024. To prepare the sequences for training and testing, a sliding window process with a window size equal to the sequence length was applied to the data for each model. The forecasting models for experiments include both statistical models (LR, PR with degree 2 (PR2), degree 6 (PR6), and FFT) and deep learning models (MLP and LSTM). These models are trained using the pre-processed dataset. During training, each method follows a separate learning process to adjust internal parameters and improve predictive accuracy. The optimal sequence length hyperparameter is determined by evaluating multiple models across different sequence lengths for each forecasting approach. Once the internal parameters of each model have been optimized, the models are evaluated using the test dataset. Denormalization is applied to convert the predicted values back to their original scale. Each model is evaluated using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) to assess forecasting accuracy. MAPE shows relative error in percentages, MAE captures average error, and RMSE highlights larger deviations. The model with the lowest values across these metrics is deemed best for future electricity demand forecasting.

This paragraph outlines the hyperparameters used for each model. For Linear Regression (LR) and Polynomial Regression (PR), separate models are built using a fixed number of previous days (sequence length) to predict next-day power consumption. LR has no additional hyperparameters beyond sequence length, while PR treats the polynomial degree as a key hyperparameter, using degrees 2 and 6 in the experiments. The FFT was applied to extract frequency-domain features from the time series. In the experiments, separate FFT coefficients were extracted and used for each next-day prediction. The coefficients were computed using only data within the sequence length. Apart from the sequence length, no additional hyperparameters were involved in the FFT process.

The proposed DL models, both MLP and LSTM, use simple architectures to minimize complexity and reduce overfitting risk. The MLP consists of three fully connected dense layers (32, 16, and 1 units) with Tanh, ReLU, and Linear activations. The LSTM model includes one LSTM layer (32 units) followed by two fully connected dense layers (16 and 1 units) using Tanh, ReLU, and Linear activations. Tanh is used for its effective non-linear transformation. From the training data, 10% was allocated for validation and 90% for model training. The model was trained using a batch size of 32, the Adam optimizer, and MSE as the loss function. Early stopping with a patience of 50 epochs was used to restore the best weights based on validation loss, allowing the number of training epochs to adjust dynamically for optimal performance.

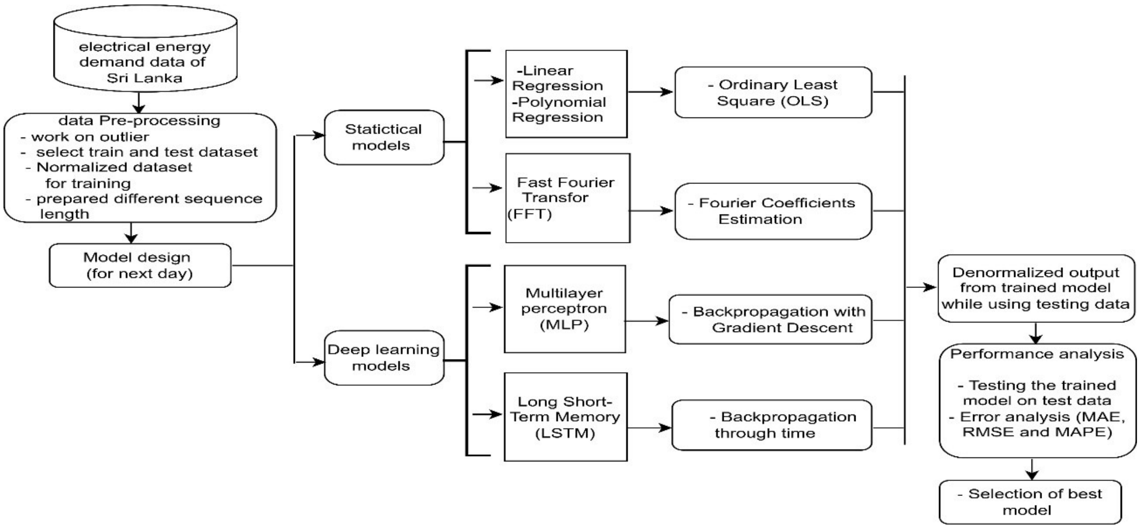

Figure 5: Proposed model for electrical demand forecasting

4. RESULTS AND DISCUSSIONS

This section presents and analyses the results of the study. Statistical and DL models were evaluated using sequence lengths based on weekly intervals. The complete set of sequence lengths is shown in Figure 6. Key lengths such as 7, 14, 21, and 28 days, along with monthly intervals, are detailed in Tables 1 to 3, presenting MAPE, MAE, and RMSE.

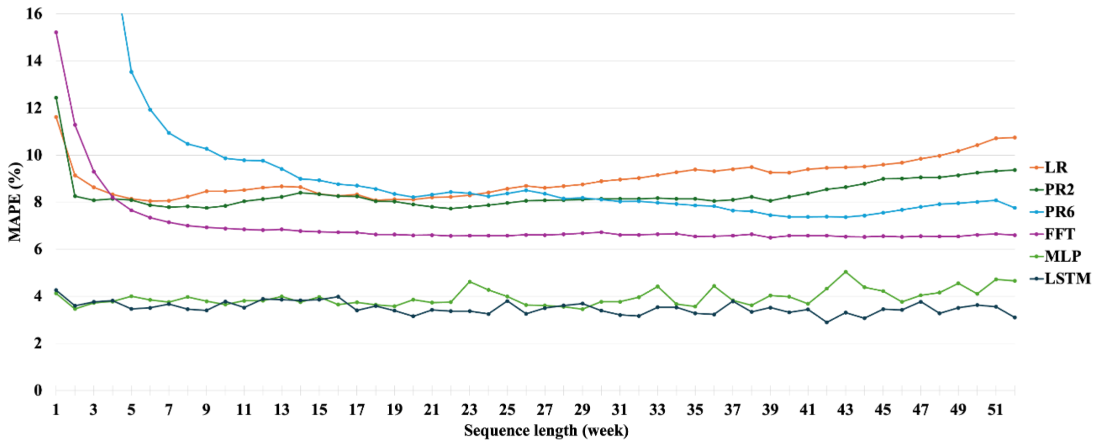

Figure 6: Demand prediction MAPE results for various sequence lengths (weekly)

The lowest error for each sequence length is highlighted in bold. Sequence length plays a significant role in forecasting accuracy. While longer sequences capture more temporal patterns, overly long ones may introduce noise and reduce model performance.

Table 1: Mean Absolute Percentage Error (MAPE) results of the models using different sequence lengths (days)

Models	7	14	21	28	56	84	112	140	168	196	224	252	280	308	336	364
LR	11.61	9.14	8.63	8.33	8.23	8.62	8.26	8.11	8.41	8.68	9.02	9.31	9.25	9.51	9.97	10.74
PR2	12.43	8.25	8.08	8.14	7.82	8.13	8.25	7.9	7.87	8.09	8.14	8.05	8.22	8.78	9.05	9.36
PR6	199.24	32.08	27.17	18.41	10.47	9.76	8.76	8.21	8.24	8.15	8.04	7.83	7.37	7.43	7.91	7.76
FFT	15.21	11.28	9.29	8.2	7	6.81	6.72	6.59	6.57	6.64	6.61	6.55	6.57	6.52	6.54	6.6
MLP	4.13	3.46	3.72	3.78	3.97	3.82	3.65	3.86	4.27	3.56	3.96	4.44	3.98	4.39	4.16	4.66
LSTM	4.26	3.6	3.76	3.82	**3.45**	3.89	3.98	**3.15**	**3.25**	**3.61**	**3.16**	**3.23**	**3.32**	**3.07**	**3.28**	**3.1**

Table 2: Mean Absolute Error (MAE) results of the models using different sequence lengths (days)

Models	7	14	21	28	56	84	112	140	168	196	224	252	280	308	336	364
LR	180.36	140.58	132.11	127.57	126.38	132.65	127.8	127.42	132.78	138.79	144.69	149.79	153.11	162.38	174.26	193.45
PR2	200.56	127.9	124.63	125.13	119.89	124.8	127.22	122.65	122	126.15	126.48	126.1	133	146.49	154.96	165.35
PR6	3257.73	522.39	434.71	297.26	165.22	152.28	135.47	127.41	127.78	125.9	123.94	120.44	114.19	118.26	128.72	131.51
FFT	254.07	188.97	155.61	136.84	114.32	109.53	107.09	105.1	104.27	105.43	104.26	102.84	104.3	105.72	108.16	111.51
MLP	63.5	52.29	57.25	59.17	61.32	58.78	55.91	60.75	67.94	56.16	62.56	69.23	62.63	71.18	68.22	78
LSTM	64.74	55.44	58.27	59.88	**52.78**	59.97	60.63	**48.73**	**50.47**	**56.45**	**49.23**	**51.18**	**53.8**	**49.78**	**53.36**	**51.48**

Table 3: Root Mean Square Error (RMSE) results of the models using different sequence lengths (days)

Models	7	14	21	28	56	84	112	140	168	196	224	252	280	308	336	364
LR	210.32	168.7	163.06	157.66	154.1	158.34	153.8	150.3	156.29	164.09	174.08	181.75	183.46	188.64	199.35	218.85
PR2	247.61	160.02	154.99	158.29	149.77	155.65	154.03	147.7	145.94	148.92	151.93	149.23	148.89	160.12	167.93	179.24
PR6	4224.31	676.93	523.08	364.82	206.67	187.95	166.78	154.65	155.03	156.96	157.16	154.53	150.78	151.89	156.6	151.8
FFT	280.09	216.06	185.43	169.08	147.78	143.81	142.72	140.49	140.09	141.87	141.02	140	141.84	143.02	145.93	149.68
MLP	95.35	84.31	87.91	86.32	86.98	89.01	83.79	84.35	92.61	82.22	84	92.79	86.83	93.31	88.17	100.57
LSTM	96.51	85.62	88.8	88.86	**84.31**	89.75	88.87	**78.38**	**79.8**	**81.96**	**75.83**	**76.17**	**76.48**	**74.95**	**82.99**	**77.29**

According to the results across all metrics, Sri Lanka's relatively stable climatic conditions, typical of a tropical country, cause little seasonal change in electricity demand, which improves forecasting accuracy. As shown in Figure 6, after using a sequence length of 14 days (two-week cycle), most forecasting models perform steadily up to 52 weeks. This suggests that weekly past data is effective for next-day demand prediction, helping with better energy planning and management in Sri Lanka.

In addition to determining the optimal sequence length, this study compared deep learning models with baseline statistical approaches. As shown in Figure 6, deep learning models outperformed statistical models by better capturing complex demand patterns. While the best statistical model (FFT) achieved a MAPE of 6.49%, the least accurate deep learning model (MLP) performed better, with a MAPE of 5.04%, highlighting the advantage of deep learning in forecasting accuracy. While FFT had the lowest error among statistical models, LSTM achieved the best overall accuracy with a MAPE of 2.89% at a 294-day sequence length. Statistical models offer simplicity and interpretability, but they fall short in accuracy. The proposed deep learning models, despite their simple architectures, significantly outperformed traditional statistical approaches.

4.1 STATISTICAL MODEL

In Figure 6, the suitable sequence length for statistical models is around 139 days (20 weeks). This means that the model learning from 20 weekly cycles provides the best results for statistical forecasting models. Interestingly, FFT provides the best performance among statistical models. FFT achieves a MAPE of 6.49% at a sequence length of 273 days (39 weeks). PR improves upon LR by capturing some non-linear trends using PR2 and PR6, but it still struggles with complex seasonal patterns. In contrast, FFT effectively captures recurring demand cycles, making it the most accurate of the four. As illustrated in Figure 7, the blue line shows actual demand, while the red line shows FFT predictions from January 2023 to March 2024.

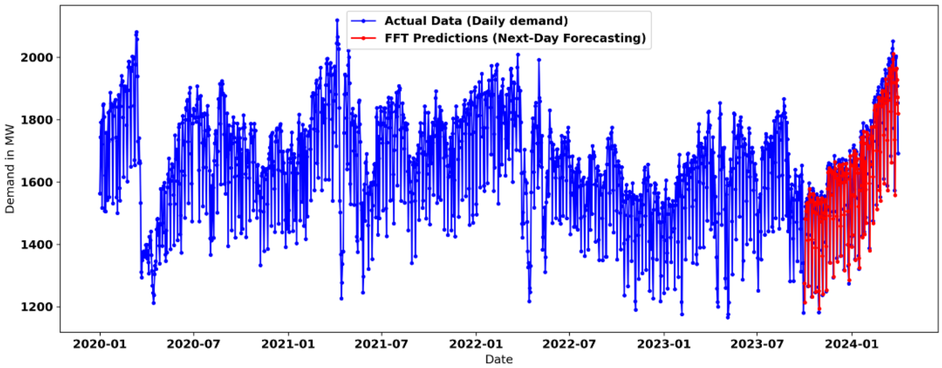

Figure 7: Demand prediction using FFT: using previous 273 days (39 weeks)

4.2 DEEP LEARNING MODELS

The results indicate that deep learning models significantly outperform statistical ones by capturing demand patterns more effectively. As shown in Figure 6, these models begin identifying patterns with just 14 days of input. This trend is also reflected across all error metrics in Tables 1 to 3, where deep learning models have more stable MAPE values. While LR and PR face difficulties with longer sequences, MLP performs more effectively with shorter sequences, especially those less than 140 days (20 weeks). However, LSTM excels with longer sequences, demonstrating a stronger ability to learn complex patterns compared to MLP.

The results reveal that LSTM achieves superior performance due to its ability to capture long-term dependencies and sequential patterns, making it better suited for modelling forecasting model. The LSTM model's performance significantly improved with sequence length extended, reaching optimal results at a sequence length of 294 days (42 weeks). Under these conditions, the LSTM achieved a MAPE of 2.89%. Figure 8 displays the prediction results, where the blue line represents actual demand data, and the red line shows LSTM model predictions from January 2023 to March 2024 (the testing data duration).

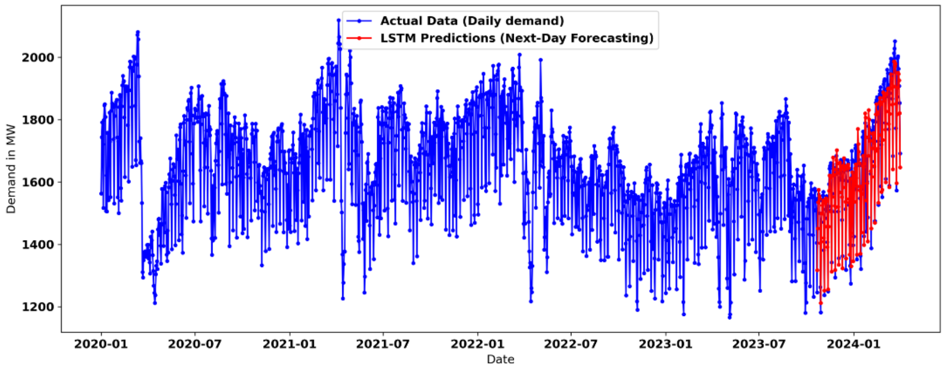

Figure 8: Demand prediction using LSTM: using previous 294 days (42 weeks)

5. CONCLUSIONS

Electricity is a form of energy generated by the flow of electric charge, used to power various devices and systems. As a key energy carrier, it plays a critical role in energy sustainability by ensuring that energy production and consumption support sustainable development throughout their lifecycle. This involves maintaining a secure and equitable energy future for both current and future generations, without compromising environmental or societal well-being. To advance energy sustainability in Sri Lanka, this study develops a STLF model using a quarter-hourly (15-minute) electricity demand dataset obtained from the CEB. The model aims to accurately predict day-ahead electricity demand across Sri Lanka.

Initially, this study examines statistical models (LR, PR, and FFT) alongside deep learning models (MLP and LSTM) for short-term load forecasting. Using 4 years and 3 months of demand data from the CEB, each model was trained with different sequence lengths to forecast day-ahead electricity demand from January 2023 to March 2024. Among the statistical methods, FFT delivered the best performance with a MAPE of 6.49%. However, deep learning models, particularly LSTM, significantly outperformed these techniques, achieving an impressive MAPE of just 2.89%. The results of this study show that the LSTM outperformed the baseline model, FFT, providing the most accurate short-term load forecasts. This indicates that the LSTM model is highly effective for electricity demand forecasting, especially for next-day predictions, even with simple model design of one LSTM layer (32 units) followed by two fully connected layers (16 and 1 units) using Tanh, ReLU, and Linear activations. The developed model can support Sri Lanka in optimizing renewable energy use, lowering operational costs, and maintaining grid stability. Accurate demand forecasting enhances energy management and long-term sustainability. However, the study is limited by not including weather-related variables, which could improve prediction accuracy and are suggested for future work.

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