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Analysing the Influence of Factors on Short-Term Electricity Consumption Forecasting: Insights from Historical Data

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Abstract:- This research investigates the forecast of short-term electricity consumption. The impact of various factors on prediction accuracy is investigated using past data. It is observed that certain factors exhibit higher importance in forecasting accuracy, with their significance diminishing over time. Two models were employed for prediction: one utilizing 24-hour past data and the other 72-hour past data for forecasting the subsequent 24-hour demand. It was unexpected to discover that the model that only used historical demand data performed better than predicted. This research contributes to a better understanding of short-term electricity demand forecasting, which is crucial for efficient energy planning.

Keywords: Artificial Neural Network, Load Demand, Load forecasting, Long Short-Term Memory Neural Network, Short term load forecasting

1. Introduction

Global energy consumption has risen sharply since the turn of the twenty-first century, revealing challenges such as depleting fossil fuel reserves and inefficiencies in renewable energy usage [1]. A new power system that emphasizes carbon peaking and neutrality emerges as the country moves closer to its double carbon target as part of its energy revolution. Precise estimation of power load is essential to maximize efficiency and minimize emissions [2]. Short-term load forecasting (STLF) is vital for daily power system operation, including electricity market clearing, and has drawn significant interest from industry and academia [3].

The ability of fossil fuel-based generators to balance energy supply and demand is essential to grid frequency stability, but the rise of renewable may reduce this reserve capacity [4]. STLF ensures economically viable electricity generation and system security. It provides advance load predictions, crucial for reducing operating costs and impacting electricity market prices. This makes it vital for regional transmission agencies, utilities, financial institutions, and energy suppliers [5]. Local load profiles combine to form the bulk load, each influenced by the regional climate. Recent load forecasting models integrate local climate, load patterns, and other factors [6]. Due to industrialization and urbanization, there has been a notable increase in electricity demand over the past decade, leading to fluctuating consumption patterns. Accurate energy forecasting is essential to tackle issues such as unnecessary generator usage and excessive fuel consumption. It provides crucial data for efficient capacity planning and optimized scheduling based on historical data and weather conditions [7]. In smart grid development, short-term load forecasting is vital for scheduling generation and managing controllable loads. Additionally, medium and long-term forecasting support maintenance, outage scheduling, and new plant installation.

With the integration of renewable and micro grids, managing multiple distributed energy generations complicates generation control, necessitating demand-side management. Dynamic pricing introduces complexity into short-term load forecasting, as changes in tariffs result in continuously shifting load demands, emphasizing the need for forecasting in dynamic price environments.

2. Materials and methods

In order to provide stability and reliability by balancing generation and demand, load forecasting is essential for power system development, maintenance, and planning. Momentarily switching generation to meet demand fluctuations can be costly, making load forecasting essential to avoid such issues.

2.1 Data gathering

In this research, Australia's load demand data is being considered, as it is openly available and consists of data for every half hour, including aggregated demand from specific regions and the price of power.

Consider load demand at time t is (t) and price/MWh is $p(t)$, then, both of these variables can be correlated using cross-correlation, as follows.

$$r_{lpr} = \lim_{M \to inf} \frac{1}{2M+1} \sum_{t=-M}^{M} l(t) * p_r(t) \tag{1}$$

If the value of r_{lpr} more than loads, demand, and price are highly dependent on each other.

Weather data, including solar irradiation, wind speed, and ambient temperature, is obtained from the NREL website. These data are not direct sensor readings but are pre-processed for use in any given year, which may hinder the accurate inference of relationships in the results.

2.2 Time Features

The time features are extracted from the load demand data by classifying based on time in three different cases.

Morning: Load Demand between 6 a.m to 12 p.m

$$f(x) = \begin{cases} 1, & if\ t \in [6\ am, 12\ pm] \\ 0, & othrwise \end{cases} \tag{2}$$

Afternoon: Load Demand between 12 p.m to 5 p.m

$$f(x) = \begin{cases} 1, & if\ t \in [12\ pm, 5\ pm] \\ 0, & othrwise \end{cases} \tag{3}$$

Evening: Load Demand Between 5 p.m. to 8 p.m.

$$f(x) = \begin{cases} 1, & if\ t \in [5\ pm, 8\ pm] \\ 0, & othrwise \end{cases} \tag{4}$$

Night: Load Demand between 8 p.m to 6 a.m

$$f(x) = \begin{cases} 1, & if\ t \in [8\ pm, 6\ am] \\ 0, & othrwise \end{cases} \tag{5}$$

Week Day: Monday to Friday

$$f(x) = \begin{cases} 1, & if\ t \in week\ days \\ 0, & othrwise \end{cases} \tag{6}$$

Weekend: Saturday and Sunday

$$f(x) = \begin{cases} 1, & if\ t \in weekend \\ 0, & othrwise \end{cases} \tag{7}$$

2.3 Correlation between features

The correlation between 2 periodic signals x(t) and y(t) can be given by following equation.

$$r_{xy} = \lim_{M \to inf} \frac{1}{2M+1} \sum_{t=-M}^{M} x(t) * y(t-l) \tag{8}$$

Equation(8) represents $r_{xy}\,(l)$ = correlation between x(n) and y(n) at given lag l, l= lag or time shift, M = Length of signal. The two signals in the above equation must have the same magnitude. So, if there are two signals of different magnitude then signals need to be scaled between 0 to 1or any desired range. To scale signals X between 0 to 1 use following equation[6].

$$x_n = \frac{x_n - min(X)}{max(X) - min(X)} \tag{9}$$

Where, (n) = Signal which is to be scaled, $mi(X)$ = min value of entire signal $X(n)$, $max(X)$ = max value of entire signal $X(n)$ and $x(n)$ = scaled signal.

$$\hat{x}(n) = \frac{x(n)-\bar{x}}{\sigma_x} \tag{10}$$

Equation (10) indicates (n) = Signal or series which is to be scaled, $\bar{x}$ = Mean of (n), σ_x= Standard deviation of $x(n)$ and $\hat{x}(n)$ = scaled series. Cross correlation can be normalized in terms of (t) and (t),

$$r_{xy} = \frac{\sum_{n=1}^{N}(x(n)-\bar{x})*(y(n-l)-\bar{y})}{N*\sigma_x*\sigma_y} \tag{11}$$

Equation (11) depicts that (n) = $first\ signal\ signal\ x$, $\bar{x}$ = $mean\ of\ signal\ x$, (n) = $second\ signal\ y$, $\bar{y}$ = $mean\ of\ signal\ y$, σ_x = $standard\ deviation\ of\ x$, σ_y = $standard\ deviation\ of\ y$ and N = $Number\ of\ samples\ of\ signal\ x, y$.

2.4 Long Short-Term Memory Neural Network

To facilitate the network's ability to identify relationships between distant time points, the LSTM conceals the state variables, h_t and C_t. These variables store short-term and long-term memory information, respectively. Each LSTM unit comprises three gates: the forgetting gate, input gate, and output gate. The forgetting gate discards irrelevant data and acknowledges when the current content of C_t has been erased. The input gate regulates the input of candidate memory cells into C_t and filters these cells accordingly. Meanwhile, the output gate manages the output data from C_t at the current time step. Through parameter exchange, each LSTM unit continuously learns and adjusts its corresponding parameters [10].

An artificial recurrent neural network (RNN) with long short-term memory (LSTM) processes sequential data. RNNs are helpful for tasks like time series forecasting and speech recognition because they leverage previous outputs to inform the creation of new ones. They have trouble with the vanishing gradient problem, though, which is a condition where long-term dependencies make the network forget crucial data. In order to address this, LSTM was developed with a unique structure that aids in memory retention and updating over longer sequences while preserving important context [10], [11], [12][13], [14].

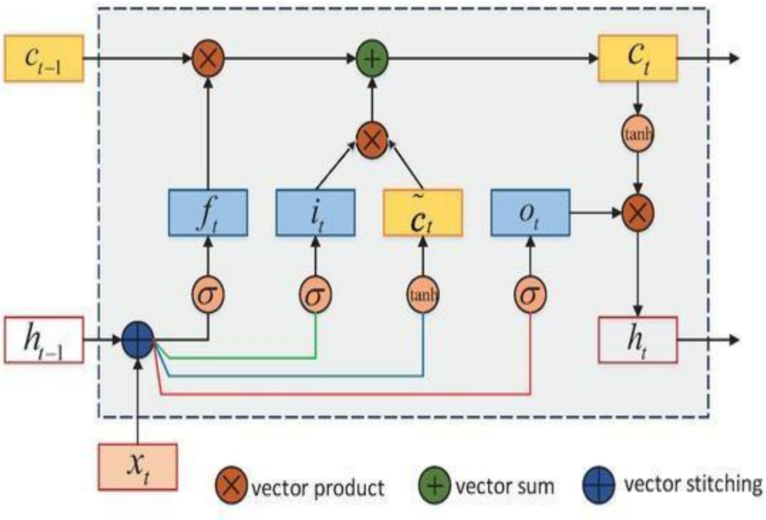

Figure 1 LSTM Cell

As shown in Figure 1, x_t is 3d input vector of size $l\ x\ m\ x\ n$, l indicates total training data points, m shows Dimension of data and n is past data points.

2.5 Utilizing LSTM for Load forecasting

There are two basic models for forecasting: one predicts the load for the next 24 hours by utilizing data from the previous 24 hours. Data that is gathered every 30 minutes is used to train this model. For LSTM takes past 48 inputs $x(t-47), x(t-46), x(t-45), \dots, x(t)$ and outputs load for next 24 hours or next 48 time -steps $l(t+1), l(t+2), l(t+3), \dots, l(t+48)$.

Structure of LSTM NN is shown in Table 1.

Table 1 Structure of LSTM NN

	Input Layer	Hidden Layer	Output Layer
No of Unit/neuron	22	44	48
Activation Function	Tanh	Tanh	Relu

3. Results and Discussion

To train the model, data from the first 20 months of two consecutive years, 2018-2019, is utilized, while the last 4 months are reserved for testing. Python is employed as the scripting language, and TensorFlow library is utilized to construct the LSTM neural network. Data is pre-processed to suit the TensorFlow library, and individual models are created for each input-output combination as indicated in the earlier combinations. To expedite training and accommodate limited computational resources, epochs are set to 100 and batch size is set to 12. Evaluation of results will be conducted using the root mean square error (RMSE) as shown in Equation (12).

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(y_i - \hat{y})^2}{N}} \tag{12}$$

Various models are employed for load demand forecasting, each leveraging different input combinations. Model 1 integrates past load demand, wind speed, solar irradiance, ambient temperature, and time features. Model 2 relies solely on past load demand data. Model 3 combines past load demand with time features, while Model 4 incorporates past load demand with wind speed. Similarly, Models 5 and 6 incorporate past load demand with solar irradiance and ambient temperature, respectively. Lastly, Model 7 combines past load demand with all environmental variables, including wind speed, solar irradiance, and ambient temperature.

As shown in Figure 2, Model 2 exhibits superior performance among the considered models for load demand forecasting, with the lowest RMSE of 209.2656 and a high correlation coefficient of 0.9845. By solely utilizing past load demand data, this model demonstrates remarkable effectiveness in capturing essential patterns and trends within the dataset.

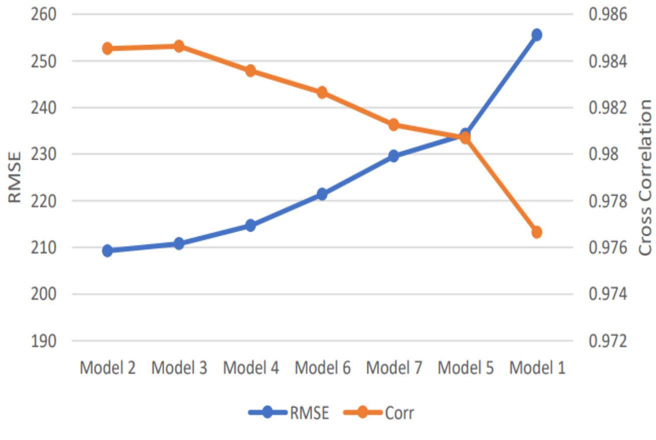

Figure 2 RMSE and Cross Correlation

Figure 3 indicates a one-day forecast, specifically predicting the next 24 hours.

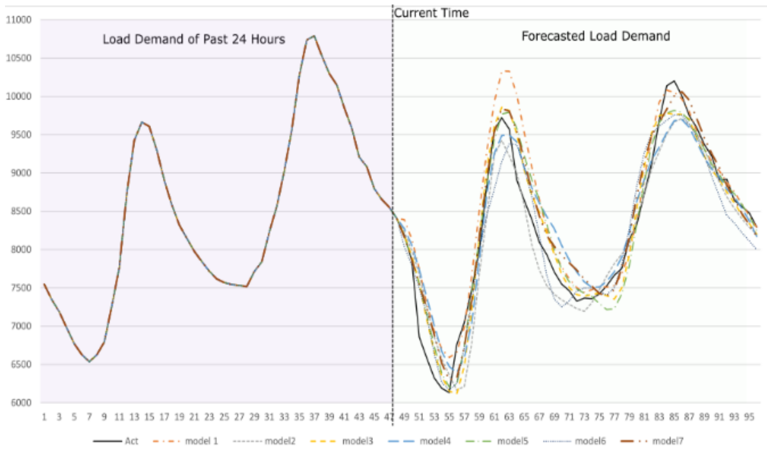

Figure 3Forecasted load demand

The Result shown in figure 4 indicates correlation coefficients and root mean square error (RMSE) values for the various features used in forecasting are as follows: Load Demand demonstrates the highest correlation coefficient of 0.83764 and the lowest RMSE of 209.2656, indicating its strong predictive power. In contrast, Wind Speed, Temperature, and Solar Irradiation exhibit lower correlation coefficients and higher RMSE values, suggesting their comparatively weaker predictive performance. These findings underscore the importance of Load Demand as a key feature in accurate forecasting models.

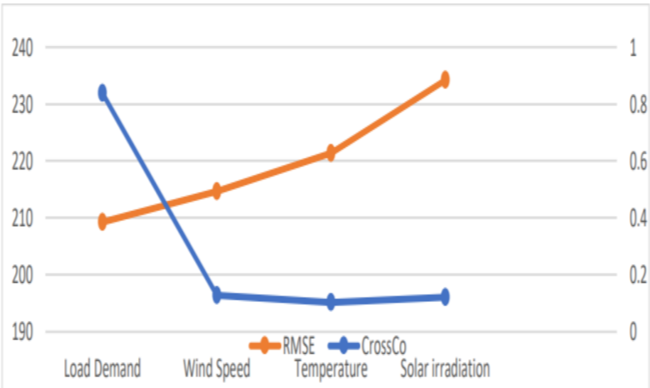

Figure 4 RMSE and Cross Correlation with Weather features

In second Model type Past 72-hour data is taken as input to forecast next 24-hour loaddemand. Network Structure is kept same as in previous model type. The models for load demand forecasting vary in their input combinations. Model 8 includes past load demand, environmental factors, and time features, while Model 9 uses only past load demand data. Models 10 to 13 combine past load demand with specific environmental variables. Model 14 integrates past load demand with all environmental factors. These models highlight the importance of leveraging different input features to improve forecasting accuracy.

The performance of various models in load demand forecasting is displayed in Figure 5. Model 9 stands out with the lowest RMSE of 197.643 and a high correlation of 0.978654, indicating its superior predictive accuracy. Model 8, on the other hand, exhibits the highest RMSE of 313.9156 and a correlation of 0.947654, suggesting comparatively weaker predictive performance. Models 10, 11, 12, 13, and 14 show intermediate results in terms of both RMSE and correlation coefficients. These findings provide valuable insights into the effectiveness of different modelling approaches in load demand forecasting.

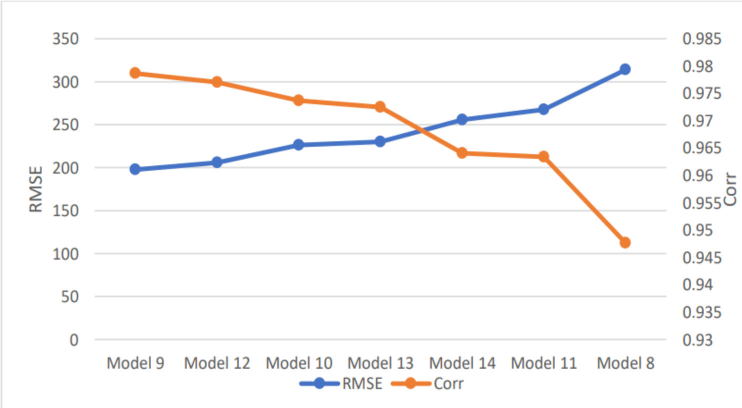

Figure 5 Forecasted load using past 3 days input

Figure 6 depicts that a model that uses load demand from the last 72 hours as input should be able to produce better forecasts than models that use other parameters. When comparing models that produce better results with less input, the model that uses the load demand from the previous 24 hours comes out on top. The results indicate that by focusing on the load demand data from the previous 24 hours, it is possible to achieve accurate load demand forecasting for the upcoming 24 hours.

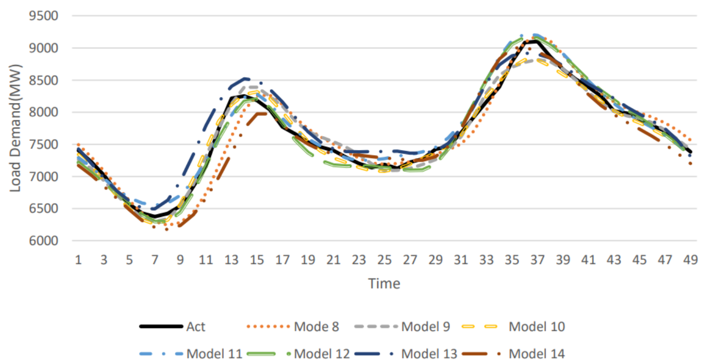

Figure 6 Forecasted load using past 3 days input

4. Conclusion

In summary, our forecasting process involved training models using data from the first 20 months of 2018-2019, reserving the last 4 months for testing. Python, along with the TensorFlow library, facilitated the construction of LSTM neural networks, with preprocessing tailored to suit TensorFlow's requirements. Employing a batch size of 12 and 100 epochs expedited training while accommodating computational constraints. Various models were explored, each utilizing different input combinations to forecast load demand. Model 2 emerged as the most effective, relying solely on past load demand data. Additionally, considering load demand from the previous 24 hours proved pivotal for accurate forecasting, as highlighted by superior results compared to models incorporating other parameters. These findings emphasize the significance of load demand data in achieving precise load demand forecasts.

5. References

[1] J. Cao et al., “A short-term load forecasting method for integrated community energy system based on STGCN,” Electric Power Systems Research, vol. 232, Jul. 2024, doi: 10.1016/j.epsr.2024.110265.

[2] H. Chen, M. Zhu, X. Hu, J. Wang, Y. Sun, and J. Yang, “Research on short-term load forecasting of new-type power system based on GCN-LSTM considering multiple influencing factors,” Energy Reports, vol. 9, pp. 1022–1031, Oct. 2023, doi: 10.1016/j.egyr.2023.05.048.

[3] M. Xiang, S. Du, J. Yu, and Y. Xu, “Short-term load forecasting based on sample weights assignment,” Energy Reports, vol. 8, pp. 783–791, Nov. 2022, doi: 10.1016/j.egyr.2022.09.101.

[4] M. Beichter, K. Phipps, M. M. Frysztacki, R. Mikut, V. Hagenmeyer, and N. Ludwig, “Net load forecasting using different aggregation levels,” Energy Informatics, vol. 5, Sep. 2022, doi: 10.1186/s42162-022-00213-8.

[5] G. Dudek, “Pattern-based local linear regression models for short-term load forecasting,” Electric Power Systems Research, vol. 130, pp. 139–147, Jan. 2016, doi: 10.1016/j.epsr.2015.09.001.

[6] M. S. Hossain and H. Mahmood, “Short-Term Load Forecasting Using an LSTM Neural Network,” 2020.

[7] T. Bashir, C. Haoyong, M. F. Tahir, and Z. Liqiang, “Short term electricity load forecasting using hybrid prophet-LSTM model optimized by BPNN,” Energy Reports, vol. 8, pp. 1678–1686, Nov. 2022, doi: 10.1016/j.egyr.2021.12.067.

[8] T. Hong and P. Wang, “Artificial Intelligence for Load Forecasting: History, Illusions, and Opportunities,” IEEE Power and Energy Magazine, vol. 20, no. 3, pp. 14–23, 2022, doi: 10.1109/MPE.2022.3150808.

[9] A. K. A. Peñaloza, A. Balbinot, and R. Leborgne, “AI application for load forecasting: a comparison of classical and deep learning methodologies,” in Monitoring and Control of Electrical Power Systems using Machine Learning Techniques, Elsevier, 2023, pp. 263–287. doi: 10.1016/B978-0-32-399904-5.00017-X.

[10] L. Wang et al., “Optimal allocation of customer energy storage based on power big data and improved LSTM load forecasting,” Energy Reports, vol. 11, pp. 3902–3913, Jun. 2024, doi: 10.1016/j.egyr.2024.03.046.

[11] W. He, “Load Forecasting via Deep Neural Networks,” in Procedia Computer Science, Elsevier B.V., 2017, pp. 308–314. doi: 10.1016/j.procs.2017.11.374.

[12] S. Pelekis et al., “A comparative assessment of deep learning models for day-ahead load forecasting: Investigating key accuracy drivers,” Sustainable Energy, Grids and Networks, vol. 36, Dec. 2023, doi: 10.1016/j.segan.2023.101171.

[13] A. Al Mamun, M. Sohel, N. Mohammad, M. S. Haque Sunny, D. R. Dipta, and E. Hossain, “A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models,” IEEE Access, vol. 8. Institute of Electrical and Electronics Engineers Inc., pp. 134911–134939, 2020. doi: 10.1109/ACCESS.2020.3010702.

[14] S. H. Rafi, N. Al-Masood, S. R. Deeba, and E. Hossain, “A short-term load forecasting method using integrated CNN and LSTM network,” IEEE Access, vol. 9, pp. 32436–32448, 2021, doi: 10.1109/ACCESS.2021.3060654.