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Comparative Analysis of Neural Network Architectures for Short-Term Load Forecasting Using Real Operational Data: A Case Study of Al-Jufra Grid

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Keywords:
Short-term load forecasting (STLF)
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Al-Jufra power grid
Recurrent Neural Network (RNN)
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ABSTRACT

One of the most application in electric power system operation is the Short-term load forecasting (STLF), due to its role in supporting operational decisions and improving load management. In this paper, three different architectures of artificial neural networks (ANN) were studied and compared, which are Feed-Forward Neural Network (FFNN), Recurrent Neural Network (RNN), and Cascade Neural Network (CaNN), to evaluate their performance in short-term load forecasting. The study was applied using real operational data of Al-Jufra grid during the period from January to mid-April including temporal variables, historical load, and climate data inputs. The results showed that all models of ANN achieved good forecasting accuracy, with the RNN model outperforming the other models. The study also showed that data quality and the selection of appropriate inputs are important factors for improving model performance and operating electrical grids effectively.

دراسة مقارنة لنماذج الشبكات العصبية للتنبؤ بالأحمال قصيرة المدى باستخدام بيانات تشغيلية حقيقية: دراسة حالة شبكة الجفرة

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الكلمات المفتاحية:
التنبؤ بالأحمال قصيرة المدى (*STLF*)
الشبكات العصبية الاصطناعية (*ANN*)
الشبكة العصبية المتكررة (*RNN*)
شبكة الجفرة
متوسط نسبة الخطأ المطلق (*MAPE*).

الملخص

يُعد التنبؤ بالأحمال قصيرة المدى (STLF) أحد أهم التطبيقات في تشغيل أنظمة الطاقة الكهربائية، وذلك لدوره في دعم القرارات التشغيلية وتحسين إدارة الأحمال. في هذه الورقة البحثية، تمت دراسة ومقارنة ثلاث بنيات مختلفة للشبكات العصبية الاصطناعية (ANN)، وهي: الشبكة العصبية ذات التغذية الأمامية (FFNN)، والشبكة العصبية المتكررة (RNN)، والشبكة العصبية المتتالية (CaNN)، وذلك لتقييم أدائها في التنبؤ بالأحمال قصيرة المدى. طُبقت الدراسة باستخدام بيانات تشغيلية حقيقية لشبكة الجفرة خلال الفترة من يناير إلى منتصف أبريل، متضمنةً متغيرات زمنية، والأحمال التاريخية، ومدخلات البيانات المناخية. وأظهرت النتائج أن جميع نماذج الشبكات العصبية الاصطناعية حققت دقة تنبؤ جيدة، مع تفوق نموذج الشبكة العصبية المتكررة (RNN) على النماذج الأخرى. كما أظهرت الدراسة أن جودة البيانات واختيار المدخلات المناسبة هما عاملان هامان لتحسين أداء النماذج وتشغيل الشبكات الكهربائية بفعالية.

Introduction

Short-Term Load Forecasting (STLF) is an important part of operating electrical power systems. It is utilized to support daily operational decisions at the generation level, such as unit commitment, demand management, and improving energy distribution. However, in modern power distribution grids, STLF becomes a critical tool at the substation and distribution levels. For substation operators, accurate load forecasting is important for making load-management decisions and organizing distribution feeders. Most importantly, it helps operators make the right decisions during power shortages, enabling them to apply planned and balanced load-shedding programs rather than relying on random shedding.

Electrical load data is highly complex and non-linear. This is because it is affected by several different factors, including temporal variables such as hour and day, climate conditions, and consumer social behavior. This complexity makes traditional statistical models limited in representing these relationships, driving researchers toward the use

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of Artificial Intelligence techniques, especially Artificial Neural Networks (ANNs), due to their high capability in modeling non-linear patterns and extracting hidden relationships within data.

In this context, Kong et al. [1] developed a short-term forecasting framework for residential loads based on the Recurrent LSTM network. Their results demonstrated the model's ability to capture precise temporal patterns in smart meter data, outperforming several traditional and comparative models, especially in representing the temporal dependency of time series. Marino et al. [2] presented two building load forecasting models using LSTM networks. First model was standard and the second was a Sequence-to-Sequence type. The results showed that the proposed building can achieve good predictive performance comparable to other deep models, with a noticeable improvement in multi-step forecasting. Alhendi et al. [3] proposed a model combining Artificial Neural Networks and Markov Chains (ANN-MC). They integrated temporal, environmental, and behavioral variables into a unified framework. The results showed a significant improvement in forecasting accuracy compared to several machine learning and deep learning models by using multiple evaluation metrics such as MAPE and MPE. Tsegaye et al. [4] developed an enhanced LSTM model using genetic algorithm (GA), incorporating additional variables such as temperature, humidity, and wind speed. The results showed an improvement in forecasting accuracy by approximately 7.5% compared to the traditional model. This shows the importance of improving the model architecture and choosing the right inputs. A study by Chakravorty et al. [5] used Artificial Neural Networks (ANN) and ANFIS models in short-term load forecasting. The results showed the ability of these models to represent the non-linear behavior of electrical loads and achieve good predictive performance compared to traditional analytical methods, reinforcing the importance of AI techniques in this field. Recent studies like Wang et al. [6] have also shown that multi-input deep models, such as Bi-GRU models, are capable of processing different variables (loads, weather, and temporal factors) independently before merging them, which contributes to improving the representation of complex temporal relationships and increasing forecasting accuracy.

However, most previous studies have focused on using standard or relatively clean data, whereas real-world operational environments, especially in developing countries, suffer from challenges related to data quality, irregularity, and the presence of missing values or noise. Furthermore, many proposed models, despite their high accuracy, lack a systematic comparison between different types of neural networks under the same operational conditions, which limits the ability to evaluate their performance fairly and realistically.

Therefore, this study aims to conduct a comparative analysis of three neural network models: Feed-Forward Neural Network (FFNN), Recurrent Neural Network (RNN), and Cascaded Neural Network (CaNN). Using real operational data from the Al-Jufra grid, which is a part of the Libyan national power grid, the study focuses on evaluating their ability to represent the temporal behavior of electrical loads and analyzing their performance under realistic conditions. The main contribution of this study is the systematic comparison of these three neural network architectures using the same input variables, network size, and training conditions, while using real operational data that contain practical data-quality challenges. In addition, an independent out-of-sample period is used to evaluate the models under previously unseen operating conditions. This approach provides a practical assessment of the suitability of different ANN architectures for short-term load forecasting in a real Libyan power-grid environment.

Methodology

This study focuses on developing a predictive model for short-term electrical load forecasting using Artificial Neural Networks, based on real operational data from the Al-Jufra grid. A clear engineering approach was designed to get accurate results and make the model easy to use in daily substation work. This approach directly helps operators manage data errors and manual recording problems. The methodology includes steps of data preparation and processing, followed by building the neural models, training them using the historical data, and ending by evaluating their performance using error metrics.

1. Data Analysis and Input Selection

The operational data utilized in this study were collected from the Al-Jufra substation (also known as Houn 220/66 kV substation). This substation plays a critical role in feeding the regional distribution network, the characteristics and performance of which have been previously investigated in [7]. Specifically, the real-time hourly electrical load profiles were officially provided by the station manager through the Public Relations Office at the Al-Jufra substation [8], covering the period from January to April 2023, with a one-hour time resolution.

To include weather factors, temperature data was added at the same time resolution, obtained from the Open-Meteo historical weather database [9] for the specific coordinates of the study location. Due to the nature of manual recording, the data presented some challenges, such as values affected by load-shedding programs, numerical approximations, and non-physical fluctuations. Therefore, light pre-processing was applied using AI-based tools. The preprocessing included identifying missing, approximate, and abnormal values and estimating or adjusting them according to the overall statistical and temporal behavior of the recorded data. The purpose was to improve data consistency while preserving the main time-dependent characteristics of the original operational data. Fig. 1 illustrates the hourly variations of temperature and electrical load during the study period.

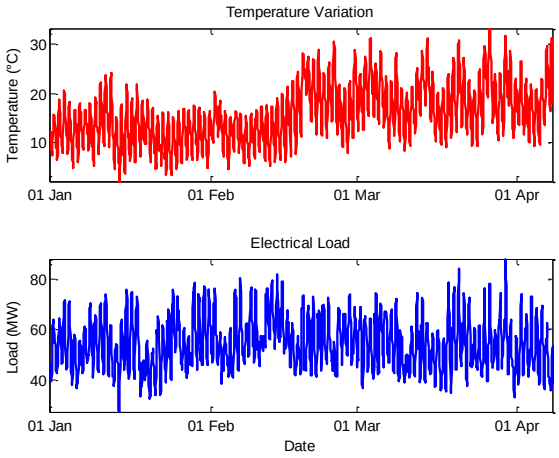


Fig 1: Hourly variations of temp. and electrical load

Data analysis showed a clear time connection, where the current load is linked to past values (hourly, daily, and weekly), showing a regular daily repeat pattern. A non-linear relationship was also found between load and temperature, especially at high values. So, twelve inputs were selected, including past load values, the load for the same hour from the previous day and previous week, in addition to time variables (hour, day, month, day of the week). Current and past temperature values were also included, while variables with low impact, such as wind speed and humidity, were removed.

2. Neural Network Architectures Used

Artificial Neural Networks (ANN) are among the most popular machine learning tools used for modeling non-linear relationships and time-series forecasting [5]. An ANN learns from historical data by adjusting internal weights to match the target output [3]. Inside the network, each neuron calculates the sum of weighted inputs, which can be expressed as:

$$sum = \sum_{i=1}^{N} v_i \times w_i \qquad (1)$$

Where: v_i : is the input variable, w_i : is the weight of that input., N : is the number of inputs.

This sum is then passed through an activation function to produce the output. Based on this, three different neural network architectures were used in this study to evaluate how the structure affects forecasting accuracy: Feed-Forward Neural Network (FFNN), Recurrent Neural Network (RNN), and Cascade Neural Network

(CaNN).

The FFNN passes data in one direction, from inputs to outputs through one or more hidden layers, without any feedback loops, as shown in Fig. 2. Although it is simple and easy to train, its ability to show time relationships is limited, making it less effective for complex time-series data. In contrast, the RNN has feedback paths that allow it to keep information from past time steps, as shown in Fig. 3. This gives it a high ability to show the time connection in electrical load data, making it very suitable for forecasting applications based on connected time sequences. The third structure is CaNN uses extra direct links connecting inputs to the output layer, along with traditional links through hidden layers, as shown in Fig. 4. This helps improve the flow of information inside the network, makes training faster, and provides a good balance between accuracy and calculation speed.

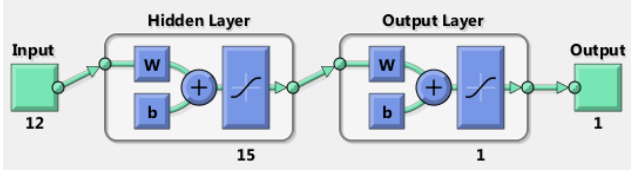


Fig 2: Feed-Forward Neural Network (FFNN) structure

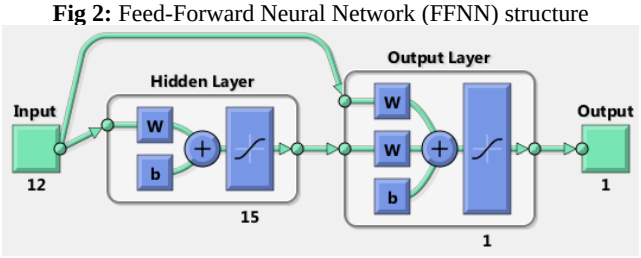


Fig 3: Recurrent Neural Network (RNN) structure

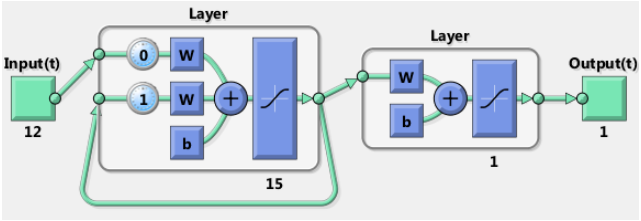


Fig 4: Cascade Neural Network (CaNN) structure

3. Model Construction

The ANN models were built using the MATLAB tool environment. The networks were designed with 12 inputs representing various factors affecting electrical load, as detailed in Table 1. One hidden layer with 15 neurons was used to get the best balance between training speed and forecasting accuracy. A non-linear Sigmoid activation function was used in the hidden layer to model non-linear relationships, while a linear function was used in the output layer to show the continuous values of the electrical load.

Table 1: Description of Network Input Variables

No.	Symbol	Description
1	M	Month of the year (1 to 12)
2	D	Day of the month (1 to 31)
3	H	Hour of the day (1 to 24)
4	WD	Day of the week (1 to 7)
5	P-1	Elec. load of the previous hour
6	P-2	Elec. load of 2 hours ago
7	P-3	Elec. load of 3 hours ago
8	P-24	Elec. load at the same hour yesterday
9	P-48	Elec. load at the same hour 2 days ago
10	P-W	Elec. load at the same hour last week
11	T	Temp. at the current hour
12	T-1	Temp. at the previous hour

The network weights were optimized using the Levenberg-Marquardt backpropagation algorithm (trainlm) with an initial learning rate of 0.01 and a maximum number of epochs set to 1000. The three ANN models were trained using the historical load data available from January through April 14, 2023. The remaining observations were kept completely unseen during the model training and were reserved for independent out-of-sample evaluation.

Performance Evaluation and Error Analysis

The performance of the different models is evaluated using the Mean Absolute Percentage Error (MAPE) [3]. This is one of the most commonly used metrics in the field of electrical load forecasting because it expresses the error as a clear percentage relative to the actual values. It can be mathematically expressed as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|Y_{ki} - Y_{di}|}{Y_{di}} \times 100 \quad (2)$$

Where:

N : Number of hours or forecasting points.

Y_{di}: Actual load value at time i.

Y_{ki}: Predicted load value at time i.

In addition, the error behavior is analyzed in detail using the Percentage Error (PEi) for each forecasting point. This metric expresses the relative deviation between the predicted value and the actual value at each specific moment in time. It is defined as:

$$PEi = \frac{Y_{ki} - Y_{di}}{Y_{di}} \times 100 \quad (3)$$

We used this indicator to study how the error changes every hour. This is especially useful during peak and low-load periods. It helps us understand how the models handle sudden changes in the electrical load. This analysis shows error patterns and the strengths and weaknesses of each model. Therefore, it helps in choosing the best model for real electrical power systems.

Results and Discussion

After designing the ANN models and defining the set of inputs and outputs as explained in the previous section, the models were trained using the historical data from January to mid-April. The training was conducted in the MATLAB tool environment to enable the models to learn the temporal patterns and non-linear relationships that govern electrical load behavior. After finishing the training, the ANN models were tested using new data that was not used during the training phase to evaluate their ability to generalize. The final two weeks of April were kept outside the training data as an independent evaluation period. From this held-out period, April 15th, 16th, and 17th (Saturday, Sunday, and Monday) were selected for detailed performance analysis by comparing the predicted load with the actual recorded load.

Based on the forecasting results, the performance of the different models was analyzed by comparing the predicted values with the actual electrical load values. This analysis was done using two error metrics: the Mean Absolute Percentage Error (MAPE) to evaluate the overall accuracy, and the Percentage Error (PEi) to study the hourly change in error during peak and low-load periods. The results showed a clear closeness between the actual and predicted load curves for all models, with limited differences at peak and low points. This reflects the high capability of these models to capture the general behavior of the electrical load with a high degree of accuracy.

1. Performance of the Feed-Forward Neural Network (FFNN)

Fig. 5 shows a comparison between the actual load curve from the data collection and the predicted curve using the FFNN model. The two curves are very close, with some limited deviations. The lower plot in the same figure shows that the relative error for each hour within the range of −7.12% to 10.05%. It is noted that most values are positive, indicating a slight tendency of the model to overestimate the load. Quantitatively. The detailed MAPE results for the test days are presented in Table 2. These results show that the FFNN performs well during stable load periods. However, it cannot easily represent

temporal dependency. This makes it less accurate when the load changes quickly.

2. Performance of the Recurrent Neural Network (RNN)

Fig. 6 shows that the RNN model tracks the actual load curve better than the previous model. There is a clearer match between the two curves, except for some small differences at the highest and lowest points. The lower plot shows that the relative error decreases, with values between −8.83% and 11.26%, which indicates a stable prediction. The specific MAPE results for this model are summarized in Table 3. These results show that the RNN model performs better than the FFNN model. This improvement is due to its ability to remember past data through its internal memory, making it more efficient in handling the complex time series of electrical loads.

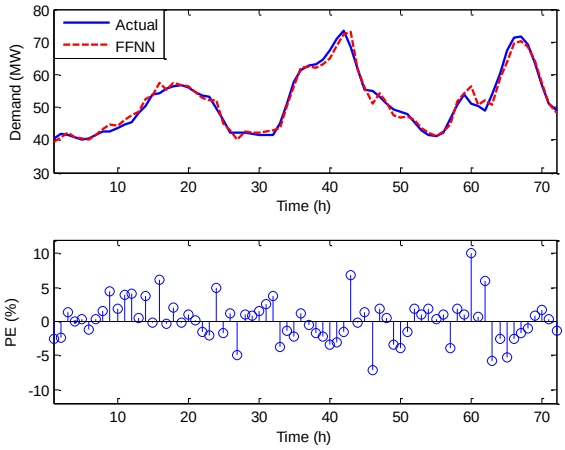


Fig. 5: Actual and predicted load curves with percentage error for the FFNN model

Table 2: MAPE Results of the FFNN Model

Saturday	Sunday	Monday	Average
1.95%	2.34%	2.56%	2.29%

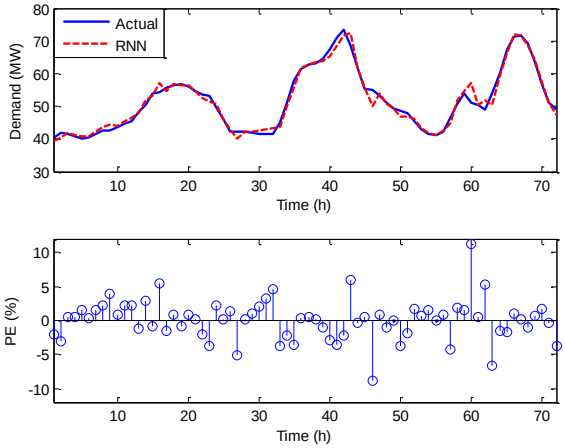


Fig. 6: Actual and predicted load curves with percentage error for the RNN model

Table 3: MAPE Results of the RNN Model

Saturday	Sunday	Monday	Average
1.81%	2.32%	2.22%	2.12%

3. Performance of the Cascade Neural Network (CaNN)

Fig. 7 shows that the CaNN model provides a performance very close to the RNN model. There is a strong agreement between the actual and predicted load curves, with only a few different points. The lower plot shows a general reduction in error, with values ranging between −6.45% and 11.31%. The detailed MAPE results for the different test days are presented in Table 4. Although the CaNN model is slightly less accurate than the RNN, it remains a very strong choice for this application. Its unique structure allows information to flow efficiently through the layers. However, its lack of internal memory limits its ability to handle some complex changes in the electrical load compared to the RNN.

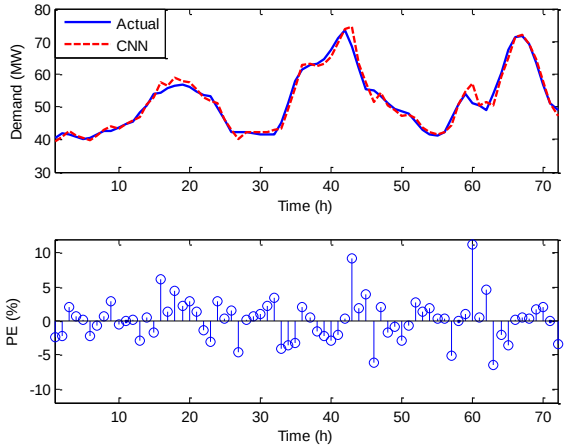


Fig. 7: Actual and predicted load curves with percentage error for the CaNN model

Table 4: MAPE Results of the CaNN Model

Saturday	Sunday	Monday	Average
1.89%	2.57%	2.25%	2.24%

4. Comprehensive Comparison Between Models

By comparing the results, the models can be ranked based on their performance as follows: the RNN achieved the best results with a MAPE of 2.12%, followed closely by the CaNN at 2.24%, and finally the FFNN, which was the least accurate at 2.29%. These results show that models using time-based data (like the RNN) achieve higher accuracy in electrical load forecasting, especially during continuous changes over time. However, the differences between all three models are quite small, meaning that all of them are suitable for real-world applications.

The results show that data quality and selecting the right inputs are key factors that directly change the performance of the forecasting models. These steps helped the models better understand how electrical loads change over time, which successfully reduced the final error values.

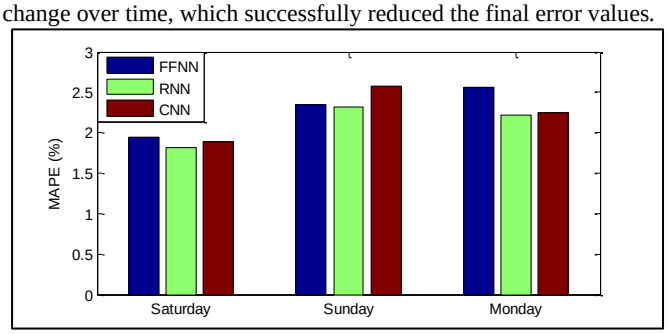


Fig. 8: Comparison of daily MAPE values for the three neural network models

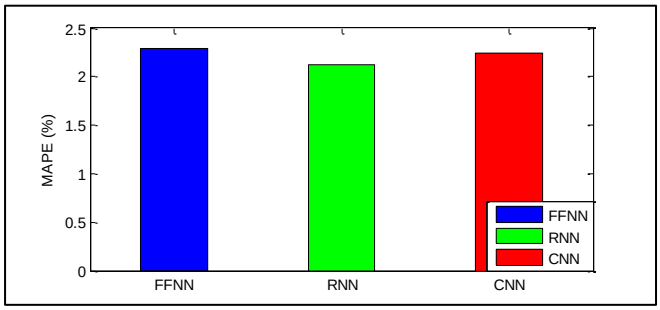


Fig. 9: Average MAPE comparison between FFNN, RNN, and CaNN models

Conclusion

This study focused on short-term load forecasting (STLF) using three different neural network types: Feed-Forward Neural Network (FFNN), Recurrent Neural Network (RNN), and Cascade Neural Network (CaNN). The study used real data of the Al-Jufra grid from January to mid-April. All studied models achieved high accuracy with low MAPE values, where the RNN model performed best, followed by CaNN, and finally the FFNN. The main contribution of the study is the practical and systematic comparison of the three architectures under the same input and training conditions using real operational data from the Al-Jufra grid, including the practical data-quality challenges encountered in real measurements. The use of an independent out-of-sample period further provides a realistic assessment of the forecasting performance.

The results proved that using time-based data and data cleaning directly improve the model's ability to track load changes. Although performance differences were small, they show the effect of network structure on forecasting quality. These accurate forecasts help substation operators make better decisions, allowing them to apply planned load-shedding programs instead of sudden shedding. For future research, the authors plan to expand data to a full year to learn seasonal variations and summer peaks, while trying advanced deep learning methods like LSTM and Transformers.

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