ISSN: 2251-9246
EISSN: 2345-6221

pp.109:115

A Medium-Term Load Forecasting of Iran Khodro Company Using Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) Deep Neural Networks

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Abstract

This paper presents a high-accuracy prediction method for Medium Term Load Forecasting (MTLF) of a manufacturing plant in Iran Khodro Company where the convolutional neural network (CNN) and a long short-term memory neural network (LSTM) are used. The performance of this method is compared with classical regression techniques as linear regression, ridge regression, and lasso. The results demonstrate a coefficient of determination (r2_score) of 0.95 for the test data using deep neural network algorithm, while the classical methods achieve an r2_score of 0.81. This significant difference highlights the superior capability of the proposed method. The model utilizes historical data based on the past time of electric charge as input to train deep learning-based neural network and implement the proposed algorithm. The monthly energy consumption data spanning 9 years from 2011 to 2019 for Iran Khodro Company is employed in this research.

Keywords: Convolutional neural network, deep neural network, linear regression, long short-term memory neural network (LSTM), medium Term Load Forecasting (MTLF)
Article history: Received 2025/02/17, Revised 2025/05/20; Accepted 2025/07/21, Article Type: Research paper

1. Introduction

The accurate prediction of future electricity consumption is crucial for efficient energy management in various industries. In particular, Medium-Term Load forecasting plays a vital role in ensuring a reliable operation of power system and optimizing resource allocation. To address the challenges associated with load forecasting, advanced machine learning techniques have emerged as powerful tools for capturing the complex relationships and patterns inherent in electricity consumption data.

Deep learning has gained a tremendous interest in recent years [1]. Convolutional neural network (CNN) [2] can be considered as one of the most established algorithms among different deep learning models. It is a class of artificial neural networks which is used in different aspects as power grid safety monitoring, control of a heat exchanger, Electroencephalography Artifact Removal, Lung Cancer Detection, identification and detection of healthy and non- healthy cells in breast cancer and robots [3-10].

Remembering long-term items in a sequence is by frequently forgetting. In case a little part in our immediate past is forgotten, a memory is left for more historic events to stay intact. Since the new memory is restricted by intentionally forgetting a little of the immediate past input, the old memory is not eroded by the new one. So, the network is called the Long-Short Term Memory (LSTM) which implies that the corresponding network has a short-term memory of immediate past events for decision making; however, it has a long-term memory for decision-making purpose [11]. LSTM network has been widely used in different aspects as automatic generation control of power system, wind power prediction, load forecast in smart solar systems and energy efficient smart buildings [12-17].

During the last three decades, various methods for load forecasting have been presented as time series, exponential smoothing, Kalman filter, neural networks and fuzzy networks. The problem that all load forecasting methods face is choosing the right input which depends on the characteristics of power system and changes with the passage of time and load pattern [18]. In [19], the challenges faced by distribution system operators (DSOs) in maintaining grid stability is addressed in the context of climate change, distributed energy resources, and political agendas. Accurate load forecasting is crucial for DSOs to effectively plan and manage their grids. In [19], a systematic approach is tested to identify and select data to forecast electricity load in Danish residential areas. The researchers evaluate and compare various types of neural networks, including recurrent neural networks (RNN), long-short-term memory networks (LSTM), gated recurrent units (GRU), and feed-forward networks (FFN) using different data inputs and forecasting horizons. Short term load forecasting is of paramount importance [20-22]. In [20-22], short term load forecasting is studied using multi-layer perception, fuzzy inference systems and artificial neural network generation two. The input variables are carefully selected through a comprehensive analysis of historical data, obtained from the INPS (Iran National Power System). The Levenberg-Marquardt Backpropagation (LMBP) algorithm is used with an evolutionary strategy (ES) method to enhance the convergence speed. In [23], a prediction model is presented for three variables of the greenhouse where the parameters considered are humidity, temperature, and CO2. The model is based on machine learning and meta-heuristic algorithms and a feedforward neural network is used. In order to reduce the prediction error, the weights and coefficients of the neural network are optimized by the grasshopper Optimization Algorithm (GOA).

In this paper, we focus on Medium-Term Load Forecasting of Iran Khodro Company, one of the leading automotive manufacturers. Our objective is to develop a robust and accurate forecasting model using Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) Deep Neural Networks. These deep learning architectures have demonstrated remarkable capabilities in capturing temporal dependencies and nonlinear dynamics, making them well-suited for load forecasting tasks. The proposed model goes beyond traditional approaches by incorporating not only historical electric load data but also additional factors that influence electricity consumption, such as the amount of production and the number of working days in each month. By considering these contextual features, we aim to enhance the accuracy and reliability of our forecasting model, considering the specific characteristics of Iran Khodro Company's power system. To evaluate the performance of our proposed model, we utilize a comprehensive dataset collected from Iran Khodro Company, encompassing several years of historical load and related information. Through extensive experimentation and comparative analysis, we assess the effectiveness of our model against other existing methods commonly used in load forecasting.

The contributions of this research lie in the development of an advanced forecasting model that leverages CNN and LSTM deep neural networks, as well as the incorporation of relevant contextual features for improved forecasting accuracy. The findings of this study are expected to provide valuable insights into the application of deep learning techniques for Medium-Term Load Forecasting in industrial settings, enabling better energy management and informed decision-making.

The remainder of this paper is organized as follows: Section 2 describes the proposed method. The results and performance analysis are discussed in Section 3. Finally, Section 4 concludes the paper.

2. Proposed Method

The most important goals considered in this research are:

- Providing an intelligent system to predict the amount of electrical energy consumed in the future with a short-term approach [24].
- Improving the accuracy and resistance of the intelligent machine for short-term prediction of electric load of the studied power system due to the highly nonlinear and chaotic nature of the power system and the electric load data collected from it using a deep learning neural network [25-26].
- Improving the behavior of LSTM deep learning neural network by determining and optimally adjusting its various parameters using the optimization algorithm [27].

The proposed method is detailed as follows:

- Input layer: If we display the input electric load series as {Lt}Nt=1, in the proposed model, we have considered N = 12, that is, from the electric load and other information, the number of working days and the amount of production is considered in the previous 12 months.
- Calculation of Autocorrelation coefficients of electric charges: in this part, we calculate the autocorrelation coefficients of the input series and use these coefficients to determine the size of the filter in the first convolutional layer.
- Standardization or conversion of Z-Score of electric charge and other inputs: In the proposed model, we standardize electric charge and other

inputs using equation (1). Where μ_L is the average and σ_L is the standard deviation of each input. Also, L is the unprocessed input data and *Lstandard* is the standardized input, which has a normal distribution with a mean of zero and a variance of one.

$$L_{standard} = \frac{L - \mu_L}{\sigma_L} \tag{1}$$

- One-dimensional convolutional layer (Conv1DLayer): As mentioned earlier, convolutional layers are capable of automatically learning features, and these layers can be used to extract features in signals. For this purpose, we use convolutional layers to extract the characteristics of the input electric charge series and other inputs. Also, according to the calculation of autocorrelation coefficients, we use the following relationship to determine the size of the filter in the first convolutional layer. Where, ACC_n is the autocorrelation coefficients and TH is a threshold value which are used to determine the size of the filter in the first convolutional layer. We have used three convolutional layers to better extract the low-level and high-level features of the input load series.

$$f_{size} = \{n | n = 1,2, \ldots ,24 \ : \ ACC_n > TH\} \tag{2}$$

- GRU layer: The features extracted by convolutional layers are entered as input to a GRU layer where the corresponding GRU layer is used to predict the next month.
- Dense Layer: The output of the GRU layer is applied as an input to the fully connected layers. In the last layer, we have used a fully connected layer with a neuron.

In the proposed model, linear activator function and SELU activator function are used. Using the Python programming language and its powerful linear regression library, we first design a raw model and then divide the data into two groups of training and testing data. After that, we train the algorithms of linear regression, ridge regression and lasso regression using the training data, and then based on the test data, we get the accuracy of its performance. For this purpose, we use the minimum square error (MSE) and coefficient of determination (R2-Score) metrics [28].

A) Linear regression

After coding and implementing the linear regression algorithm, the proposed function for this data is as follows [29]:

$$f(x_1, x_2, x_3, x_4, x_5) = 59149x_1 + 2087x_2 + 324232x_3 - 384176x_4 + 12895x_5 + 11163945 \tag{3}$$

Where x_1 to x_5 show the month, number of productions, number of working days, temperature and the square of temperature, respectively. The criteria of root minimum square error (RMSE) and determination coefficient (R2-Score) are as follows:

$$Linear\_model\_rmse = 1561443$$
$$Linear\_model\_r2score = 0.81 \tag{4}$$

B) Ridge regression

After coding and implementing the ridge regression algorithm, the proposed function for this data is [30]:

$$f(x_1, x_2, x_3, x_4, x_5) = 59159x_1 + 2087x_2 + 324226x_3 - 384152x_4 + 12894x_5 + 11163766 \tag{5}$$

Where x_1 to x_5 show the month, number of productions, number of working days, temperature and the square of temperature, respectively. The criteria of root minimum square error (RMSE) and determination coefficient (R2-Score) are as follows:

$$\text{Ridge\_model\_rmse} = 1561448$$
$$\text{Ridge\_model\_r2score} = 0.8 \tag{6}$$

C) Lasso regression

After coding and implementing the lasso regression algorithm, the proposed function for this data is [31]:

$$f(x_1, x_2, x_3, x_4, x_5) = 59151x_1 + 2087x_2 + 324232x_3 - 384169x_4 + 12895x_5 + 11163874 \tag{7}$$

Where x_1 to x_5 show the month, number of productions, number of working days, temperature and the square of temperature, respectively. The criteria of root minimum square error (RMSE) and determination coefficient (R2-Score) is as follows:

$$Lasso\_model\_rmse = 1561445$$
$$Ridge\_model\_r2score = 0.79 \tag{8}$$

Now, according to the dataset and the load forecasting algorithm, implementation of this intelligent and optimal algorithm is discussed based on the LSTM algorithm. The parameters of the aforementioned algorithm are optimally selected by the Bayesian algorithm with the aim of maximizing the efficiency and accuracy of forecasting and consequently minimizing the load forecasting error in the coming months. In this way, after implementing, evaluating and achieving an acceptable quality level, the proposed algorithm will predict the electric load, gas and water consumption in Iran Khodro complex which is divided into six main sections in the following months.

Therefore, in the following, the proposed algorithm is implemented using Python programming language and its results are extracted and presented in different scenarios. In the implementation and training of the proposed LSTM network, in order to predict the electric load in Iran Khodro based on the dataset presented in the previous sections, the results obtained are as Table 2. After designing the desired deep neural network, the data which is not used for neural network training is used as the neural network input. The aforementioned data is related to the energy consumption of 12 months from March 2021 till September 2022. The largest share of electricity consumption is related to the color hall and other units is shown in Figure 1. Figure 2 shows that the color hall has the highest gas consumption.

Table.1.
Design variables and the minimum and maximum values

Decision variable	*Number of layers*	*Number of LSTM units*	*Number of BILSTM units*	*Initial learning rate*	*L2 Regularization Index*	*training repetitions number*	*optimization iterations Number*
Minimum value	1	50	1	0.01	10^{-1}	400	60
Maximum value	4	200	2	1	0.01		

Table.2.
Optimal value of design variables in the proposed algorithm

Decision variable	*Number of layers*	*Number of LSTM units*	*Number of BILSTM units*	*Initial learning rate*	*L2 Regularization Index*	*training repetitions number*	*optimization iterations Number*
The optimal value	1	199	1	0.025835	0.0028718	400	60

3. The Simulations and Results

In the current research, to design, implement and evaluate the proposed method of predicting energy consumption, the constants installed in each aforementioned section record various parameters as the amount of product produced (Q), the average temperature (T), the square of average temperature ($T2$) and the number of working days in the corresponding month (D).

Table.3.
Data used regarding the electricity consumption in terms of watts, the temperature, square of temperature, production rate and number of working days in different months of the years 2011 to 2019.

	year	month	Production	Work_Days(D)	Temperature(T)	Squared_Temp(T^2)	Elec_Consum(Ce)
0	91	1	28493	16	15.800000	249.640000	2.038810e+07
1	91	2	39065	22	21.900000	479.610000	2.589055e+07
2	91	3	31424	21	27.200000	739.840000	2.558384e+07
3	91	4	33212	24	30.100000	906.010000	2.821548e+07
4	91	5	20266	21	30.900000	954.810000	2.395869e+07
...	...	...	...	...	...	...	...
120	1401	1	15786	14	17.677419	312.491155	1.468596e+07
121	1401	2	25675	23	22.145161	490.408169	1.745322e+07
122	1401	3	44999	27	27.935484	780.391259	2.415973e+07
123	1401	4	36776	26	30.983871	960.000260	2.275059e+07
124	1401	5	25103	17	30.741935	945.066597	1.880701e+07

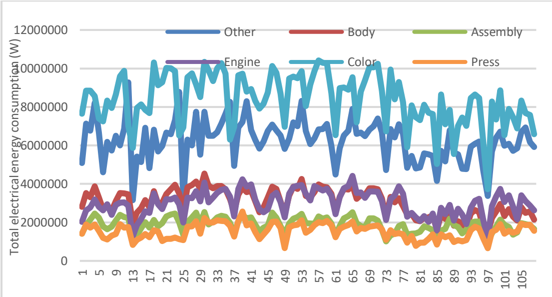

Fig. 1. The diagram of changes in total electrical energy consumption in different parts of Iran Khodro complex from 2011 to 2019 by month.

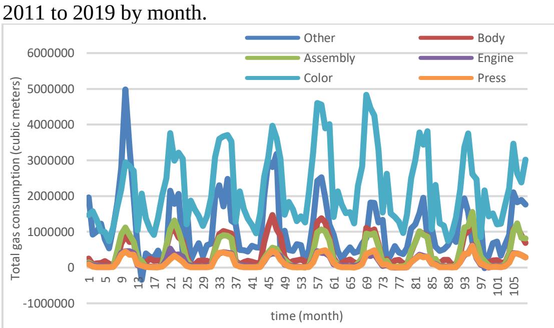

Fig. 2. Chart of changes in total gas consumption in different departments of Iran Khodro Company from 2011 to 2019 by month.

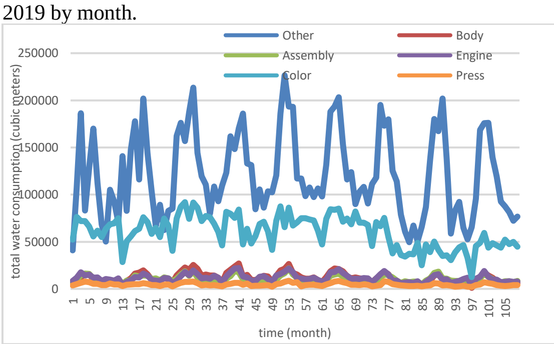

Fig. 3. Chart of total water consumption changes in different parts of Iran Khodro complex from 2011 to 2019.

As can be seen, the amount of water consumption in the engine, press, assemble and body building halls is much less comparing with the amount of water consumption in the paint hall and other units. Table (1) and Figures (1) to (3) show that the changes in energy consumption, including electricity, gas and water depend on the changes of production and the number of working days per month. In order to predict the energy consumption in the six departments of Iran Khodro Automobile Company, we need the changes in the amount of production and the number of working days in each month. The collected dataset has provided information related to 9 years, which is used for training, testing and evaluating the intelligent and optimal machine in the current research. Figure 4 shows that the predicted amount of electricity consumption matches the actual amount of electricity consumption with high accuracy.

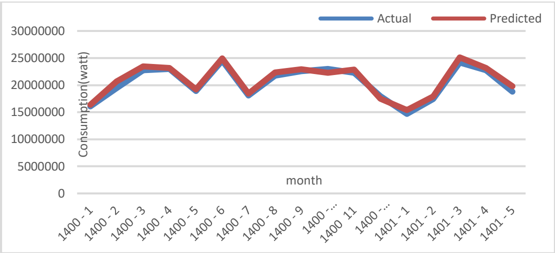

Fig. 4. Comparison of actual consumption with the predicted values of the neural network.

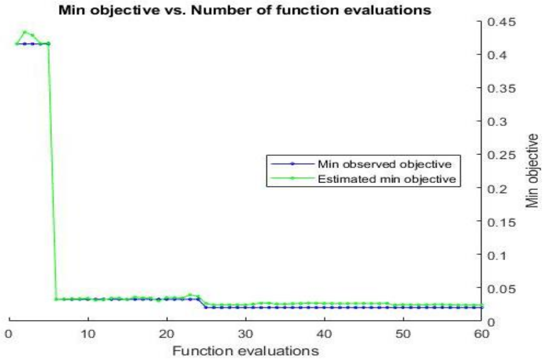

Fig. 5. The optimization process of the proposed LSTM algorithm

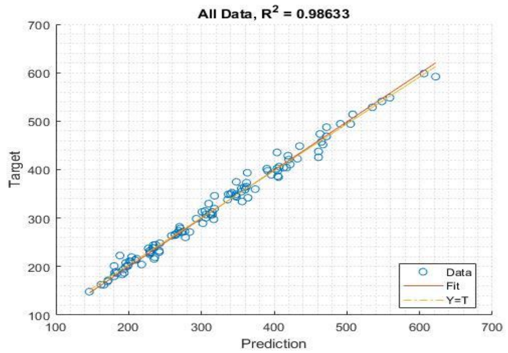

Fig. 6. The regression function resulting from the proposed algorithm

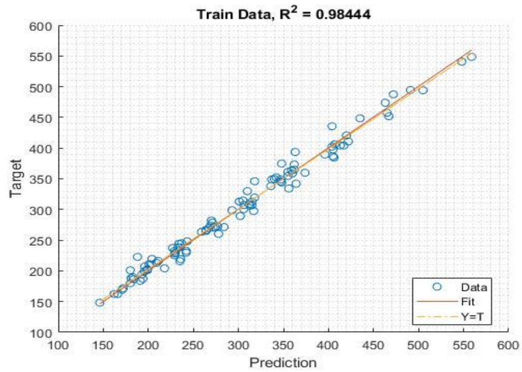

Fig. 7. The regression function obtained from the proposed algorithm based on the training data

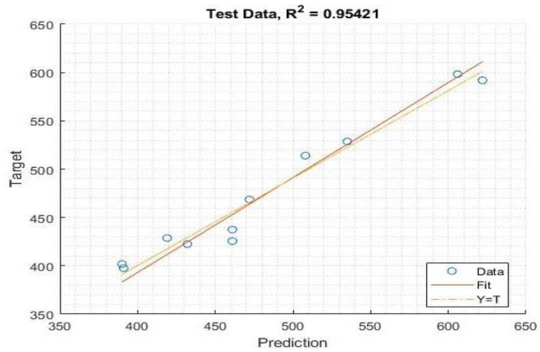

Fig. 8. The regression function resulting from the proposed algorithm based on the test data

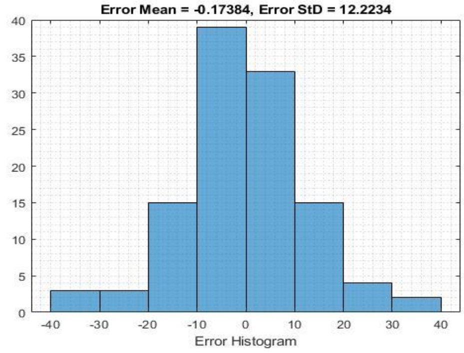

Fig. 9. Histogram chart of the proposed algorithm error based on all data

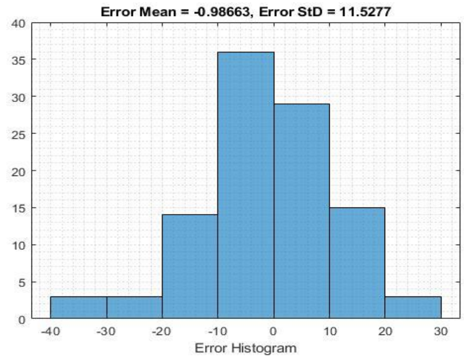

Fig. 10. Histogram diagram of the proposed algorithm error based on the training data

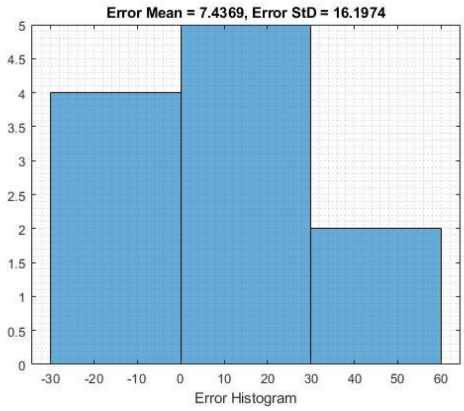

Fig. 11. Histogram of the proposed algorithm error based on the test data

Table.4.
Comparison of all methods

Row number	*The algorithm*	*R2-Score*
1	Linear regression	0.81
2	Ridge regression	0.8
3	Lasso regression	0.79
4	Convolutional neural network	0.95

4. Conclusion

In this paper, we proposed a model for Medium-Term Load Forecasting of Iran Khodro Company using Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) Deep Neural Networks. The model incorporates not only the historical electric load data but also additional information as the amount of production and the number of working days in each month as input features. Three convolutional layers CNN is employed to extract relevant features from the input data, followed by a fully connected layer to predict the electric load for the next month. To assess the performance of our model, data collected from Iran Khodro Company as one of the most advanced collections in the automotive industry is utilized. The prediction results demonstrate the superior performance of our proposed model compared to other existing methods. It outperforms other models in the tested database, indicating its potential as a generalizable approach for load forecasting in other databases as well. Our findings highlight the importance of leveraging deep neural networks, specifically CNN and LSTM, for accurate and reliable Medium-Term Load Forecasting. The incorporation of relevant input features and the utilization of advanced deep learning techniques contribute to the enhanced predictive capability of our proposed model. This paper contributes to the advancement of load forecasting methods, particularly in the context of industrial applications, and paves the way for future research and implementation in similar domains.

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