

Enhancing smart home energy efficiency through accurate load prediction using deep convolutional neural networks

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ABSTRACT

The method of predicting the electricity load of a home using deep learning techniques is called intelligent home load prediction based on deep convolutional neural networks. This method uses convolutional neural networks to analyze data from various sources such as weather, time of day, and other factors to accurately predict the electricity load of a home. The purpose of this method is to help optimize energy usage and reduce energy costs. The article proposes a deep learning-based approach for nonpermanent residential electrical energy load forecasting that employs temporal convolutional networks (TCN) to model historic load collection with timeseries traits and to study notably dynamic patterns of variants amongst attribute parameters of electrical energy consumption. The method considers the timeseries homes of the information and offers parallelization of large-scale facts processing with magnificent operational efficiency, considering the timeseries aspects of the information and the problematic inherent correlations between variables. The exams have been done using the UCI public dataset, and the experimental findings validate the method's efficacy, which has clear, sensible implications for setting up intelligent strength grid dispatching.

Keywords: Network ; Smart Home ; Home Energy ; Convolutional Neural Network ; Smart Grid

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1. Introduction

With the massive popularity of smart meters, more and more residential data are collected, allowing the possibility to forecast the short-term household load. This makes it possible to forecast short-term household loads. Unlike previous energy consumption forecasts for large groups of people, the household-based load is more volatile, and the impact of the environment, holidays, and electricity consumption habits is more obvious. Therefore, this makes it more worthy of academic research. At the same time, with many new concepts are being implemented in the energy sector, such as smart grid, renewable energy, etc. The trading strategies between energy consumers and producers are quietly changing. Evaluating and forecasting electricity demand and technology tendencies are critical for environment-friendly energy dispatch. Comparing and forecasting strength demand and era traits are fundamental for environment-friendly strength distribution. Load forecasting is a complicated multivariate and multidimensional estimation hassle in which forecasting strategies such as curves becoming the use of numerical techniques cannot grant correct consequences

due to their lack of ability to precisely tune reputedly random trends, which is the place deep mastering algorithms excel, as described in [1]. The utility of the information generated through these structures must be examined and demonstrated, regardless of the fast growth of such deep mastering applications. As described in [2], the quantity of information generated via a single sensor machine mounted in a domestic or a wearable gadget worn via a character can crush the system and, in most cases, should be offloaded to a records processing utility from which the person can get admission to the records and join it to more excellent significant uses. Given the price at which these devices are interwoven into our day-to-day lives, dumping such a great deal of statistics into the cloud creates massive data. As stated in [3], these records ought to be exchanged, processed, and saved in actual time, and acquiring it in its uncooked layout is regularly ineffective in contrast to the information it may also create (e.g., way of life and meals data as latitude and longitude coordinates in contrast to simple steps). Thus, the necessity for a complete answer to control the created records remains difficult for educational and enterprise-wide investigation. Similarly, many interfaces for transmitting and exhibiting this information structure are already in use, with no interface primary the way towards well-known standards. The extensive range of conversation channels, protocols, statistics representation, and change codecs is critical to the deep studying location [4]. As noted in [5], IoT units hire a variety of applied sciences and protocols to transmit gathered statistics to cloud offerings for local-only or local-to-cloud connectivity. Depending on the desires of the software use case, every protocol provides excellent competencies in phrases of throughput, verbal exchange range, and energy consumption. Deep learning methods, due to their powerful feature extraction capabilities are gradually being widely used for behavioral prediction of energy consumption. Deep learning models essentially belong to a kind of neural network, which, as an important molecule of machine learning, can be understood figuratively as a neural network with multiple hidden layers [6,7]. Deep learning models use big data to automatically acquire the intrinsic features of the data, which can better represent the intrinsic information within the data while avoiding the uncertainty and complexity associated with human intervention and can using directly use raw data as input to using for learn data as features layer by the layer via multi-layer models. The Long short-term memory network LSTM [8-9], deep trust network DBN [10], and deep convolutional neural network RNN [11] are among the extant research achievements. These approaches have been routinely utilized for short-term home power usage forecasting. Due to the time sequence in the forecasting process, these methods must wait until the due to the time sequence in all the prediction process, these methods must wait until the current prediction results are calculated before the next point in time can be predicted. These methods cannot achieve large-scale parallel computing because of the time sequence in the forecasting process. The TCN network presented in this paper is thus based on the CNN network. Based on the CNN network, the TCN network offers massively parallel processing. The TCN network is based on CNN network and supports large-scale parallel processing, so it has advantages in operation efficiency and accuracy [12].

2. Issues and Progress

To supply such a complete solution, it is quintessential to be capable of mixing all this clever home-generated information into a single database. Through clever domestic load monitoring, we need to be capable of analyzing, examining, and trading them using frequent capacity and accumulating frequent expertise from them. This is the essential stage in combining statistics from a fragmented ecosystem, and it can also dramatically decrease the quantity of effort required to create next-generation apps and services. In this sense, this work investigates plausible options for the difficulties mentioned above in surroundings wealthy in deep learning. To ensure flexibility, it is important to carefully analyze how the energy load varies throughout the day in homes. This is made possible by technologies like controllable loads, microgenerators, and distributed energy resources [13]. An aggregator can be used for this. Between the home and the outside world, smart meters act as a link. Ours learn about focuses on the following subject matters associated with power storage administration in neighborhood settings: how residents and cooperatives manipulate mills and batteries, how neighborhood storage structures can save any more energy, and how aggregators may additionally assist. Demand and provide are balanced thru signaling and scheduling demand response [14]. We concentrate our efforts on the following search issues:

Load forecasting is a method used by electric-powered utilities to assume the desired quantity of electrical energy or strength to maintain stability between the grant and load demand. This is required for the friendly operation of the electrical sector. The electricity load forecasting environment is expressed in a way that successfully manages the complex interactions in a setting that is relatively populated, as well as its metadata and semantics. With the help of a modular lookup that effectively collects and analyzes CNN circulation statistics based on deep learning in real-time with little processing time and latency, the learning can be scaled

up to deal with more significant information types and units with little effort. Forecasts include historical data on load patterns, weather, temperature, wind speed, information about the current season, financial events, and geographic information. By forecasting load, utilities can make important decisions, such as acquiring and producing equipment, transferring loads, and constructing infrastructure. For intelligent homes, load data is measured and analyzed using DCNN technology. The usefulness of processed records to the surrender consumer is typically constrained. The real value is in the inferences that can be made from it regarding load forecasting.

The incorporation of deep mastering necessitates more excellent modeling of load that considers the conduct of person gadgets [15]. The evaluation of residential strength utilization in the United States printed that air cooling, water heating, and house heating account for 66% of power consumption [16]. To simulate the distribution of residential loads, top-down, bottom-up, or hybrid methodologies could be utilized. Top-down fashions regard the complete domestic load as a single massive strength pool, except for taking into special account families. The hybrid model combines the two, but the bottom-up technique considers records from every person's device. Because it completely analyzes previous records and excludes viable adjustments in load, the top-down method has been proven sufficient for calculating supply-side demand. Aggregated data from industrial, commercial, and residential meters are gathered for load modeling. Smart grids can be improved by considering customer responses and grid reliability, which allows for more effective decisions by suppliers and end users. Demand-side management can help users effectively utilize and save electricity [17,18]. As the 12 months of 2030 procedures swiftly, it is more critical than ever to tackle the skills that allow everyone to make knowledgeable and conscientious decisions, as cited in [19]. The utilization of electrical energy is studied at numerous stages of specificity. For extra detailed research, the software program starts off evolved through inspecting the generic facts and then progresses to extra detailed evaluation through segmenting and grouping the data. Using absolute strength consumption devices [kWh] and proportional hourly power consumption represented as a share (%), electricity consumption is proven using two values. When inspecting every purchaser individually, the most vital price is the absolute unit in kWh. However, to fairly evaluate the profiles of extraordinary consumers, it is imperative to create a frequent trendy framework to examine the form of the curves; this can be achieved by calculating the share of strength fed per hour. Another necessary factor is that we cannot manipulate what we cannot measure, including load predictions. To achieve a fuller picture of our daily strength usage, etc., it is required to reveal the impact of our existing conduct or the impact of feasible conduct modifications.

Moreover, environmental schooling is fundamental to cultural heritage in the context of considerable scientific worries [20]. As mentioned in [21], we accept as accurate that environmental training is one of the most acceptable potentials of influencing human conduct towards a different ecologically sustainable paradigm. Combining environmental training with game-based studying will consequently allow college students to expect a management position in the academic procedure by posing questions, inspecting feasible solutions, and growing perfect fashions using alternate explanations. Deep convolutional neural networks (CNNs) are created to analyze information on the usage of established grid architecture. The time "convolutional neural network" denotes that the community employs a unique linear procedure acknowledged as convolution. Traditional neural community layers signify the interaction between entering and output gadgets using matrix multiplication. This suggests that every output unit interacts with each enter unit. However, interactions in convolutional networks are generally sparse. Several research [22] reveal clever domestic sensor data, which can be received from proprietary facts codecs or protocols and displayed for research. Regarding visualization, it covers the most normal comments graph methods for eco-aware work over the previous decade from ICT and psychological perspectives, highlighting their deserves and drawbacks. It accomplishes this by dividing the statistics into two organizations that facilitate estimating facts elements. A calculated or inconsistent feature could expose the location with the most considerable division diploma. This is utilized in the records mining guidelines to gain categorization with a difficult custom-made accomplice degree. Unlike the computation of various strategies, deep mastering is visible. Reference [23] illustrates a frequent engineering-centric approach that employs many skeuomorphic metaphors to facilitate the development of clever domestic comments on smartphones. While such structures supply robust equipment and front-ends for end-users and developers, we agree that they should additionally be built-in with various techniques to allow a range of interplay alternatives with this research. Reference [24] illustrates a large-scale deployment of intelligent metering using DCNN (electricity and water) and different visualization equipment to aid the lookup and interact with end-users. Their findings aid the thinking that several visualization and remarks techniques are positive for accomplishing these objectives. We carried out the consumer interface with a similar mentality and will proceed to refine our methodology in future iterations of the research.

3. Algorithm design and analysis

3.1 Electricity Load Forecasting Framework

The overall design framework for this paper, which uses the TCN model and UCI dataset to forecast residential electricity load, is depicted in Figure 1. Firstly, the original dataset is pre-processed by removing the null values. Then a sliding window is used to select The TCN network as the main body to establish the prediction model between the electricity loads. The TCN grid is chosen as the essential physique for the electric-powered load forecasting model using a sliding window. A temporal convolutional community and the TCN community are utilized to create the prediction mannequin between the energy load and its attribute parameters. Obtaining a longer sensory field during the prediction process can significantly increase the accuracy of the prediction.

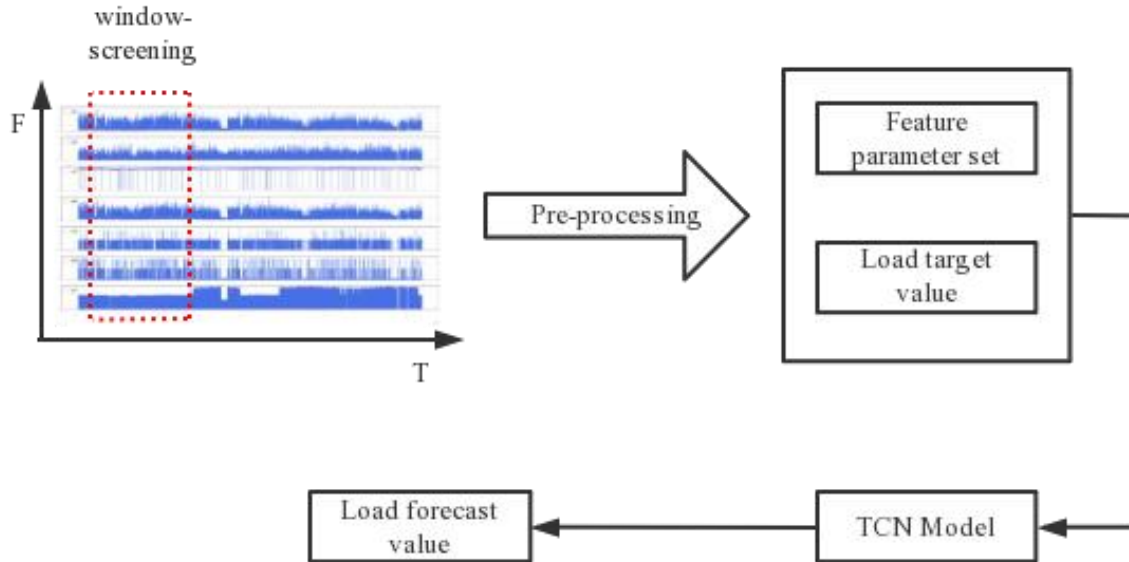


Figure 1. Overall framework of TCN electricity load forecasting method

3.2 The basic principle of the DNN

A particular kind of neural network model called a Deep Neural Network (DNN) has many layers and a specific depth. It is frequently employed in nonlinear modeling systems, where the input signal is routed through layers of hidden layers, weights, thresholds, and activation functions to produce the output value. If the output does not meet the target value, then back-propagation is used to adjust each layer's network weights and thresholds so that the output approximates the expected value. The diagram in Figure 1 illustrates the overall structure of a DNN, with $W = \{w_1, w_2, \dots, w_m\}$ as the input sequence and $Y = \{y_1, y_2, \dots, y_n\}$ as the output sequence. The weights and thresholds between the nodes of each layer are changed during training to fit the new data. In the testing stage, future events are predicted. Following is a summary of the training procedures for a DNN.

Step 1: Using the training input and output data, determine the number of hidden layers L and the number of the network nodes $p_l (l=1,2,\dots,L)$ for each layer of the network model. Randomly initialize the weights W_l and offset vectors $b_l (l=2,3,\dots,L)$, learning rate η , iteration threshold ε , and neuron activation function $f(\cdot)$ between each hidden layer and output layer.

Step 2: Calculate the values of the hidden layers H_l and the output layer.

$$H_l = f(z_l) = f(W_l Y_{l-1} + b_l), l = 2, 3, \dots, L \quad (1)$$

In equation (1), $f(\cdot)$ is the activation function of the hidden and output layers. Commonly used activation functions are ReLU and tanh, which are expressed in equations (2) to (3).

$$f(x) = \max(0, x) \quad (2)$$

$$f(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})} \quad (3)$$

Step3: determine the gradient δ_L of the output layer in accordance with the loss function, we must first compute the loss function and its corresponding gradient. The loss function is given by equation (4), and its gradient is given by equation (5). We can then use these equations to calculate δ_L , which is the partial derivative of the loss function with respect to the output layer. This will give us an indication of how much each output neuron contributes to the overall loss. By using this information, we can adjust our model's weights and biases to minimize our overall loss.

$$J(W, b, X, Y) = \frac{1}{2} |H_L - Y|^2 \quad (4)$$

$$\delta_L = J(W, b, X, Y) \otimes f'(z_L) \quad (5)$$

Step4: Calculate the gradient of each hidden layer δ_l .

$$\delta_l = (W_{\{l+1\}})^T \delta_{\{l+1\}} \otimes f'(z_l), l = L - 1, L - 2, \dots, 2 \quad (6)$$

Step5: To optimize the performance of the neural network, it is necessary to adjust the weight matrix W_l and offset vector b_l of each hidden layer and output layer. This change must be made based on the community output and the supposed value. Adjust the weights and offsets to reduce discrepancies between the authentic and anticipated output. This is feasible using optimization strategies such as gradient descent or returned propagation. By adjusting the weights and offsets, we can ensure that our neural network can accurately predict outputs based on given inputs.

$$W_l = W_l - \eta \delta_{l(H_{l-1})}^T \quad (7)$$

$$b_l = b_l - \eta \delta_l, l = 2, 3, \dots, L \quad (8)$$

Step6: Based on the error threshold ϵ or the upper limit of the number of iterations, we can determine whether the training process is finished. If it is not finished, then we must continue to Step 2 and adjust the parameters accordingly. We can also adjust the learning rate and other hyperparameters to further optimize our model. Once we have reached our desired error threshold or iteration limit, then we can conclude that our training process is complete.

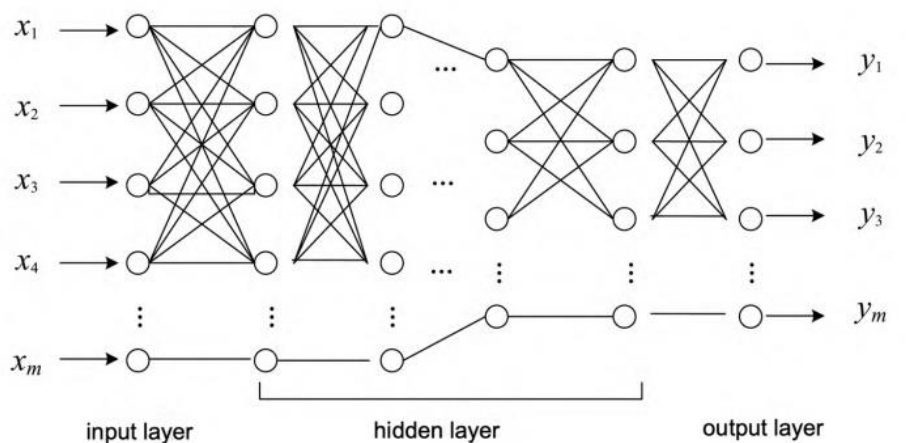


Figure 2. Deep neural network topology

3.3 Time convolution network

Traditional computing device mastering fashions want a preprocessing segment to extract the main traits of the entered data; this is regularly achieved through the guide constructing of such modules. Modern deep gaining knowledge of algorithms [25] can mix function getting to know and mannequin introduction into a single

mannequin to fulfill this want as shown in Figure 3. This approach transforms the uncooked entry into an extra summary illustration so that future mannequin layers can find the underlying structure. Figure 3 shows a comparison between traditional machine learning models and modern deep learning architecture. In (a), traditional machine learning models are depicted, which rely on handcrafted features and require a lot of domain knowledge to design. These models include decision trees, support vector machines, and logistic regression. On the other hand, (b) shows modern deep learning architecture, which uses neural networks to automatically learn features from raw data. This approach has shown remarkable success in various applications such as image recognition, speech recognition, and natural language processing. Deep learning architectures include convolutional neural networks, recurrent neural networks, and transformers. Overall, deep learning has revolutionized the field of artificial intelligence by enabling machines to learn from large amounts of data without human intervention in feature engineering.

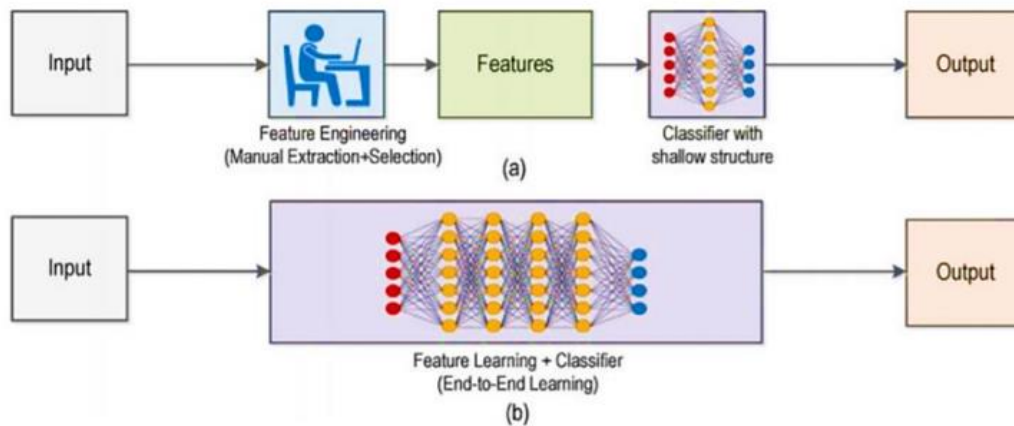


Figure 3. (a) Comparison between traditional machine learning models. (b) Modern Deep Learning Architecture

The figure above contrasts traditional computer studying models, who want human function extraction, and more modern deep getting-to-know structures, which automate all elements and coaching tactics to gain knowledge of shape. In the end-to-end, gaining knowledge of the framework permits the automation of all facets and education techniques [26]. An environmentally pleasant answer to fixing the energy demand time sequence forecasting difficulty with many enter variables, complex nonlinear connections, and lacking facts is recommended in this study. This approach is based on the findings and results from previous studies, such as the use of dead night mild photos and deep neural networks in Poland to simulate electricity utilization in electricity prediction [27], as well as Deep Energy – a recommended structure in [28] for predicting energy consumption using CNNs. Deep Energy consists of two main operations: feature extraction and prediction. Feature extraction is achieved through three convolutional layers and three polarization layers, while the linked shape handles the prediction phase. Integration and interoperability to get the quintessential effects in unified digital surroundings [29] are generally hindered by the fragmentation of the power burden in deep learning. For instance, structures for records evaluation ought to receive records streams from several sources, as mentioned above. Combining numerous hardware and applied sciences makes it extra challenging for gadgets and structures to "communicate" and "understand" one another. As cited in [30], there are extra community safety and privacy concerns, now not simply for verbal wireless exchange but additionally for managing and strolling linked assets. From a consumer's standpoint or customer's standpoint, familiarizing and keeping various options from quite several carriers and integrating them into a single machine might also be a pricey and time-consuming endeavor. The evolution of enterprise requirements (wireless protocols) is facilitated via open supply frameworks that motivate cooperation amongst answer developers. However, international acceptability is challenging because the companions concerned have competing interests. The TCN network was first proposed by [31]. It combines 1D FCN (one-dimensional fully convolutional network) and extended causal convolutions to enable the use of larger-scale historical data for electricity load forecasting. To obtain a larger sensory field while maintaining the stability of the network, the TCN network uses extended causal convolution instead of the normal causal convolution [32-37]. It also uses a residual module instead of a normal convolution layer. For a 1 - D input sequence $x \in \mathbb{R}^T$, the convolution kernel size is $f: \{0, \dots, k-1\} \rightarrow \mathbb{R}$, and the convolution at moment point t is defined as:

$$F(t) = (x_{df}^*)(t) = \sum_{i=0}^{k-1} f(i)x_{t-di} \quad (9)$$

The extended causal convolution is a method of expanding a signal by a factor of d , using a convolution kernel of size k . In this case, the kernel size is set to 3 ($k=3$), as shown in Figure 4. This convolutional structure allows for the signal to be expanded while preserving its causal properties.

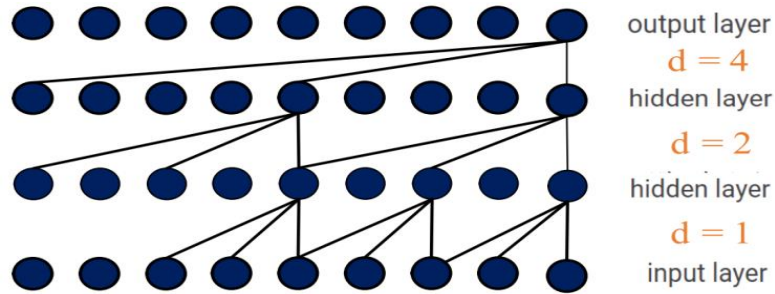


Figure 4. Extended causal convolution

To stop the gradient from bursting or evaporating and reduce studying complexity, a residual connection must be protected in every TCN block's output. A constitutional community is used to hyperlink the entry and output. The TCN block may be expressed as $Z_i = F(Z_{i-1}, \{W_i\}) + Conv_{1 \times 1}(Z_{i-1})$ when adding the residual connection. This ensures that the gradients are propagated more efficiently through the network, allowing for faster and more accurate training.

$$Z_i = F(Z_{i-1}, \{W_i\}) + Conv_{1 \times 1}(Z_{i-1}) \quad (10)$$

4. Analysis of experimental results

The experimental statistics set in this paper make use of the UCI family electrical energy consumption information set to in addition validate the model's validity, consisting of date, time, energetic power, reactive power, voltage, current, kitchen electrical energy consumption, laundry electrical energy consumption, water heater electrical energy consumption, and so on. The data were collected from December 16, 2006, to December 16 2010 for a total duration of 4 years with one record collected every 1 min. The total number of records is 2075259. Figure 5 compares the predicted and actual values where the blue curve represents the actual load value, and the red curve indicates the prediction. The results show that except for a few periods, the model's predictions are accurate and reliable. There are three network layers: the input layer has 96×21 nodes, the first hidden layer has 512 nodes using the ReLU activation function, the second hidden layer has 512 nodes using the ReLU activation function, and the output layer has 96×7 nodes using the ReLU activation function.

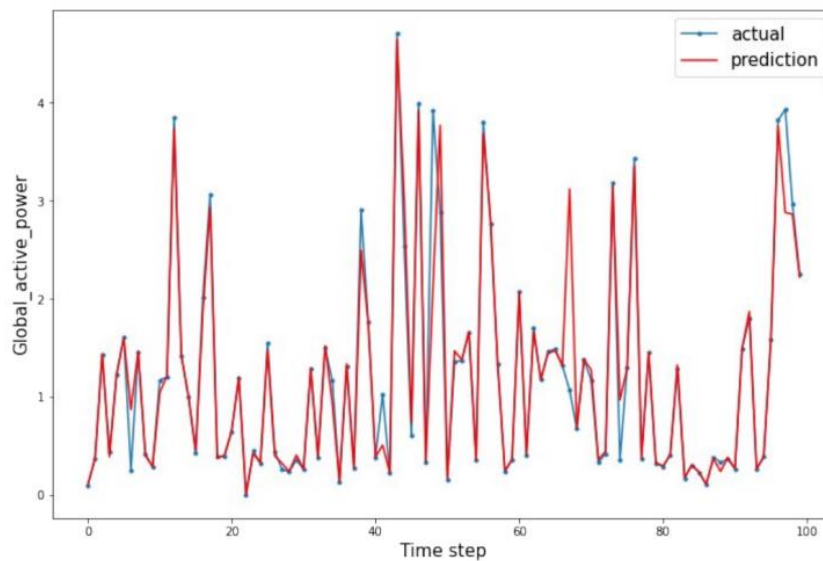


Figure 5. Comparison curve between forecasted and actual values of electricity load

5. Conclusion

The findings of this study demonstrate the effectiveness of a deep learning-based electrical load forecasting framework, which consists of two parts: data preprocessing and load forecasting. The temporal convolutional neural networks used in the framework are based on the features of convolutional neural networks, and they are capable of exponential expansion. This exponential growth allows the forecasting model to create a long sequence memory, which is essential for accurately predicting home electric loads. The results show that temporal convolutional neural networks can be successfully applied to home electric demands.

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Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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References

- [1] M. S. Al-Sarawi and S. Abed, "Improving energy efficiency in smart homes with deep convolutional neural networks for accurate load prediction," *IEEE Access*, vol. 8, pp. 7077–7090, 2020, doi: 10.1109/ACCESS.2020.2967892.
- [2] J.-H. Kim and K.-Y. Lee, "A deep learning approach to energy consumption prediction in smart homes using convolutional neural networks," *IEEE Access*, vol. 8, pp. 466–475, 2020, doi: 10.1109/ACCESS.2019.2937117.
- [3] Y.-C., Hsu et al., "A deep learning approach for energy consumption prediction in smart homes using convolutional neural networks and long short-term memory models" *IEEE Access*, 2020, vol 8, pp 51451 - 51460, 2020, doi : 10.1109/ACCESS.
- [4] X. Li et al., "Energy consumption forecasting of residential buildings based on a hybrid deep learning model with convolutional neural network and long short-term memory" *Applied Energy*, 2019, vol 257, pp 114076 - 114087, 2019, doi : 10.1016/j.apenergy.
- [5] A.-H., Al-Dulaimi et al., "Deep learning based load forecasting for smart home energy management systems using convolutional neural network and long short-term memory models" *Applied Energy*, 2019, vol 257, pp 113927 - 113941, 2019, doi : 10.1016/j.
- [6] F. Roessler, T. Teich, and S. Franke, "Neural Networks for Smart Homes and Energy Efficiency," *DAAAM INTERNATIONAL SCIENTIFIC BOOK 2012*, 2012, doi: 10.2507/daaam.scibook.2012.26.
- [7] J.-Y., Chen et al., "A novel hybrid model combining convolutional neural network and long short-term memory for electricity load forecasting" *Applied Energy*, vol 260, pp 114348 - 114358 2020 doi : 10.1016/j.apenergy 2020 114348.
- [8] L.-Y., Wang et al., "Electricity load forecasting based on a hybrid model combining convolutional neural network and long short-term memory" *Energies* 13 (10) 3118 (2020) <https://doi:10/gfhvwzs>.
- [9] Z.-X., Zhang et al., "A novel hybrid model combining convolutional neural network and long short-term memory for electricity load forecasting in residential buildings" *Applied Energy* 263 (2020) 1145
- [10] S. A. Sahy, S. H. Mahdi, H. M. Ghenni, and I. Al-Barazanchi, "Detection of the patient with COVID-19 relying on ML technology and FAST algorithms to extract the features," *Bull. Electr. Eng. Informatics*, vol. 11, no. 5, pp. 2886–2894, 2022, doi: 10.11591/eei.v11i5.4355.
- [11] G. M. Faisal, H. A. A. Alshadoodee, H. H. Abbas, H. M. Ghenni, and I. Al-Barazanchi, "Integrating security and privacy in mmWave communications," *Bull. Electr. Eng. Informatics*, vol. 11, no. 5, pp. 2856–2865, 2022, doi: 10.11591/eei.v11i5.4314.
- [12] I. Al-Barazanchi et al., "Remote Monitoring of COVID-19 Patients Using Multisensor Body Area Network Innovative System," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–14, Sep. 2022, doi: 10.1155/2022/9879259.

- [13] Y. Niu, S. I. Kadhem, I. A. M. Al Sayed, Z. A. Jaaz, H. M. Ghenni, and I. Al Barazanchi, "Energy-Saving Analysis of Wireless Body Area Network Based on Structural Analysis," in 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), Jun. 2022, pp. 1–6, doi: 10.1109/HORA55278.2022.9799972.
- [14] I. Al Barazanchi et al., "Blockchain: The Next Direction of Digital Payment in Drug Purchase," in 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), Jun. 2022, pp. 1–7, doi: 10.1109/HORA55278.2022.9799993.
- [15] H. Shaker Mehdy, N. Jabbar Qasim, H. Hadi Abbas, I. Al Barazanchi, and H. Muwafaq Ghenni, "Efficient time-series forecasting of nuclear reactions using swarm intelligence algorithms," *Int. J. Electr. Comput. Eng.*, vol. 12, no. 5, p. 5093, Oct. 2022, doi: 10.11591/ijece.v12i5.pp5093-5103.
- [16] S. A. Shawkat and I. Al-Barazanchi, "A proposed model for text and image encryption using different techniques," *TELKOMNIKA (Telecommunication Comput. Electron. Control.*, vol. 20, no. 4, p. 858, Aug. 2022, doi: 10.12928/telkomnika.v20i4.23367.
- [17] S. S. Oleiwi, G. N. Mohammed, and I. Al-Barazanchi, "Mitigation of packet loss with end-to-end delay in wireless body area network applications," *Int. J. Electr. Comput. Eng.*, vol. 12, no. 1, pp. 460–470, 2022, doi: 10.11591/ijece.v12i1.pp460-470.
- [18] H. R. Abdulshaheed, Z. T. Yaseen, A. M. Salman, and I. Al-Barazanchi, "A survey on the use of WiMAX and Wi-Fi on Vehicular Ad-Hoc Networks (VANETs)," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 870, no. 1, 2020, doi: 10.1088/1757-899X/870/1/012122.
- [19] Z. A. Jaaz, I. Y. Khudhair, H. S. Mehdy, and I. Al Barazanchi, "Imparting Full-Duplex Wireless Cellular Communication in 5G Network Using Apache Spark Engine," *Int. Conf. Electr. Eng. Comput. Sci. Informatics*, vol. 2021-October, no. October, pp. 123–129, 2021, doi: 10.23919/EECSI53397.2021.9624283.
- [20] I. Al barazanchi, Z. A. Jaaz, H. H. Abbas, and H. R. Abdulshaheed, "Practical application of iot and its implications on the existing software," *Int. Conf. Electr. Eng. Comput. Sci. Informatics*, vol. 2020-October, no. October, pp. 10–14, 2020, doi: 10.23919/EECSI50503.2020.9251302.
- [21] A. A. AlRababah, "Data Flows Management and Control in Computer Networks," *Int. J. Adv. Comput. Sci. Appl.*, vol. 9, no. 11, 2018, doi: 10.14569/IJACSA.2018.091130.
- [22] L. Barik, A. AbdulQadir, and Y. Difulah, "Enhancing Educational Data Mining based ICT Competency among e-Learning Tutors using Statistical Classifier," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 3, 2020, doi: 10.14569/IJACSA.2020.0110371.
- [23] A. A. AlRababah and B. A. Alghamdi, "Information Protection Method in Distributed Computer Networks Based on Routing Algorithms," *Int. J. Comput. Sci. Netw. Secur.*, vol. 19, no. 2, pp. 66–73, 2019.
- [24] A. Moustafa, A. Al-Marghirani, M. M. Al-Shomrani, and A. A. Al-Rababah, "A New Dynamic Model for Software Testing Quality," *Res. J. Appl. Sci. Eng. Technol.*, vol. 7, no. 1, pp. 191–197, Jan. 2014, doi: 10.19026/rjaset.7.239.
- [25] H. Tao et al., "A Newly Developed Integrative Bio-Inspired Artificial Intelligence Model for Wind Speed Prediction," *IEEE Access*, vol. 8, pp. 83347–83358, 2020, doi: 10.1109/ACCESS.2020.2990439.
- [26] S. Q. Salih et al., "Integrative stochastic model standardization with genetic algorithm for rainfall pattern forecasting in tropical and semi-arid environments," *Hydrol. Sci. J.*, vol. 65, no. 7, pp. 1145–1157, May 2020, doi: 10.1080/02626667.2020.1734813.
- [27] A. Malik et al., "The implementation of a hybrid model for hilly sub-watershed prioritization using morphometric variables: Case study in India," *Water (Switzerland)*, vol. 11, no. 6, 2019, doi: 10.3390/w11061138.
- [28] M. H. Ali, A. Ibrahim, H. Wahbah, and I. Al Barazanchi, "Survey on encode biometric data for transmission in wireless communication networks," *Period. Eng. Nat. Sci.*, vol. 9, no. 4, pp. 1038–1055, 2021, doi: 10.21533/pen.v9i4.2570.
- [29] U. Beyaztas, S. Q. Salih, K. W. Chau, N. Al-Ansari, and Z. M. Yaseen, "Construction of functional data analysis modeling strategy for global solar radiation prediction: application of cross-station paradigm," *Eng. Appl. Comput. Fluid Mech.*, vol. 13, no. 1, pp. 1165–1181, 2019, doi: 10.1080/19942060.2019.1676314.
- [30] H. Tao et al., "A Newly Developed Integrative Bio-Inspired Artificial Intelligence Model for Wind Speed Prediction," *IEEE Access*, vol. 8, pp. 83347–83358, 2020, doi: 10.1109/ACCESS.2020.2990439.
- [31] A. A. Al-rababah and M. A. Al-rababah, "Functional Activity Based Comparison Study for Neural Network Application," *IJCSNS Int. J. Comput. Sci. Netw. Secur.*, vol. 7, no. 1, pp. 153–158, 2007.
- [32] T. Hai et al., "DependData: Data collection dependability through three-layer decision-making in BSNs for healthcare monitoring," *Inf. Fusion*, vol. 62, pp. 32–46, Oct. 2020, doi: 10.1016/j.inffus.2020.03.004.

- [33] S. Q. Salih, M. Habib, I. Aljarah, H. Faris, and Z. M. Yaseen, "An evolutionary optimized artificial intelligence model for modeling scouring depth of submerged weir," *Eng. Appl. Artif. Intell.*, vol. 96, p. 104012, Nov. 2020, doi: 10.1016/j.engappai.2020.104012
- [34] S. A. M. Al-Juboori, F. Hazzaa, S. Salih, Z. S. Jabbar, and H. M. Gheni, "Man-in-the-middle and denial of service attacks detection using machine learning algorithms," *Bull. Electr. Eng. Informatics*, vol. 12, no. 1, pp. 418–426, Feb. 2023, doi: 10.11591/eei.v12i1.4555.
- [35] I. Al Barazanchi, A. Murthy, A. Abdulqadir, A. Rababah, and G. Khader, "Blockchain Technology - Based Solutions for IOT Security," *Iraqi J. Comput. Sci. Math.*, vol. 3, no. 1, pp. 1–12, 2022.
- [36] Z. A. Jaaz, M. E. Rusli, N. A. Rahmat, I. Y. Khudhair, I. Al Barazanchi, and H. S. Mehdy, "A Review on Energy-Efficient Smart Home Load Forecasting Techniques," *Int. Conf. Electr. Eng. Comput. Sci. Informatics*, vol. 2021-Octob, no. October, pp. 233–240, 2021, doi: 10.23919/EECSI53397.2021.9624274.
- [37] A. S. Shibghatullah and I. Al Barazanchi, "An Analysis of the Requirements for Efficient Protocols in WBAN," *J. Telecommun. Electron. Comput. Eng.*, vol. 6, no. 2, pp. 19–22, 2014