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Cement Plant Power Demand Prediction Using 1D Convolutional Neural Network Model: A Case Study

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Abstract

The management and operation of the power system would be significantly enhanced if accurate prior knowledge of the electrical power exchanges is available. Such information reveals valuable insights into the system's operation, assists predictions of energy requirements, and helps developing appropriate solutions to address various challenges and preventing failures. The power consumption, reactive power, and power factor are critical parameters for assessing the performance of power system operations and planning. This paper presents One-Dimensional Convolutional Neural Networks (1DCNN) models for forecasting fluctuations of these parameters within the electrical power demand of a cement factory, thereby facilitating effective monitoring of the cement production process. In addition, Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (Bi-LSTM) models adapted to enhance the prediction effectiveness. Subsequently, the outcomes of the models were compared with those of conventional ARIMA models. Meanwhile, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), and Mean Absolute Percentage Error (MAPE) are used to evaluate the predictive model's accuracy. The results indicated that the suggested models can effectively predict the behavior of such a power system with an RMSE of less than 3%.

Keywords: Bi-Directional, Deep Learning, Long Short-Term Memory, One-Dimensional Convolutional Neural Networks, Power Factor, Power System Consumption.

1. Introduction.

Naturally, the operation of an electrical plant involves integrating various equipment, and it is necessary to identify which parts of the system have higher energy demands than those with lower requirements to assess the quality of operation and management. This assessment can be achieved by monitoring the load consumption variations over long periods using meters, which may be coupled with high-specification microcontrollers or computer systems for the necessary analysis, but this will result in additional costs. The quality and operational behavior of the electrical power system must be examined and monitored using several parameters; the most critical are power factor, power consumption, and reactive power variation [1].

Measuring these parameters within an electrical system will provide valuable insights into the system's functionality, and power management can assist in assessing energy consumption and controlling levels, thereby improving the efficiency and performance of many systems, even in modern internet-based services [1]. Different utilities are incorporated to measure most of these parameters. Nowadays, the Internet of Things (IoT) is used to facilitate many functions and easily interact with computer-based systems [2].

For each of these parameters, there is an effective way to monitor the operation of the electrical energy provided to the loads. A high power factor signifies that the electrical loads are being used effectively. Conversely, a low power factor indicates that a smaller amount of active power is utilized despite a higher power supply. It results in increased reactive power and current wastage within the network. This inefficiency necessitates regulatory measures to mitigate energy losses and reduce electricity costs [3]. To address this issue, various techniques are employed to improve (correct) the power factor.

On the other hand, by monitoring power consumption, reactive power, and the power factor, one can assess energy costs, system quality and performance, device ratings, power regulation, and the quality of industrial products. For these reasons, monitoring systems or predicting changes in the conditions of these parameters became essential for system modification and problem-solving. Forecasting the behavior of these parameters offers additional advantages, such as aiding operational decisions, reducing maintenance costs, and reducing the likelihood of introducing disturbances into the network. In fact, developing a reliable prediction model will incur lower costs than real-time monitoring [4].

Different methods and models were used for prediction and forecasting in power systems (Section 2 presents some of them). Recently, there has been a trend towards using CNN models, which have been proven to be compatible with these goals.

Different CNN models were applied to forecast the mention parameters (power factor, power consumption, and reactive power). Furthermore, the CNN approach helps identify and rectify potential failures within the electrical system, thereby contributing to cost savings for the supplier. Recall that the CNN models involve examining the data obtained from measurements and subsequently preprocessing it to create appropriate patterns for analysis using estimation modeling techniques. The aim of this study is to apply CNN configurations, which have proven effective for forecasting signals in the time domain, to analyze one-dimensional power consumption, reactive power, and the power factor. Achieving accurate predictions would be highly advantageous, as it would streamline network requirements for monitoring and reduce the number of electrical variables recorded, thereby lowering investment costs. Hence, the main contributions of this work can be summarized as follows:

- To review and discuss existing literature on relevant forecasting techniques applied to electrical systems.
- To collect and categorize the dataset comprising power factor, power consumption, and reactive power measurements, followed by the preprocessing of this data to align with the chosen model design.
- To develop One-Dimensional Convolutional Neural Networks (1DCNN) for predicting power demand in cement plants and make modifications to Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (Bi-LSTM) models. Thus, the models are capable of predicting the optimal suitable values, utilizing a proposed characteristic function as the loss function to enhance prediction accuracy.
- To conduct a comprehensive evaluation of the CNN models and a comparison between the deep learning models and the ARIMA models using the collected data.
- To assess the potentials of the proposed CNN-based approach in supporting efficient power system operations and management.

The rest of the paper is organized as follows. Section 2 presents a comprehensive review and discussion of existing forecasting techniques applied to electrical power systems. Section 3 provides a detailed explanation of the proposed methods. Section 4 describes an adaptation of the proposed methods for a cement plant as a case study for this paper. Section 5 presents experimental results of evaluations and comparisons of the proposed models. Finally, Section 6 concludes the paper and outlines future research directions.

2. Related Works.

Numerous researchers have recently shown that the operation and management of electrical power systems may greatly benefit from forecast results, especially those of high accuracy and those aligned with the interests of the system requirements. Accurately estimating power demand is crucial to saving energy, reducing power generation costs, and improving economic performance. Energy load demand forecasting has become increasingly important as power systems have developed, enabling the steady, effective operation to be readily analyzed [5], [6]. The studies used traditional statistical methods, such as the autoregressive and seasonal ARIMA methods, to forecast load consumption. For these methods, a recommendation was to combine multiple methods to achieve accurate results. A method presented in [7] proposes using a mathematical model based on an equivalent circuit to estimate motor parameters and performance metrics, such as current, speed, power factor, efficiency, and torque, from manufacturer-provided data. Graphical representations were used to display the engine performance in order to analyze the different engine parameters. The short-term load prediction technique was also used to forecast power demand for the Energy Management System (EMS), providing data for load flow and emergency analysis. There is a deviation between the predicted and measured data because the machine parameter environments (skin effect, temperature) must be taken into consideration, and this method needs modifications with other methods.

An Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to predict Power Peaking Factors (PPF) in [8]. Meanwhile, the TRIGLAV code was used to collect data output with two input variables (control rod positions and neutron flux). These datasets were used to build, train, and test the ANFIS models. Four ANFIS models were used for two different input space partitioning methods, demonstrating effective prediction capabilities and suggesting significant correlation between predicted and observed PPF values. They suggest increasing the data and inserting AI into the method. Unfortunately, there is limited ability to handle time-chain dependence on long-term exponent variations; hence, Artificial Neural Networks (ANNs) and expert systems are preferred [9]. Improved performance in handling complex nonlinear data sequences was achieved successfully with ANNs modeling for load forecasting of energy systems. These studies indicate that robust performance evaluation and access to larger datasets are essential for achieving accurate and reliable forecast results.

The advances in smart energy infrastructure have made the measurements and monitoring more flexible and accurate. For example, in [10] the prediction of energy usage was examined in a smart building using information attained from intelligent sensors connected to power outlets. The information can then be preprocessed with suitable techniques of an ANN-based system to enable the estimation of the peak demand for the purpose of electric data analysis, assessing the distribution range, and predicting future trends from data patterns. The limitation of this study was the complexity and time taken for running the proposed algorithm; also, more data is needed, and they propose to use a hybrid method. In addition, various data mining techniques were used in [5] , including historical load data and load-time equations. The analysis of power consumption was performed with combined energy source patterns (a hybrid approach) based on machine learning, where Multi-Layer Perceptron (MLP), Support Vector Regression (SVR), and Cat-Boost are aggregated to predict electrical performance. Furthermore, machine learning techniques were introduced in [11] to develop a predictive model for the occurrence of electrical faults. The proposed model was employed for feature selection and classification of power faults using open-source offline datasets. Ant colony optimization was used for feature selection, and five machine learning techniques were used for classification. This technique was implemented not under real-time operation conditions, like direct disturbances and fluctuation of load demand, so neglecting these conditions reduces the accuracy.

Meanwhile, a machine learning algorithm was used in [12] to predict the changes in power factor in three-phase power systems. The proposed model was developed and evaluated on a medium-voltage system. It demonstrated good accuracy and offers a more cost-effective option for power quality monitoring. The model depends on the simplification of dealing with only current variation and does not consider the high correlation between the phase currents obtained from the results and other specific operation conditions.

In terms of clustering methods, machine learning approaches were used to analyze electricity consumption in Paraguay by applying K-means and hierarchical ensemble clustering to real data [13]. Four raw datasets (consumption types of the supply network) had to be pre-processed to obtain the load curve of the system, based on four validation index values. The best results were obtained by evaluating 36 models consisting of six clusters, two distance metrics, and five linkage criteria. In this study, various deep learning architectures, such as 1D CNN, various LSTM layers, and Bi-LSTM, were employed to predict the power consumption, reactive power, and power factor changes in the electrical power system of a cement plant. The authors found that their algorithms need to do more clustering with more real-time data.

In another work, soft computing solutions for energy prediction had been applied for resolving several stability issues between the energy usage and the required energy sources to create trustworthy energy policies [5], [6]. On the other hand, to maximize the load capacity to be contracted in the upcoming months, Nafkha et al. [14] propose methods for implementing deep learning and genetic algorithms to predict the exceedance level of loads over a month-long period. A model was constructed in that work to provide the necessary supply using multiple outputs of ANN forecasts. However, to assess the best capacity contract, the deep learning model (a hybrid technique) was also used to estimate the maximum needs of the consumers [14]. The model was applied only for consecutive months (not well enough to deal with the seasonality demands), and there is a limit to the volume for the capacity optimization.

A model called Electrical Energy Consumption Prediction was proposed in [9], where CNN and Bi-LSTM (EECP-CBL) were combined to predict power consumption. The proposed framework consists of three components: CNN, Bi-LSTM, and a fully connected energy consumption prediction module. The first module used two layers to extract data from the dataset. Then, the results from the previous stage and the time series patterns in both directions are passed to a subsequent module called the Bi-LSTM module, which consists of two Bi-LSTM layers. EECP-CBL used two layers (fully connected) for energy consumption prediction, after training the model and comparing it with other models on the dataset using various metrics. Experimental results confirmed that the proposed model performs better than state-of-the-art methods in predicting residential energy consumption in the dataset.

3. Research Methods.

Deep learning models automatically discover the intricate temporal patterns through high-level abstractions and non-linear transformations. The primary concept of this prediction is to use CNN models to make predictions after processing the collected data for the cement plant.

3.1. Long Short-Term Memory (LSTM).

Internal memory allows LSTM to memorize long-term dependencies, which enables it to perform very well in situations involving sequence-dependent behavior, such as electrical load and demand [15], [16]. The LSTM network structure is depicted in Fig. 1. Language modeling, sentiment analysis, speech recognition, and time-series models are just a few of the fields that have extensively used LSTM models, which are members of the deep recurrent neural network family [17]. When the temporal dependence in the sequential data is a significant implicit characteristic and learning from previous stages is crucial for forecasting, LSTM models and their variations perform well. Compared to standard feed-forward propagation neural networks, LSTMs contain cycles in which the network activations from the previous time step are fed as network inputs to influence the prediction at the current time step [18]. LSTM works well for modeling long-term dependencies and processing sequential data. Variable-length inputs can be handled. It can selectively forget knowledge or keep it for extended periods of time.

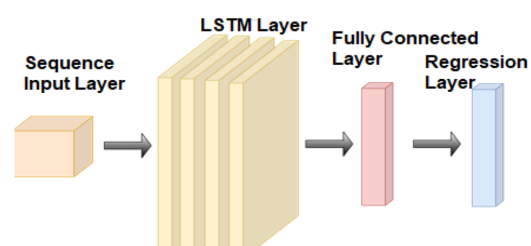


Figure 1. Structure of the LSTM network.

Performance can be enhanced by combining it with other models, such as CNNs [19], [20]. Its computational cost and potential for over-fitting on small datasets are its drawbacks. A continuous data collection of an energy system, a layer sequence including a sequence input layer, an LSTM layer, and a fully connected layer, was used in this study to build an LSTM network (see Fig. 1). By adding a second LSTM layer with sequence output mode before the LSTM layer, the LSTM network may also be made deeper.

3.2. Bidirectional Long Short-Term Memory Bi-LSTM.

Usually, LSTM networks are used for one-way prediction of time series data. However, the Bi-LSTM network has a double-sided stacked LSTM. Fig. 2 shows the structure of Bi-LSTM, where the previous value-based learning is made by the forward direction LSTM network, while the backward direction learning is applied for the next values.

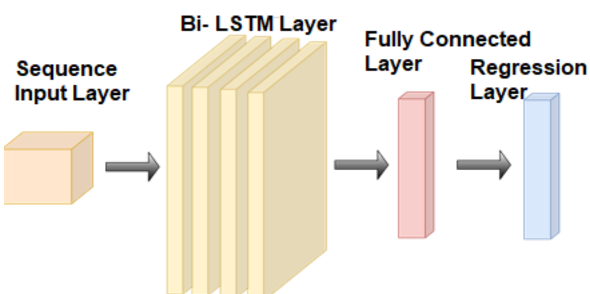


Figure 2. Structure of Bi-LSTM network.

Both pieces of information learned through the hidden states are combined in the last layer. (1), and (2) describe the relation utilized in a Bi-LSTM unit [21]:

$$h_t = \sigma(w_1 x_t + w_2 h_{t-1}) \times tanh(C_t)1),$$

$$h'_t = \sigma(w_3 x_t + w_4 h'_{t-1}) \times tanh(C'_t), \quad (1)$$

$$og_t = w_5 h_t + w_6 h'_t \quad (2)$$

Where x_t is the input at time t, w_i is the gate weight of the LSTM cell, h_t and h'_t Regarding the forward and backward outputs, respectively. The output gate og_t stores information about the bidirectional step.

3.3. One-Dimensional Convolutional Neural Networks.

A One-dimensional Convolutional Neural Network (1DCNN) is a deep feed-forward network that builds on a "classic" ANN by adding more layers (deep learning), including convolution blocks. The term "convolutional" comes from the application of the convolution relation in the designed network. A CNN model can read a series of observations and extract the most important information from them, treating them as one-dimensional data. CNNs can forecast time series with the advantages of the Multi-Layer Perceptron (MLP) [5]. Fig. 3 shows the structure of the 1D-CNN used in this work. Convolutional layer, which is used to make a vector of feature extraction in a. A one-dimensional input vector x [N] is given for the first layer of the CNN. The filter/kernel generates the feature map (as output) after applying convolution on the input data. The number and size of the kernels are important to properly capture the relevant features from the input data [10]. 1D-CNN has benefits for predicting the next parameters reading or sensor values compared to other models, as it is straightforward and has slower training times, requiring only minimal adjustments for hyperparameter optimization. 1DCNN is an effective tool for precise short-term predictions. This method is robust with many types of noise that may be present in the input datasets and the mapping function, producing accurate predictions and learning linear and nonlinear correlations despite the presence of missing values and produces accurate prediction results [22].

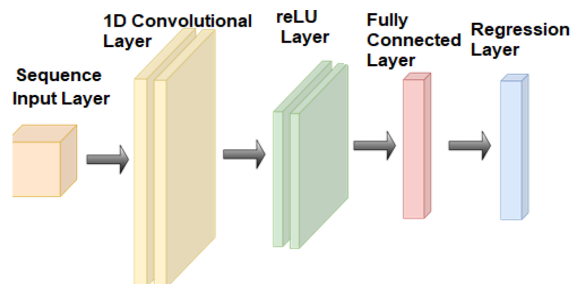


Figure 3. Structure of 1DCNN of LSTM network.

In this work, the 1DCNN model is used for predicting cement plant power demand and is compared with other CNN models, including ARIMA (autoregressive integrated moving average), LSTM, and Bi-LSTM. There are numerous benefits to using 1DCNNs, including strong performance on smaller datasets, reduced computational complexity compared to two-dimensional CNNs and other deep learning frameworks, quicker training times, and effective feature extraction for sequential data and time series (such as signal data) [23], [24]. These qualities make it especially beneficial for forecasting power demand in the cement plants. Fig. 4 illustrates the flow chart and the methodology employed in this research, which leverages the 1DCNN model to forecast various power parameter signals based on power measurements from a cement plant. It depicts the design of the 1DCNN model framework. As evident from this figure, the process for the proposed network commences with the input data, where raw data is obtained from the cement plant's power signals in the time domain (electric feeders). Subsequently, data preprocessing occurs, wherein the data is normalized in the initial layer through standard score normalization. This normalization technique adjusts a dataset to achieve a mean of 0 and a standard deviation of 1. The input size is dictated by the number of features present in the input data. Following this, our proposed model is executed (training and testing initially), wherein the convolution process is conducted using the 1DCNN model. This model comprises at least four layers if a single 1DCNN layer is utilized. These layers include the 1DCNN layer, the Rectified Linear Unit (ReLU) layer, the fully connected layers (FCL), and the regression layer. The first convolution layer is composed of 50×100 (filters of size × number of filters) in conjunction with the ReLU layer. The ReLU layer applies a threshold operation to each input element, converting any value below zero to zero. The initial layers all employ the same padding. Subsequently, at layer 3, the fully connected layer (FCL). These components gather the information from the preceding layers and consolidate it into a single vector, which will be utilized in the final layer for the ultimate regression.

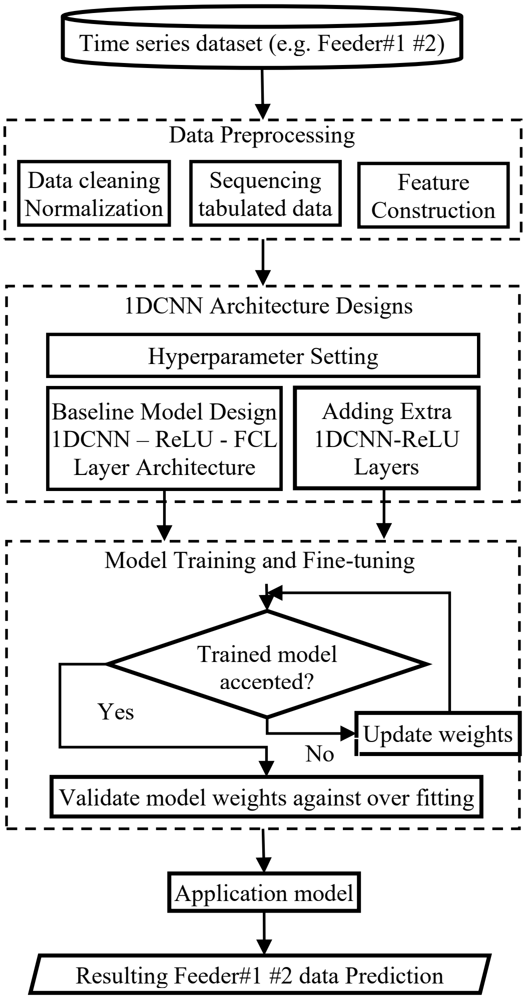


Figure 4. Flow chart (Overview) of the present CNN-based classification strategy.

4. Case Study – Cement Industry.

Instead of using a complete sensor network to record and track the phase currents, voltages, and power system parameters needed in Power Factor Compensation (PFC) systems and power quality analyzers in real time [12], which implies significant financial expenses, it could be better to predict power factor variation effectively and power variables daily. This reduction would lower the consumer's investment cost and streamline the monitoring process. ANNs may offer a practical solution to power factor (as well as power consumption and reactive power) prediction problems, assessing for accurate power quality.

A CNN model for the above parameter prediction was analyzed in this paper for the electrical power system of the cement plant. The cement plant's process flow schematic diagram is displayed in Fig. 5. It is typically formed in four steps: mixing, burning, grinding, and storing. Two feeders of 11 kV are followed by a step-down transformer of 6.7 MVA rating to supply the facility's cement loads [24]. A three-phase analyzer (VIP/MK3 energy analyzer) was used to record the data of this plant. The data was stored for 65 monitoring days, with a one-hour step each day. Measurements are made for each feeder with the power factor calculation in real-time.

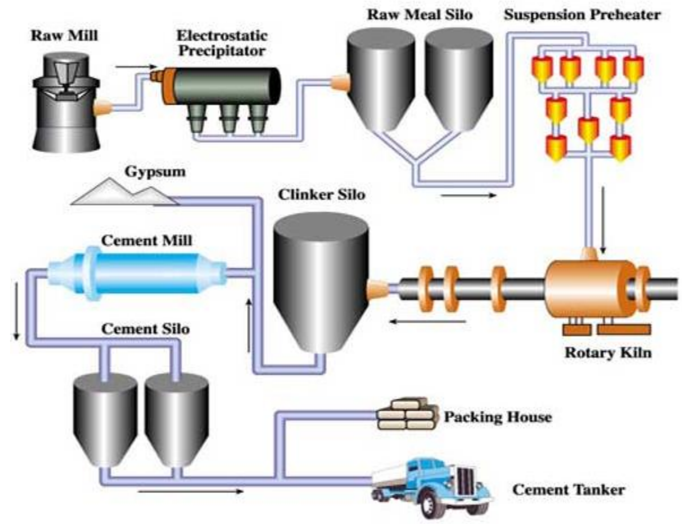


Figure 5. A schematic of the cement manufacturing process.

Table 1 shows a sample of the measurement results for this cement plant case study. The case study was conducted at the ALMURKEB cement factory in Libya by installing measurement equipment on the primary feeders (No.1 and No.2) of 11 kV [24]. Datasets underwent preprocessing (cleaning and tabular formatting) before being used as the basis for site selection. The performance of various regression models is then evaluated after they have been trained. Ultimately, the model is evaluated by testing it in additional sites that have been chosen and analyzing the statistical results. LSTM, based on the CNN models BILSTM and 1DCNN, provides a trustworthy forecast of power system parameter variations.

Table 1. Sample Measurements of the Case Study Dataset.

Feeder#1				Feeder#2			
Hour	**MWh**	**Mvarh**	**PF**	**Hour**	**MWh**	**Mvarh**	**PF**
0:27	273	103	0.81	0:32	270	114	0.82
1:27	274	103	0.85	1:32	271	114	0.83
2:27	275	103	0.82	2:32	271	115	0.84
3:27	275	103	0.83	3:32	272	1150	0.83
4:27	276	104	0.84	4:32	273	115	0.83

5. System Parameters Prediction Performance Evaluation.

Standard metrics for prediction evaluation tasks, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), and Mean Absolute Percentage Error (MAPE), are used to evaluate the performance of CNN models. Smaller values of the error metrics indicate higher forecasting accuracy. As demonstrated in [25], RMSE is a frequently used metric for assessing a predictive model's accuracy, especially in regression tasks. It calculates the average magnitude of the errors between predicted and actual values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

As demonstrated in (4), MAE is an error that is computed by dividing the total absolute errors by the sample size.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(y_i - \hat{y}_i)| \quad (4)$$

According to (5), MBE is the mean value of the variations between the true and predicted values.

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \quad (5)$$

Finally, as demonstrated in (6), MAPE is used to quantify the average magnitude of error generated by a model, or the average deviation of predictions [25].

$$\mathrm{MAPE} = \frac{100}{\mathrm{n}}\sum\left|\frac{(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i})}{\mathrm{y}}\right| \quad (6)$$

y_i : is the actual testing value; $\hat{y}_i$ is the forecasting result of y_i; and n is the total number of testing samples [25].

6. Simulation Results of the Case Study.

In this section, the experimental data are demonstrated and discussed for the power system. These data were demonstrated as a way of using the datasets to train CNN models. The data are initially preprocessed to aid in CNN model learning. As shown in (7),

$$\mathrm{z} = \frac{\mathrm{X} - \mu}{\sigma} \quad (7)$$

Where X is the input variable, μ is the mean, and σ is the standard deviation, the data preprocessing step of normalizing the input datasets scales the datasets to have a mean of 0 and a standard deviation of 1.

The data is split into 70%, and then 15% of the data is used for training and validation, while 15% is used for testing. Also, to improve the accuracy of the CNN/LSTM and Bi-LSTM models, it is preferred to reduce over-fitting and expedite convergence during training; specific hyper-parameter values can be used. These include utilizing a convolutional layer with 50 filters, each with a kernel size of 100, and using 'same' padding to maintain input size. The model has 500 hidden units, is trained over 2000 epochs, and uses the ReLU activation function to add nonlinearity. The Adam optimizer is utilized to perform efficient weight updates, and a mini-batch size of 20 is used during training. The prediction models are deployed to the datasets for performance analysis using CNN's toolbox in the MATLAB software package. A machine with 16 GB of RAM and an Intel® Core™ i7-8550U CPU running at 1.80 GHz powers MATLAB.

The first experiment is conducted with a public multi-scale time-series dataset called Zenodo [26] before employing the intended case study to validate the proposed models. The aim is to show the validity of these experiments on this dataset to support the development of CNN. The dataset of [26] is constructed from combined electric transmission and distribution lines to study the important interactions and uncertainties of grid dynamics. This includes power, voltage, and current observations at different spatiotemporal scales. It makes reliable hierarchical load and renewable energy forecasting possible. The datasets cover the entire year from January 1, 2018, to December 31, 2018, and include measurements for wind speed, relative humidity, temperature, solar power, and load power collected at 1-minute intervals in Houston, emphasizing seasonal changes, notable fluctuations in renewable energy, and a remarkable decrease in load attributed to the pandemic. They are used for forecasting both load and renewable energy. Table 2 outlines the performance metrics on the load power demand dataset of the proposed models: LSTM, 2-layer LSTM, Bi-LSTM, and 1DCNN forecasting model for one-hour-ahead load predictions over the same year (from January 1, 2018, to December 31, 2018). As illustrated in the table, the MAPE for these models was less than 5%, where the predicted values closely approximated the actual data, indicating that CNNs are highly effective models for time series forecasting.

Table 2. Performance evaluation of a 1-hour-ahead point forecast using LSTM for the load power demand dataset.

Model	RMSE%	MAE	MBE	MAPE%
LSTM	0.0257	0.0228	-0.0187	2.4404
2-Layer LSTM	0.0232	0.0192	-0.0147	2.2020
Bi-LSTM	0.0478	0.0410	-0.0372	4.1301
1DCNN	0.0697	0.0391	-0.0246	4.3822

For the case study presented in this work, many experiments are conducted using the proposed CNN models. Fig. 6 displays the electrical power system for the two months of the three datasets: power factor, kWh, and kvar. Strong periodicity in the observational features (like power factor) over the two months is depicted in the figure.

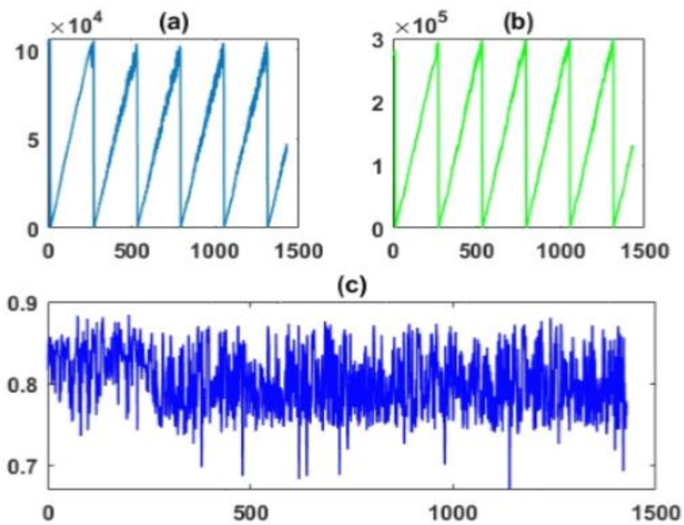


Figure 6. Visualization of the electrical power system for two months. (a) kWh (b) kvar (c) Total Power Factor.

For one-hour step-ahead load forecasting, Tables 3-8 present the performance metrics RMSE, MAE, MBE, and MAPE for the four distinct models: ARIMA, LSTM, two-layer LSTM, Bi-LSTM, and 1DCNN. These are for the power factor, kWh, and kvar of the Feeder 1 and Feeder 2 datasets.

Table 3. Accuracy of the four different models for the total three-phase power factor of the Feeder 1 dataset (two months).

Model	RMSE%	MAE	MBE	MAPE%
ARIMA	58.49	0.2557	-0.0008	18871.39
LSTM	0.0309	0.0229	-0.0057	2.8110
2-Layer LSTM	0.0286	0.0223	0.0029	2.7532
Bi-LSTM	0.0312	0.0237	-0.0084	2.9085
1DCNN	0.0021	0.0016	-0.0003908	0.01911

Table 4. Accuracy of the four different models for the total three-phase power factor of the Feeder 2 dataset (two months).

Model	RMSE%	MAE	MBE	MAPE%
ARIMA	60.95	0.2546	-0.0150	354.11
LSTM	0.0310	0.0219	-0.0094	2.6335
2-Layer LSTM	0.0261	0.0212	-0.0032	2.5677
Bi-LSTM	0.0256	0.0229	-0.0027	2.7817
1DCNN	0.0113	0.0047	-0.0020	0.5595

Table 5. Accuracy of the four different models for the total power consumption kWh of Feeder 1 dataset (two months).

Model	RMSE%	MAE	MBE	MAPE%
ARIMA	57.44	0.2449	0.0175	3476.70
LSTM	0.0143	0.0071	0.0032	3.3070
2-Layer LSTM	0.0108	0.0059	-0.000207	2.3470
Bi-LSTM	0.0027	0.0027	-0.0027	7.5739
1DCNN	0.0210	0.0128	0.0041	3.9469

Table 6. Accuracy of the four different models for the total power consumption kWh of the Feeder 2 dataset (two months).

Model	RMSE%	MAE	MBE	MAPE%
ARIMA	60.62	0.2457	0.0139	734.26
LSTM	0.0188	0.0138	0.0021	8.3704
2-Layer LSTM	0.0137	0.0105	0.0027	6.4635
Bi-LSTM	0.0104	0.0085	-0.0022	12.3387
1DCNN	0.0131	0.0090	-0.0025	4.6868

Table 7. Accuracy of the four different models for the kvar of Feeder 1 dataset (two months).

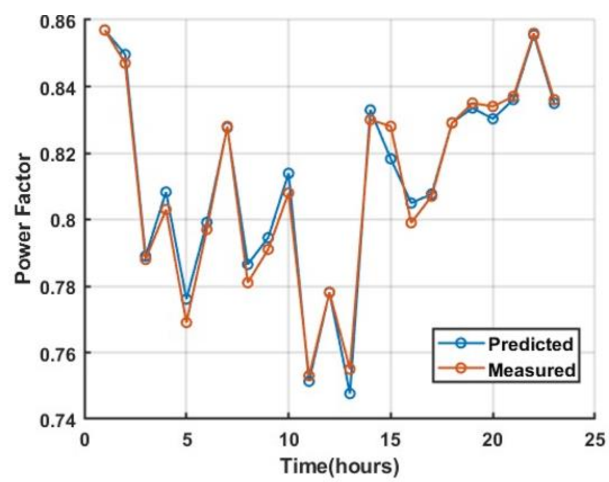
Model	RMSE%	MAE	MBE	MAPE%
ARIMA	31.14	0.1639	0.0362	32.92%
LSTM	0.0139	0.0090	0.0046	3.9934
2-Layer LSTM	0.0118	0.0064	0.0048	1.6945
Bi-LSTM	0.0437	0.0302	-0.0039	11.0939
1DCNN	0.0214	0.0143	0.0024	4.7269

Table 8. Accuracy of the four different models for the kvar of the Feeder 2 dataset (two months).

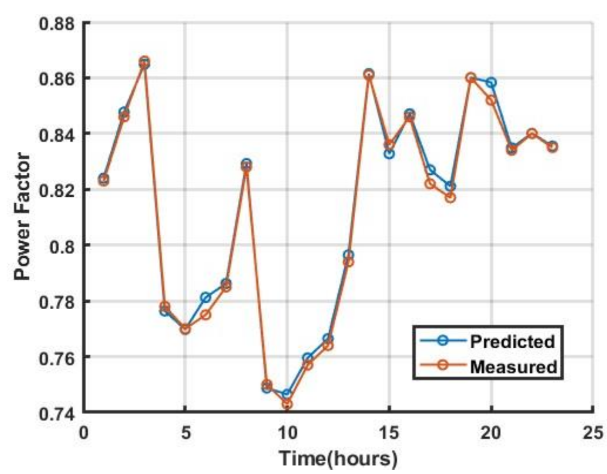
Model	RMSE%	MAE	MBE	MAPE%
ARIMA	20.70	0.1087	0.0274	17.58
LSTM	0.0126	0.0062	0.0028	3.3454
2-Layer STM	0.0152	0.0092	0.000904	3.7158
Bi-LSTM	0.0135	0.0122	-0.0088	5.5867
1DCNN	0.0181	0.0085	-0.0016	4.7902

These tables clearly show that the 1DCNN model performs better than the statistical and various LSTM models. The results indicate that these models effectively predicted the behavior of the power system, with RMSE across all models less than 3%. Accurately forecasting electrical power consumption would achieve economic investment goals, and efficient supply operation will be maintained.

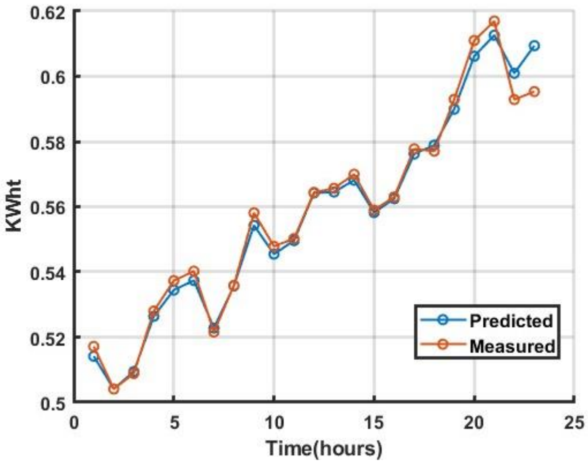
Fig. 7 shows the total power factor, kWh, and kvar for values predicted by the 1DCNN model one hour in advance. This figure shows that the actual data (red) and the predicted data (blue) are highly similar. Comparing to LSTM and Bi-LSTM that perform well in both short-term and long-term predictions, 1DCNN performs better in short-term prediction. Fig. 8 shows the RMSE performance accuracy for one-hour step-ahead prediction values using all the models for electrical feeders 1 and 2 of the cement plant.



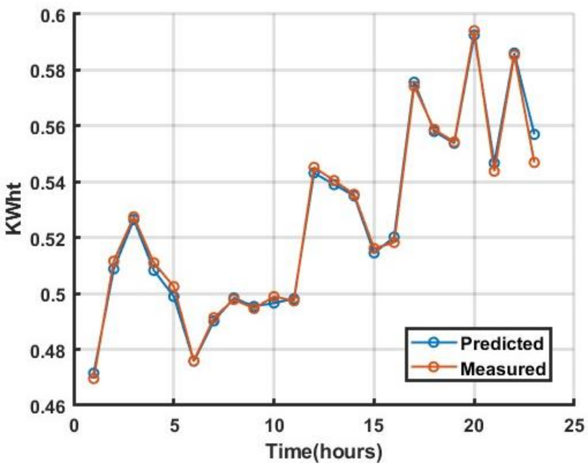
(a) Feeder 1 (power factor data).



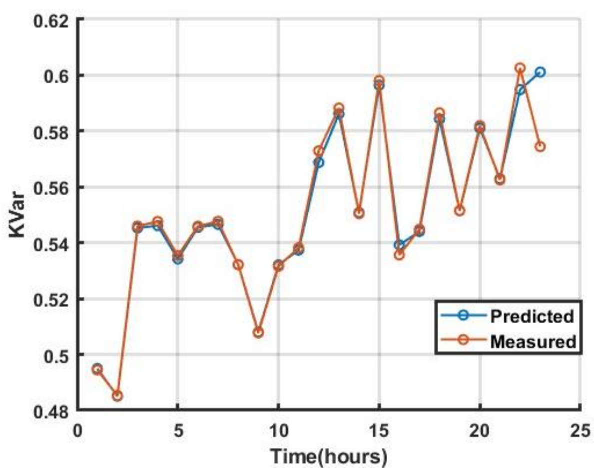
(b) Feeder 2 (power factor data).



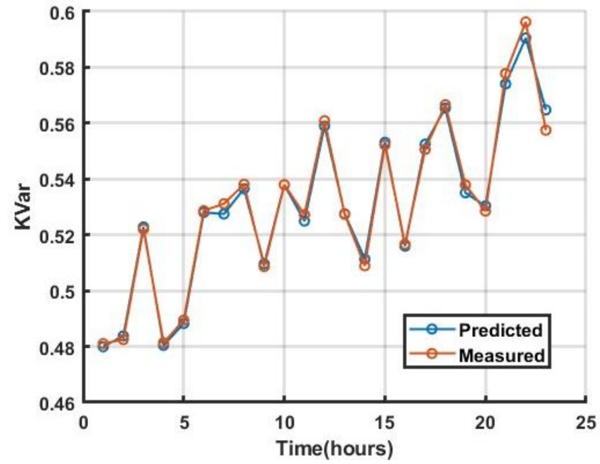
(c) Feeder 1 (kWh data).



(d) Feeder 2 (kWh data).



(e) Feeder 1 (kvar data).



(f) Feeder 2 (kvar data).

Figure 7. One-hour step-ahead prediction values using a 1DCNN model for electrical power system feeders 1 and 2.

As shown, the RMSE for all models is less than 3%. The outcomes show that the forecasted electrical power factor for both feeders closely matches the actual values. These results indicate that these models effectively predict power factor variations solely based on phase currents as input variables in power systems, where the power factor specifies the useful electricity usage. To sum up, 1D CNN has a number of clear advantages over earlier deep learning techniques, especially when dealing with sensor-based datasets like power factor signals, time-series data, or sequential signals. This was clearly apparent in the evaluation factor calculations with this method. Furthermore, a lot of sensor signals and time-series applications include short-term and local dependencies, which 1D CNNs are good at capturing.

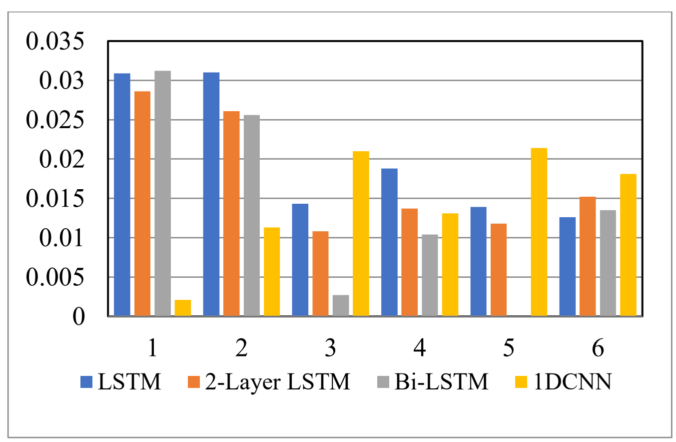


Figure 8. RMSE performance accuracy for one-hour step-ahead prediction values using all the proposed models for electrical feeders 1 and 2.

7. Conclusions and Future Works.

This paper proposes a 1DCNN deep learning framework together with modified an LSTM, a 2-layer LSTM, and a Bi-LSTM CNN architectures for electrical power system prediction. The proposed method aims at enhancing the monitoring efficiency while reducing the time and costs associated with power quality analysis. All model performances are benchmarked against the classical statistical forecasting method ARIMA. The dataset from the cement plant was used to analyze a model for power factor and power consumption prediction. The results indicated that these models effectively predicted the behavior of such power systems with a Root Mean Square Error of less than 3%. A series of experiments shows that power factor data in a cement plant are influenced by both short-term factors (such as frequent operational variations) and long-term factors (such as maintenance schedules). A 1D CNN is usually appropriate for short-term prediction; however, an LSTM or Bi-LSTM model is useful for capturing both short- and long-term trends, the 1DCNN models have greater advantages and particularly effective for short-term forecasting. The RMSE and the coefficient of determination obtained were quite acceptable. The effects of variations in the number of hidden-layer neurons and the dimensionality of the input data on the prediction horizon period were examined in relation to acceptable error values for the prediction process. Finally, the suggested model can be extended to predict power system exchange parameters when phase currents are considered in the analysis and operation of power system conditions, and to account for other power system plants, such as renewable energy sources, when combined. A suggestion is to make smart meters in combination with CNNs so that updating data and reanalyzing can be done to get good results.

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Conflict of interest

The authors make sure that there are no conflicts of interest when it comes to publishing this research.

Author Contribution Statement

The problem for the study was put forth by Tawfeeq E. Abdulabbas. The theory was developed, and the calculations were carried out by Sawsan M. Mahmoud and Hanan A.S. Al-Jubouri.

Prof. Hongbo Du conducted technical proofreading and revision.

The data was prepared and study with help of khalid S. Aleja and Mustafa Salim Agha.

The results of this work were supervised by all authors, who also examined (a particular aspect) and validated the analytical techniques. All the authors also participated in the final manuscript and discussed the findings.

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