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Convolutional Neural Networks for Predicting Power Outages in Baghdad

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Abstract

Power outages are a common and persistent problem in Iraq, significantly impacting various aspects of life and business. These interruptions disrupt routine household tasks and hinder more complex technical operations in industries and services. Emphasizing the need for careful management and proactive solutions. This paper introduces a real-world time series dataset for Baghdad city, including historical outages, weather conditions (such as temperature), and power overloads, and analyzes the correlation among these parameters in different seasons. The research uses this dataset to train one-dimensional Convolutional Neural Networks (1D CNN) to find patterns and relationships that can accurately predict when power outages can happen in the long term and short term to improve the management of the Baghdad electricity grid through data-driven networks. This model was evaluated using performance metrics, and the results show that CNN is accurate in predicting outages in the short term with a Mean Absolute Error (MAE) of (0.0077), whereas, in the long term, it has achieved an MAE of (0.0775). These predictive models have the potential to facilitate the development of proactive measures aimed at reducing the impact of power outages by anticipating potential outages in advance. This research focuses on enhancing the reliability and efficiency of Baghdad's electricity supply, ultimately contributing to economic growth and stability.

Keywords: CNN, Electricity Outage, Deep Learning, Baghdad City.

الشبكات العصبية الالتفافية لتوقع الانقطاعات الكهربائية في بغداد

سجى جعفر جواد، شيماء وليد الشمري

الخلاصة:

انقطاع التيار الكهربائي مشكلة شائعة ومستمرة في العراق، مما يعطل بشدة العمليات اليومية والأنشطة التجارية. تغطي هذه المشكلة كل شيء من المهام المنزلية الروتينية إلى العمليات الفنية المعقدة، مع التأكيد على الحاجة إلى الإدارة الدقيقة والحلول الاستباقية. تقدم هذه الورقة مجموعة بيانات متسلسلة زمنية في العالم الحقيقي لمدينة بغداد، بما في ذلك الانقطاعات لفترات زمنية سابقة ، وظروف الطقس (مثل درجة الحرارة)، وزيادة الأحمال الكهربائية، وتحلل الارتباط بين هذه المعلمات في مواسم مختلفة. يستخدم البحث هذه المجموعة من البيانات لتدريب الشبكات العصبية التلافيفية أحادية البعد (1D CNN) لإيجاد الأنماط والعلاقات التي يمكنها التنبؤ بدقة بموعد حدوث انقطاع التيار الكهربائي على المدى الطويل والقصير لتحسين إدارة شبكة كهرباء بغداد من خلال الشبكات التي تعتمد على البيانات. تم تقييم هذا النموذج باستخدام مقاييس الأداء، وتظهر النتائج أن CNN دقيقة في التنبؤ بانقطاعات التيار الكهربائي في المدى القصير بمتوسط خطأ مطلق (MAE) قدره (0.0077)، بينما حققت في المدى الطويل متوسط خطأ مطلق قدره (0.0775). تتمتع هذه النماذج التنبؤية بالقدرة على تسهيل تطوير التدابير الاستباقية الرامية إلى الحد من تأثير انقطاع التيار الكهربائي من خلال توقع الانقطاعات المحتملة مسبقًا. يركز هذا البحث على تعزيز موثوقية وكفاءة إمدادات الكهرباء في بغداد، مما يساهم في تعزيز النمو الاقتصادي والاستقرار.

1. Introduction

A power outage is a catastrophe in any nation since it impedes local social and economic activity. Additionally, it has an impact on a variety of industries and has the potential to seriously harm several institutions and businesses, including hospitals, phone companies, and industrial installation.

A power outage occurs when there is a partial or whole loss of the network's electric power supply, which impacts end users. Three primary categories can be applied to categorize the causes of power outages: natural events, human errors, and hardware and technical malfunctions. Electrical utility companies must utilize an Outage Management System (OMS) to recognize the location of a power failure [1]. Numerous environmental elements, including the weather, trees, and animal activity, can cause outages. The capability to precisely forecast these failures is a critical step in improving the reliability of power distribution networks, as they account for an important portion of outages. An electric power distribution system's dependability is a measure of its capacity to provide uninterrupted electricity to its consumers [2]. Iraq faces a major challenge from its frequent power outages caused by temperature variations, inadequate energy production, and the widespread use of consumer appliances[3]. The main problem in our research is the electricity outages in Baghdad, which lead to many disturbances, this can be achieved by creating a predictive model by utilizing past data on temperature fluctuations, energy supply shortages, and the rising use of electrical devices to mitigate the negative effects on locals and the economy, this model will help identify patterns and possible future outages, enabling better resource allocation and infrastructure planning.

Deep learning is a subset of Artificial Intelligence (AI) and Machine Learning (ML) that works with multilayer neural networks, also known as deep neural networks, to mimic how the human brain processes information and creates programs to decide. Deep learning algorithms are particularly useful for applications such as natural language processing autonomous systems, language recognition, image classification, etc., because they are able to extract features from raw data and learn from large amounts of dataset [4].

In this paper, the dataset is time series data, so deep learning methods like one-dimensional Convolution Neural Networks can identify the patterns in sequential data. The categorization of predicted power outages is based on these times.

Predicting events or circumstances for a short time frame, like hours or weeks, is identified as short-term forecasting. Predicting short-term power outages is crucial to enhancing grid stability and reducing the effect of disruptions on customers.

The main applications of short-term power forecasting:

- **Grid Management:**

Outage prediction models are used by grid operators to oversee and improve grid operations in real-time. This facilitates decision-making on the effective rerouting of power or the deployment of repair crews.

- **Maintenance on Preventive:**

Predicting breakdowns minimizes downtime and maintenance costs by enabling the scheduling of preventative maintenance before problems become serious enough to cause failures.

- **Systems for Notifying Customers:**

Some utilities use predictive models to notify consumers about impending outages so they can make necessary preparations (e.g., charging batteries, stockpiling supplies, etc.).

- **Forecasting and balancing of loads:**

Outage prediction can aid in load balancing and forecasting by identifying locations that may encounter disruptions, facilitating better load distribution.

Predicting conditions or events over a long time, often months or years, is known as long-term forecasting. This kind of forecasting is essential for long-term decision-making and strategic planning [5]. The applications of long-term forecasting includes.

- **Planning and Investing in Infrastructure:**

Companies use long-term forecasts to direct grid infrastructure investments, including modernizing distribution networks, substations, and transmission lines. Resources can be distributed more effectively by forecasting regions more likely to have future disruptions.

- **Planning for the Community and Economy:**

Local governments and communities use long-term outage forecasts for economic development and urban planning. To increase resilience and provide consistent electricity for vital infrastructure, regions at higher risk of outages can concentrate on developing microgrids or other localized alternatives.

- **Road Mapping for Innovation and Technology:**

Long-term projections drive research and development of new technologies to enhance grid resilience. These could include advancements in smart grid technology, sophisticated infrastructure materials, or novel algorithms for outage management and predictive maintenance.

- **Management of the Supply Chain:**

Long-term forecasts are used by businesses whose operations and output depend on a steady supply of electricity to manage supply chain risks. Planning for backup power options, modifying production schedules, or even moving operations to locations with more dependable power sources are all made easier with an understanding of probable future outages.

The contributions of this research are that the dataset used in this study is novel and has not been utilized before. This ensures the originality and uniqueness of the analysis conducted. Principal factors were analyzed to discover their impact on one another, thereby enhancing performance and operational efficiency.

The goal of this paper is to design a deep learning model to predict electricity outages in Baghdad for both short and long terms based on 1DCNN to discover its efficiency in dealing with time series data.

This paper is arranged as follows: Section Two offerings the literature review, Section Three shows the proposed deep learning method used in this research, Section Four describes the research methodology, Section Five displays the results obtained in this research, the main conclusions and recommendations for future work are introduced in section six.

2. Literature Review

Many studies have been conducted in this field. Amarasinghe et al. (2022) [6] explored the use of

Convolutional Neural Networks (CNN) for forecasting the energy load of individual buildings, convolutions on previous loads are used to apply the methodology to a benchmark dataset of residential customer electricity consumption. The result showed that CNN outperformed deep learning Artificial Neural Network (ANN) and Support Vector Machine (SVM) techniques. Wu et al. (2020) [7] introduced a hybrid neural network model that combines CNN and a Gated Recurrent Unit (GRU) called GRU-CNN. The model allowed for more data utilization and short-term load forecasting because it had the minimum Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) among CNN, Backpropagation Neural Network (BPNN), and GRU forecasting methods, as demonstrated by testing it in a real-world experiment. GOH et al. (2021) [8] described a hybrid neural network that combineed elements of Long Short Term Memory Networks (LSTM) and 1D-CNN. The CNN-LSTM network (MCNN-LSTM) was used to extract calendar, weather, and load features by using multiple heads. For processes with one step and twenty-four steps, the model improved load prediction by 16.73% and 20.33%, respectively. FARSI et al. (2021) [9] proposed a method predicting daily electric power consumption in Malaysia and Germany by using the Parallel LSTM-CNN Network (PLCNet) model, which performed better in terms of accuracy than other machine learning models ((AutoRegressive Integrated Moving Average) ARIMA, SVR, LSTM, etc.).Parallel LSTM-CNN achieved a lower RMSE=0.061 for the German dataset and a lower RMSE=0. 031 for the Malaysian dataset compared to other models used. DENG et al. (2019) [10] suggested a novel multi-scale CNN model with time cognition (TCMS-CNN). In addition to extracting various level features, the model used a novel time-coding technique known as periodic coding. The TCMS-CNN exceeded recursive multi-step LSTM by 34.73%, 14.22%, and 19.05% on MAPE for 48-step point load forecasting. The TCMS-CNN showed potential for real-world applications. Saidi et al. (2021) [11] presented research that analyzed lightning events using three-month datasets from May, October, and November 2019. Data was pre-processed using machine learning, removing unnecessary features and sorting based on sequenc correlations between polarity amplitude and lightning data were explored. The study used Logistic Regression(LR), and Decision Tree(DT) for power outage classification, achieving 100% accuracy. The Fine Tree model had the highest Area Under the Curve (AUC) value of 0.79. Mubarok and Sapanta (2018) [12] used ANN with backpropagation to minimize blackouts. The Levenberg-Marquardt training algorithm, Quasi-Newton, and Gradient Descent Variable Learning Rate were used. The results were seen with the average error percentage rates, resulting in errors of 0.194%, 0.15%, and 0.14%.Al-Nasiri et al. (2022)[13] proposed an ANN for load forecasting. Load and weather data were used for a single year in Mosul. An ANN was employed to forecast the load using the MATLAB R17a software program. The model's performance was evaluated with an accuracy of MAPE equal to 0.0402. AlHaddad et al. (2023) [14] introduced predicting outages caused by line vulnerabilities or grid disruptions; the researchers developed a machine learning-based method for outage prediction for smart grids. The study evaluated five machine learning algorithms, including ANN, (SVM), (DT), (LR), and Naive Bayes (NB), using the bagging ensemble method. The results showed a precision rate of 99.98%, enabling sustainable energy integration into power networks and facilitating energy manufacturing. The research contributed to energy management systems by predicting grid vulnerabilities and laying the basis for improving resilient and dependable power infrastructure. Abumohsen et al. (2023) [15] proposed a study aimed at developing forecasting models for electrical load estimation based on current measurements of electricity companies. The models used deep learning algorithms such as Recurrent Neural Networks (RNN), GRU, and LSTM. The GRU accomplished the optimal precision and lower error performance compared to other models, with an MSE of 0.00215, MAE of 0.03266, and R-squared of 0.90228. Ribeiro et al.(2022)[16] compared the performance of three deep learning models (RNN, LSTM, GRU), three machine learning models (Support Vector Regression (SVR), Random Forest, and Extreme Gradient Boosting (XGBoost)), and a classical time series model, ARIMA, in predicting daily energy consumption. The dataset, which included 8040 entries from an Irish logistics facility, was evaluated using grid search techniques. The XGBoost models outperformed the others for very short-term load forecasting and short-term load forecasting, whereas the ARIMA model underperformed.Wu and Wu (2024) [17] proposed a combined CNN, BiLSTM, and Self-Attention SA mechanisms(CNN-BiLSTMSA) model to predict residential electricity consumption in Paris, France. Experimental results show it outperformed existing methods like(SVM, GRU, CNN-LSTM, and linear regression(LR). Koukaras et al.(2024)[18] improved that The resampled one-hour, one-step-ahead forecast outperformed the other models for short-term load forecasting by using many machine learning models such as Histogram Gradient-Boosting Regression (HGBR), Light Gradient-Boosting Machine Regression (LGBMR), Extra Trees Regression (ETR), Ridge Regression (RR), Bayesian Ridge Regression (BRR), and Categorical Boosting Regression (CBR) based on data resolution and time step forward. Oqaibi and Bedi(2024) [19] introduced a hybrid technique by combining data smoothing and decomposition strategies with deep neural networks. It employs an attention strategy to acquire long-term dependencies between load demand measurements. A comparative analysis of a real-world dataset from five southern Indian states validates the method's efficiency.
Table 1 below compares the literature review in terms of the techniques used, advantages and disadvantages, and the main results.

Previous studies have shown that electrical loads can be forecast globally and in various Iraqi governorates, but no studies have predicted outages in Baghdad. As a result, our study employs specialized data for Baghdad that has been studied to determine its significance and is used to forecast outages in Baghdad in the long and short term.

Tabel (1): Comparison of the literature review

Ref.	Used technique	Advantage	Drawbacks	Main Results
[6]	CNN, SVM, ANN	Compared different methods to predict a single residential customer	The research did not consider the impact of weather data on load forecasting accuracy.	RMSE=0.732
[7]	GRU-CNN	Real-world experimentations of Wuwei region electrical load forecasting	lacks a detailed discussion on its interpretability and robustness in handling varying data characteristics or external factors.	MAPE=2.8839
[8]	CNN-LSTM	Produced appropriate results for both multi-step and single-step load prediction	The proposed model's scalability and generalizability may be limited due to the lack of in-depth discussion of its application across real-world applications.	Maine dataset MAPE=2.93 Ireland dataset MAPE=2.01
[9]	Parallel LSTM-CNN	Introduced a novel technique	The data, such as weather data, was not taken into consideration	Malaysian RMSE=0.031 German RMSE=0.061
[10]	TCMS-CNN	Introduced a novel technique	Didn't consider weather effects	MAPE=0.98%
[11]	LR, DT	Studied lightning events affects	Limited dataset	Accuracy =100% Classify outage
[12]	ANN	The ANN technique, which employs the Levenberg-Marquardt, Gradient Descent Variable Learning Rate, and Quasi-Newton algorithms, produced remarkable accuracy in load forecasting with error rates as low as 0.14%.	Designing and training ANNs could be difficult and time-consuming, particularly when working with huge datasets and several parameters.	average error =0.322619%.
[13]	ANN	Studied the effects of weather on electrical load	The study's reproducibility and transparency may be compromised because of the lack of detailed knowledge of the data collection and preprocessing methodology.	MAPE=0.0402
[14]	(SVM), (ANN), (LR), (DT), (NB)	Studied the effects of weather on the power grid	ANN didn't introduce good accuracy. It can be replaced by LSTM, GRU RNN, CNN	LR MAE=0.00025 RMSE=0.016100
[15]	(LSTM), (GRU), and (RNN).	Gave accurate results in the prediction	Changing the learning rate and optimizer was done manually, which could be achieved using an optimization method	MSE = 0.00215, MAE =0.03266 RMSE = 0.04647.
[16]	(SVR), Random Forest, (XGBoost), RNN, LSTM ARIMA	Compared deep learning, machine learning, and classical ARIMA	The study focuses on short-term, which may not be as useful for long-term energy planning.	RMSE=0.0844 MAE=0.0461
[17]	CNN-BiLSTM-SA	Proposed a CNN-BiLSTM-SA model for predicting household electricity consumption	Did not consider Factors like holidays affect the electric device consumption and lead to more accurate results	RMSE=0.1554 MAE=0.2280
[18]	(HGBR), (LGBMR), (ETR), (RR), (BRR), (CBR)	Studied the effect of energy and weather parameters on power consumption by using different Machine learning methods	The study did not extensively discuss the limitations or potential drawbacks of the machine learning models analyzed, which could provide a more balanced view of the effectiveness of these techniques.	RMSE=0.158 MAE=0.092
[19]	Proposed a hybrid method combining data smoothing and decomposition strategy with (GRU, LSTM, and BIGRU) for improving forecasting results	Collected and analyzed the real-time electricity consumption dataset of five southern states in India for seven years	used an energy dataset and did not analyze the effect of other factors like weather	Andhra Pradesh RMES=2.854 Karnataka RMES=4.230 Kerala RMES=2.486 Tamil Nadu RMES=6.875

3. Deep Learning Method

A specific kind of convolutional neural network called a 1D CNN is made for analyzing data that has only one dimension. 1D CNNs are particularly good at extracting features from sequences, such as time series data, in contrast to traditional CNNs that are used for images (2Dimension) or video (3Dimension) data. The convolutional layer extracts features and finds patterns in the input data by operating filters (learned weights) that move along the data. These filters (e.g., a filter size of 3) look at three subsequent data points at a time; they are smaller than the input sequence. This layer output is a feature map that shows where those features are present in the data at different points [20].

Max Pooling: The max pooling layer takes the maximum value within the feature map as it moves across a given window (pool size). In doing so, the data's spatial dimension (length) is decreased while the main characteristics are preserved.[21]

Flattening Layer: In a 1D CNN architecture, the flattening layer acts as a link between the convolutional/pooling layers and the fully connected layers. Convolutional and pooling layers frequently yield multi-dimensional outputs (feature maps), but fully connected layers require a one-dimensional vector as input. In essence, flattening transforms the data into a single, long vector from its multi-dimensional form (width x height, for example, in a 2D feature map). All the features that were extracted from the earlier layers are included in this vector in a format that can be fed into the fully connected layers. After this vector has been flattened, the fully connected layers use the learned features for further calculations and making forecasts [22]. Fig. 1 shows the main layers of the 1DCNN.

4. Methodology

This section shows the methodology designed for the proposed research. Fig. 2 shows the main steps used to manage the deep learning process.

4.1 Data Collection

The power data, including load and outage for both the short-term and long-term, were collected from the Al-Rusafa Electricity Distribution-Control and Communications Department for Baghdad. Temperature data was taken from the National Aeronautics and Space Administration (NASA) estimation of global energy resources dataset. The dataset, including the weather information provided by the website [24], was arranged by date to predict short-term and long-term outages. The short-term prediction of Baghdad city was taken as a case study, where the loads data of Baghdad city measured in megawatts per hour were entered in addition to the temperature measured in Celsius and outages in hours, where the readings included 24 readings per day for a full year (2023), so the total number of readings became 8760 records that were included in the Excel sheet. As for predicting long-term outages, the 132-kilo Volt (KV) stations in Baghdad were taken into consideration, as daily data was entered as total loads of the Al-Waziriya and Al-Ghazali groups, each of them consisting of (15) 132 KV stations. In addition to temperature data in Baghdad measured in Celsius, the outage was measured by the number of hours, and the data were entered for five years from 2019 to 2023. The data constituted 1826 records that were included in the Excel sheet.

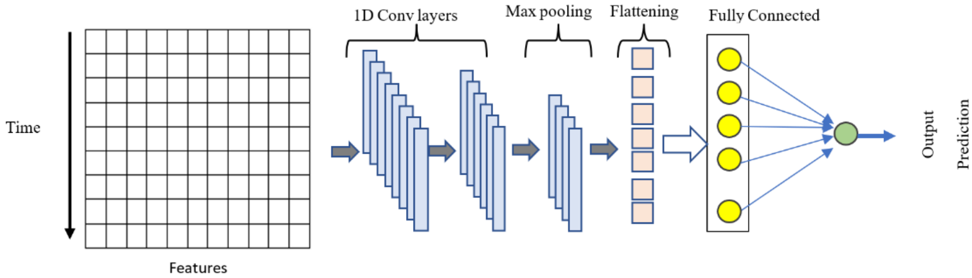


Figure (1): 1DCNN[23]

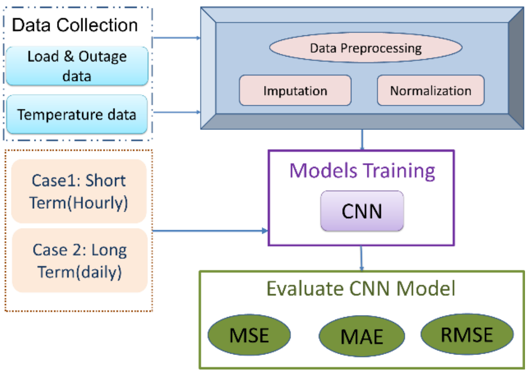


Figure (2): Methodology

4.2 Data Pre-processing

This section presents the data preprocessing, which involves both imputation and normalization. The electrical load data and outage hours were obtained as paper records, manually entered, and organized by date in an Excel file. The temperature data was obtained as a CSV file, then converted to an Excel file and arranged according to the same dates as in the first file to ensure data consistency during analysis.

4.2.1 Imputation

Imputation in time series data refers to the procedure of completing missing values to preserve the temporal sequence's continuity.

Two frequently used data imputation approaches, namely Last Observation Carried Forward(LOCF) and Next Observation Carried Backward (NOCB), are missing data filling. LOCF imputation method replaces the unfilled cells with the last observation before them, while the NOCB with the next available value [25].

4.2.2 Normalization

In deep learning, normalization is an essential pre-processing step that entails scaling data features (columns) to a specified range before training the model. Using the min-max scaling technique, the features are scaled to a range of 0 to 1, as accomplished by using eq. (1). which prevents features with bigger scales from overcoming other features [15].

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \text{.... (1)}$$

4.3 Models Training

Training the one-dimensional CNN was done using the Keras library, a high-level neural network API written in Python for building and training deep learning models because Keras has the necessary functions for processing sequential data. The training process began with a batch size (10), meaning the model updates its internal weights after processing every 10 samples. The model's architecture includes two 1D Convolution layers. The first 1D Conv layer employs 100 filters with a kernel size of 2 and uses the tanh activation function, which introduces non-linearity by outputting values between -1 and 1. The second 1DConv layer has 64 filters and a kernel size of 2, but it uses the ReLU activation function, which outputs the input directly if positive and zero otherwise. Following the convolutional layers is a 1D MaxPooling layer with a pool size (2), which downsamples the input by taking the maximum value over a window of (2). This layer reduces the dimensionality and helps to prevent overfitting. After the convolutional and pooling layers, the model includes a flattened layer, which exchanges the multi-dimensional production from the previous layers into a single dimension. This flattened data is then fed into two Dense layers. The first Dense layer has 100 units and uses the tanh activation function to learn complex representations by connecting every input with every output. The second Dense layer is the output layer, which provides the expected results. The model is compiled using the Adam optimizer, used for its efficiency, and learning rate (0.001). The training was continued for 100 epochs, during which the entire dataset was processed through the neural network 100 times. Adjusting these hyperparameters, like the number of filters, kernel size, activation functions, pool size, and optimizer, can significantly impact the model performance and its capability to generalize to new data. The same procedure is repeated for long terms. In this case, the batch size was considered 5 instead of 10, the number of filters is 64,32 in two 1DCNN, and the number of epochs is 300.

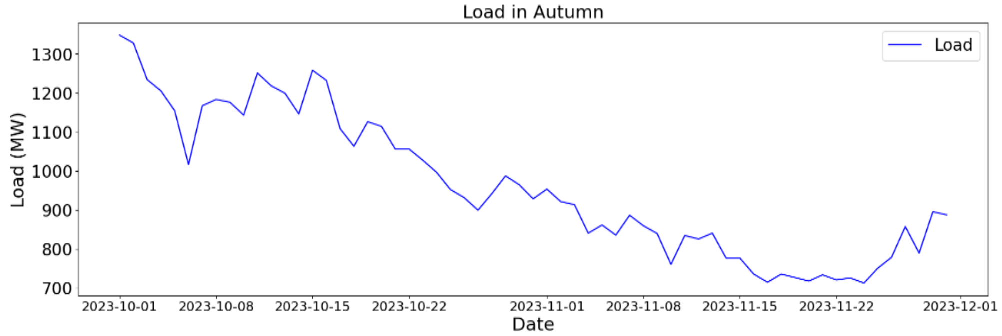
5. Results

This section introduces two subsections. The first one is the collected data analysis according to different seasons to study the effect of key factors considered in this paper on each other, and the second subsection shows the main results obtained by using 1DCNN to predict electricity outages in Baghdad for long and short-term.

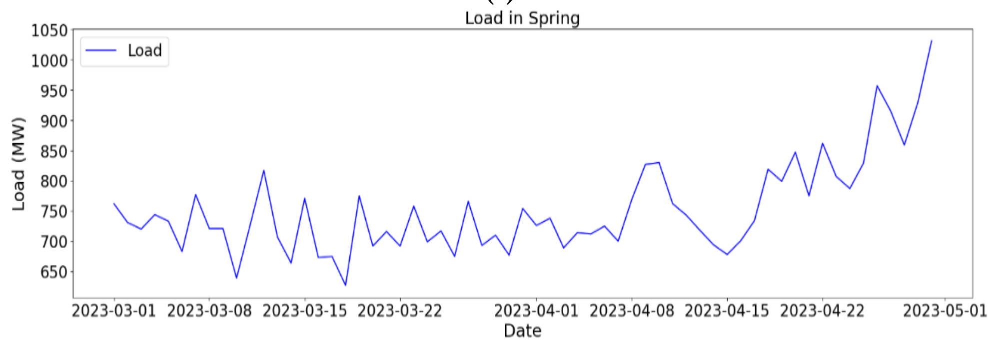
5.1 Analyzing Dataset

This paper considers studying the effect of temperature and load on outage rates for different seasons (months and hours per day). Fig. 3 contains four graphs, each of which represents the load on the Baghdad power grid for the year 2023. The horizontal axis (x-axis) denotes time. The vertical axis (y-axis) denotes the load. The figures represent the applied electricity (load) flowing through the internal grid in (MW). The graphs show the change in this load over time. Peaks indicate periods of high electrical load, while valleys indicate periods of low load. The electricity grid in Baghdad exhibited notable seasonal variability in 2023, with different peaks and valleys occurring at different times of the year. Fig. 3 (a) in autumn (November and October), the electricity load reached 734 MW on the 2nd of October, 2023, and the minimum load reached 388 MW on the 17th of November, 2023. In Fig. 3(b), which represents Spring (March and April), on the 30th of April,2023, the maximum load reached a peak of 1031 MW, while the minimum load on the 18th of March, 2023 decreased to 627 MW. During the summer season (May to September), Fig. 3(c) shows the maximum load of 1604 MW was observed on the 16th of August, 2023, and a minimum of 784 MW was observed on the 29th of July, 2023. These summer months saw a significant change in loads. Fig. 3 (d) during the winter season (January, February, and December): on the 7th of February, 2023, the maximum load is 888 MW, and on the 14th of January, 2023, the minimum load is 329 MW. These numbers show how Baghdad's power loads vary throughout the year, with summertime displaying the highest power load. Fig. (4) shows four graphs, each of which could show the Baghdad power grid's 2023 outage rate. Time is represented by the horizontal axis (x-axis). The Baghdad hourly outage rate is represented by the vertical axis (y-axis). The outage rate fluctuates over time, as seen in the graphs. Periods of low outage rates are represented by the valleys, and periods of high outage rates are indicated by the peaks. Seasonal graphs in 2023 showed how Baghdad's rates of power outages varied dramatically with the seasons. Fig. 4 (a) in autumn (November and October), it can be noticed that only a few days had witnessed one or two hours of outage during this time, while the outage rate was zero on most other days, indicating generally stable conditions for the power supply. Fig. 4 (b) Spring (March and April) reflects that on a few days, the maximum outage rate in the spring could reach five hours. On other days, there were blackouts that lasted for two or three hours. On the other hand, most days were without power outages, indicating sporadic but larger disruptions than in the autumn. Fig.4 (c) shows that in Summer (May to September), the maximum rates of 14, 13, and 12 hours were experienced on numerous days during summer, which saw the worst power outages.This suggests a time when the power infrastructure is under significant stress, most likely because of rising cooling demand. Fig.4 (d) in winter (January, February, December), on the 11th of January, 2023, the maximum outage rate was recorded at 13 hours. But there were also a few days, like February 27th, 2023, when there were no outages, indicating variations in power stability in the winter months. These findings demonstrate the notable seasonal variations in Baghdad's power reliability, with the summer months exhibiting the highest frequency and length of outages, probably because of higher demand and strain on the electrical grid.

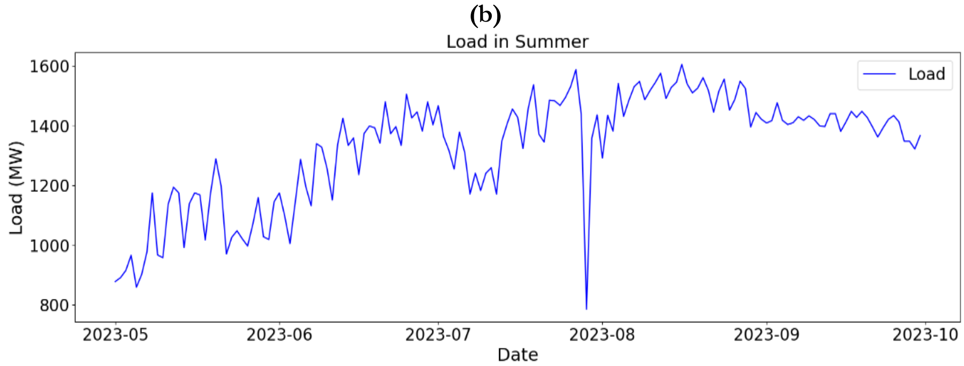
Fig. 5 shows four graphs representing the temperature in Baghdad at different seasons of the year. The horizontal axis (x-axis) denotes time. The (y-axis) shows the temperature in Baghdad in Celsius. The graphs show the change in temperature with time. Peaks indicate high temperatures, while valleys indicate low temperatures. The data for each season can be analyzed to identify specific seasonal changes in Baghdad for 2023. Fig.5(a) shows that in Autumn (November and October), the maximum temperature on 11th October 2023 was 31.63°C, while the minimum was 11.01 °C on November 29th, 2023. Fig.5 (b) shows that in Spring (March and April), On April 28th, 2023, the temperature reached a maximum of 28. On April 1st, 2023, the minimum temperature for the season was 11.59 degrees Celsius. During the summer season (May to September) in Fig.5(c), the maximum temperature was 51.24°C on March 13th, 2023, while the minimum temperature was 29.05 °C observed on May 4th,2023. Fig. 5 (d) shows that in winter (January, February, and December), the maximum temperature on February 26th, 2023, was 17.49°C, while the minimum temperature recorded on February 10th,2023, was 5.37°C. These temperature records show the seasonal variability of Baghdad's climate, which includes an extremely hot summer and a mild, cool winter.



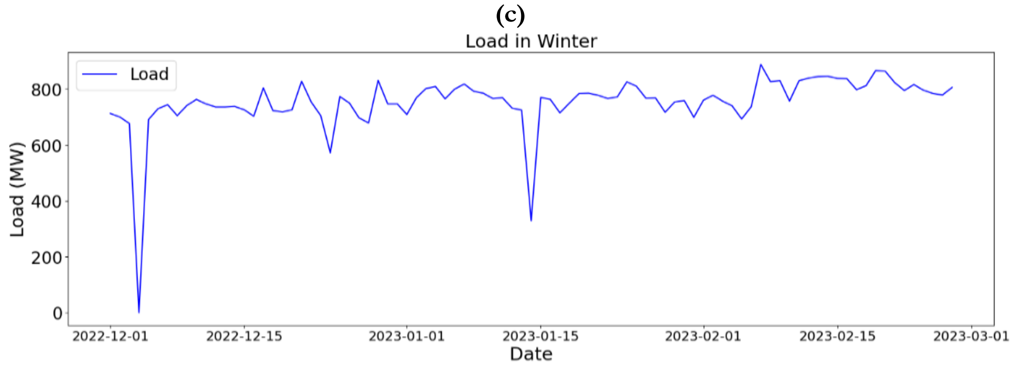
(a)



(b)

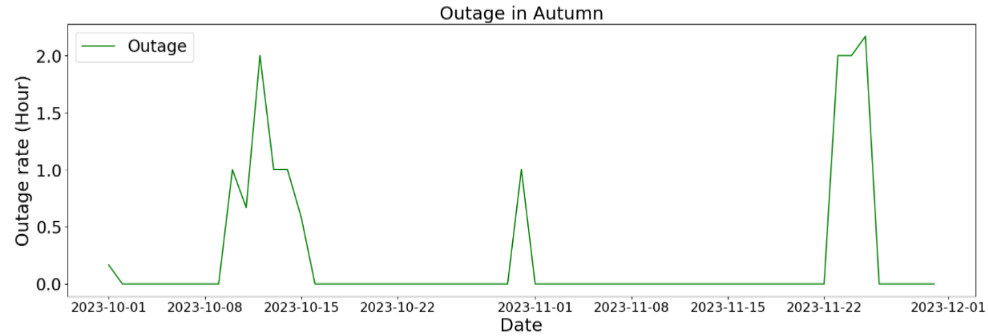


(c)

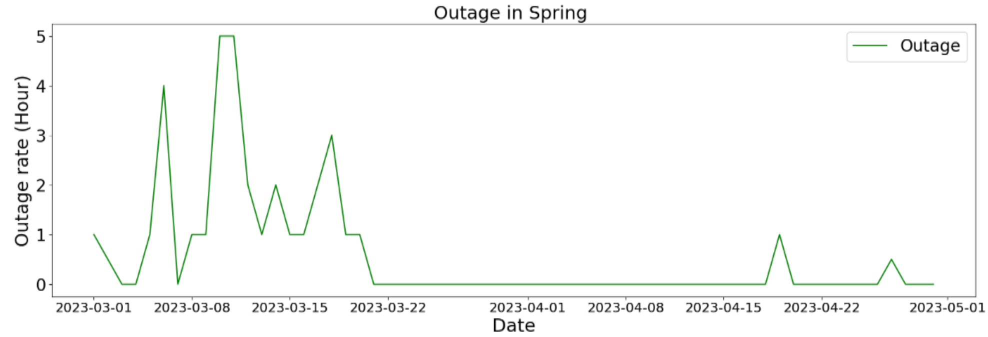


(d)

Figure (3): load vs. Date for different seasons in Baghdad (2023) (a) Autumn (b) Spring (c) Summer (d) Winter



(a)



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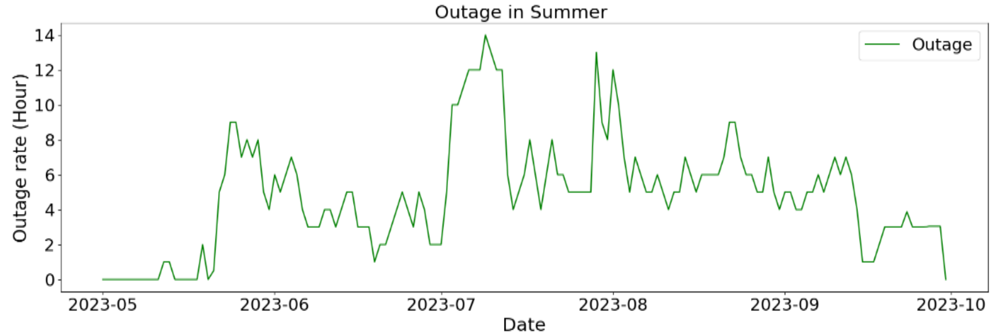

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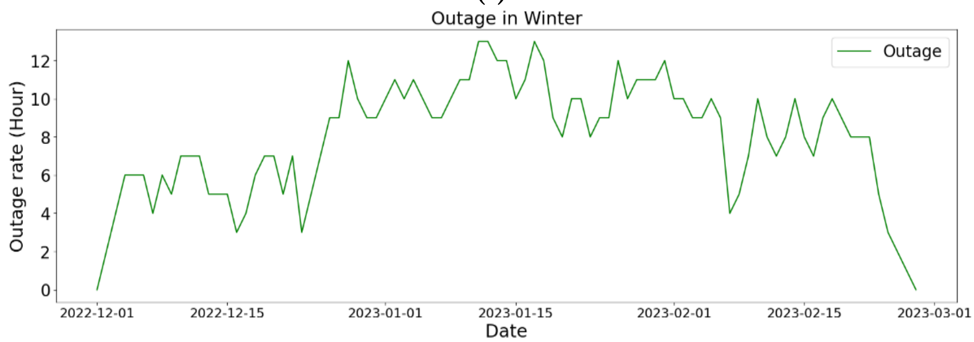
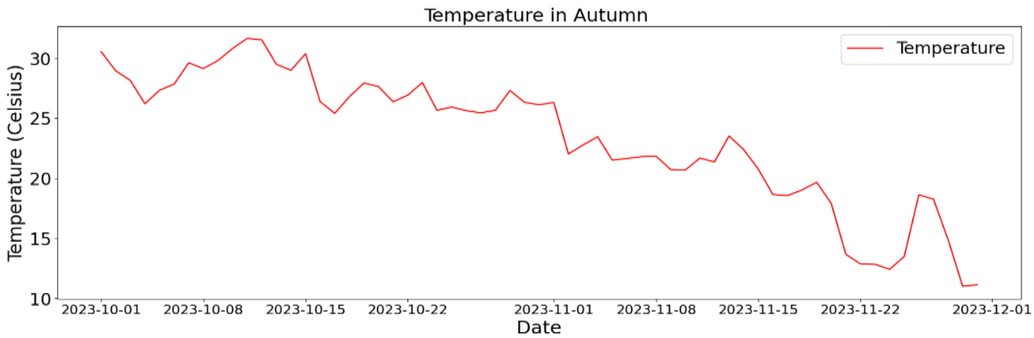
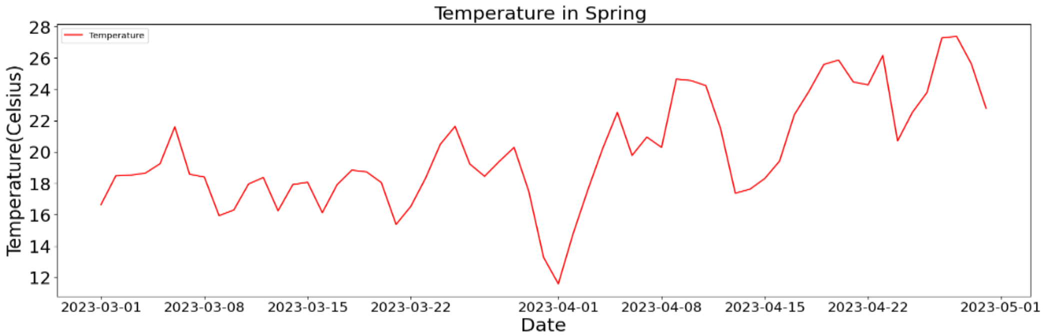


(d)

Figure (4): Outage Rate vs. Date for different seasons in Baghdad (2023)(a) Autumn (b) Spring (c) Summer(d) Winter



(a)



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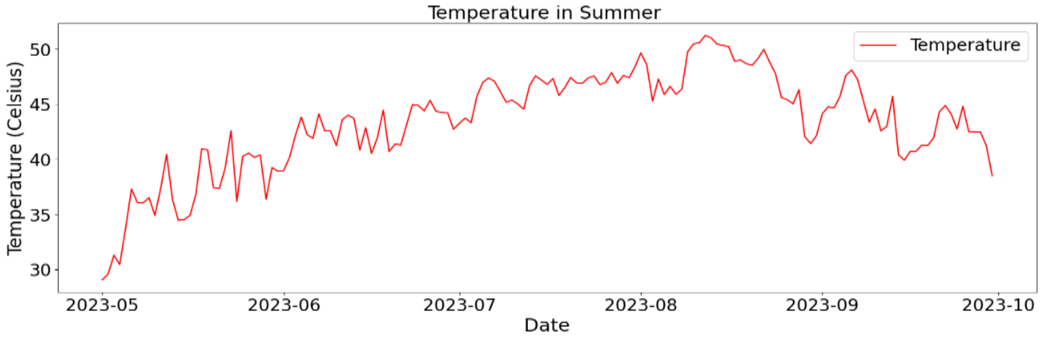

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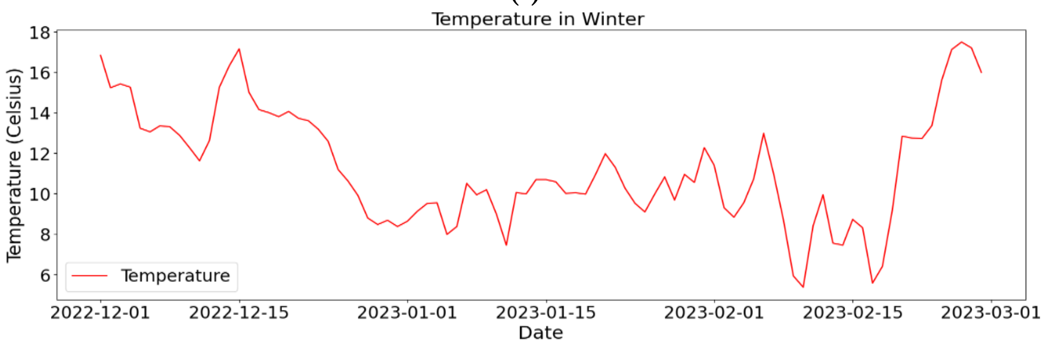
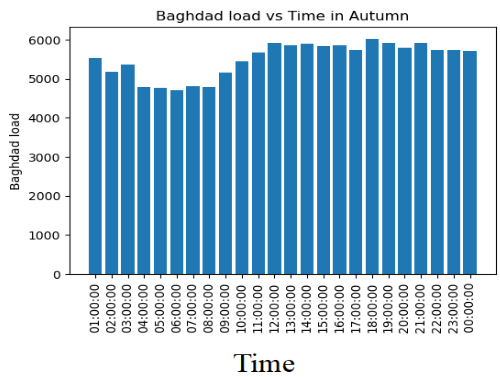


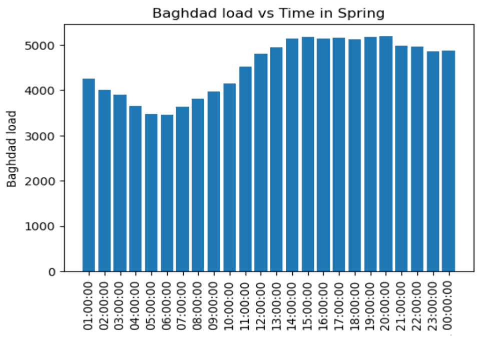
(d)

Figure (5): Temperature vs. Time in Baghdad city for(2023) (a) Autumn (b) Spring (c) Summer(d) Winter

Fig.6 shows the amount of power consumed in each of the four seasons: Spring, Autumn, Summer, and Winter over a 24-hour period. Each graph is explained in detail below: Fig.6 (a) in Autumn, Approximately 5500 MW of power were consumed at 1 AM in the morning; by 5-6 AM, it dropped to roughly 4900 MW by 12 PM, the load had stabilized after increasing gradually. For the remainder of the day, this steady level is maintained. Fig.6 (b) In spring, the power load was about 4250 MW at 1 AM. By 5 or 6 AM, it significantly drops to roughly 3800 MW. Then, the load begins to increase and reaches a peak of about 4800 MW by 4 PM up until 9 PM; when it starts to decline, it stays steady at this peak. Fig. 6 (c) In summer, during the whole 24-hour period, the power load was essentially constant. There is a small variation between 6400 MW and 6500 MW. Fig.6 (d). During the day of winter, the power load remains consistent. It falls between 5700 and 6000 MW. In conclusion, power load is more variable in the spring and autumn, showing observable daily peaks and valleys but staying comparatively constant in the summer and winter.

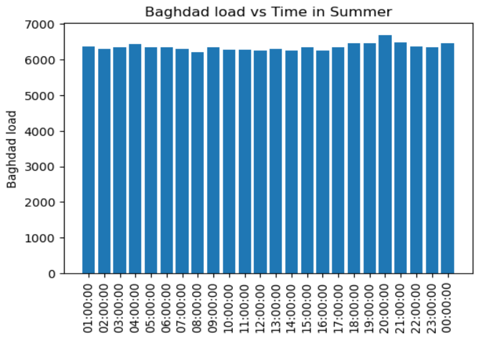


(a)



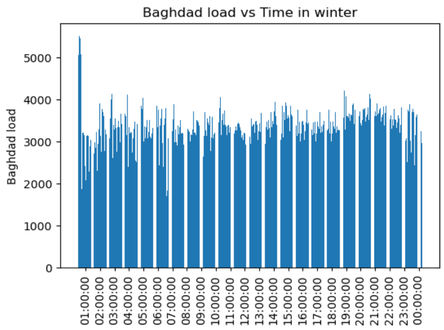
Time

(b)



Time

(c)



Time

(d)

Figure (6): load vs time (Hours) in Baghdad(2023) (a)Autumn (b) Spring(c) Summer(d) Winter

Overall, from the Figs. (3, 4, 5, and 6) shown above, it can be observed that the rising temperature in Iraq during the summer leads to increased loads (due to the use of cooling devices, such as fans and air conditioners), which in turn results in a higher rate of power cuts. Additionally, the elevated temperatures adversely affect the quality of power plants, causing a reduction in the number of supply hours. In contrast, during the Winter in January, despite the lower loads, there is an increase in the rate of power cuts. This is due to the impact of low temperatures on the cables. Typically, the sheaths of wires and cables are composed of PVC or rubber. When subjected to low temperatures, they solidify and become fragile. This results in the cable sheaths becoming damaged and detaching easily when subjected to even the slightest external strain, causing them to malfunction and consequently increasing the rate of power outages. Meanwhile, moderate temperatures in spring and autumn don't lead to more load, which causes balance in the power supply.

5.2 Prediction Results

This section presents the main results obtained by using CNN to predict power outages in the long and short term. The simulation test was conducted on (CPU Core i7 13620H, RAM 16GB DDR5, GPU RTX 4050 6GB, Storage 1TB SSD, OS WIN11) using The Anaconda Jupyter environment used with the libraries Keras, Numpy, Pandas, and Matplotlib to train the model to predict power outages. The deep learning models were examined by dividing the short and long-term datasets into 80% to train the models and 20% to test their performance. The deep learning method, CNN performance is evaluated by metrics like Mean Squared Error (MSE) by using eq. (2)calculates the average squared difference between predicted and actual values, Mean Absolute Error (MAE), by using eq. (3)measures the average absolute difference, and (Root Mean Squared Error) measures the square root of the MSE as the RMSE using eq. (4). The model is better the closer RMSE, MSE, and MAE are to zero. Table 2 shows the performance metrics for 1D-CNN in short-term and long-term conditions. In the short term, CNN performs well, as evaluated by the low error metrics with MAE of 0.0077126, MSE of 0.0004874, and RMSE of 0.0220765. These values indicate high accuracy and low error in the prediction. But the performance of CNN deteriorates for long-term forecasting, with higher error metrics, especially MAE of 0.077521, MSE of 0.0108372, and RMSE of 0.104101687; this difference in results between short-term and long-term results is caused by the fact that many factors will influence accuracy because the model's numerous inputs change over time. Fig.7 shows the comparison between actual data and predicted data for short-term datasets, and Fig.8 depicts the comparison between the actual data and predicted data for long-term datasets. Table 3 shows the predicted outage rate obtained by the CNN for both short and long term.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - y^{\wedge})^2 \quad \ldots\ldots(2)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - y^{\wedge}| \quad \ldots\ldots(3)$$

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y^{\wedge})^2} \quad \ldots\ldots(4)$$

Tabel (2): Results of CNN

Case study	Metrics		
	MAE	MSE	RMSE
Short-Term	0.0077	0.00048	0.0220
Long -Term	0.0775	0.01083	0.1041

Tabel (3): Samples of outage rate predicted by models

Prediction for long-term (outage rate (Hours))		Prediction for short-term (outage rate (Hours))	
Actual (Hours)	Predicted (Hours)	Actual (Hours)	Predicted (Hours)
5	4.903309345	1	1.030387878
2	1.881246567	1	1.041221142
3	3.022894382	1	1.031022787
3	3.210447788	1	1.017275929
3	3.011624575	1	1.007216334
3	3.349903584	1	1.001157641

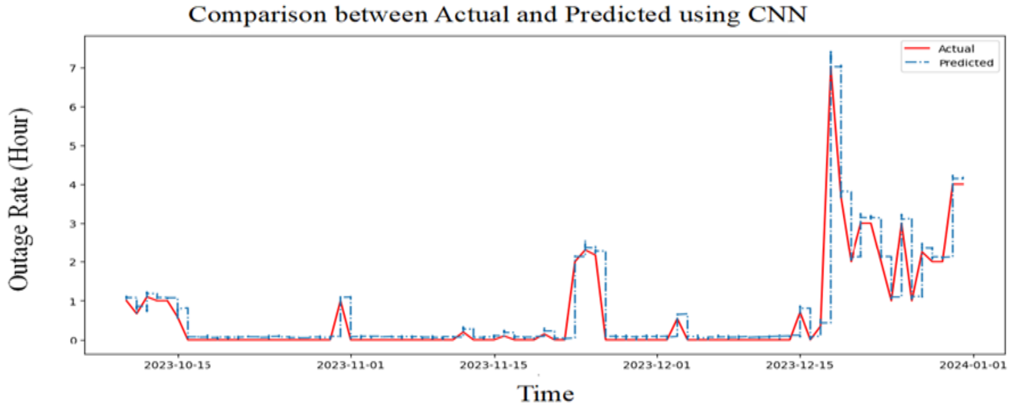


Figure (7): Comparison between actual and predicted data for the short term using CNN

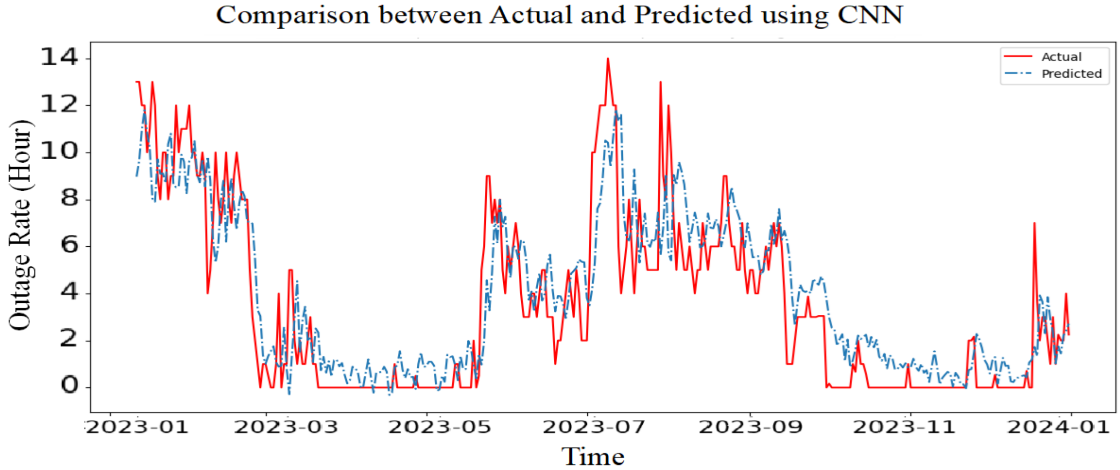


Figure (8): Comparison between actual and predicted data for the long term using CNN

6. Conclusion

The purpose of this study is to analyze data for the city of Baghdad collected from the Iraqi Ministry of Electricity and NASA website. The key factors considered in this study include temperature, electrical loads, and power outage hours, which are examined to show their variation across seasons and the relationships between them. This paper also explored how temperature and electrical loads influence power outages in Baghdad. The data was used to train a 1D-CNN model for predicting power outages in Baghdad over both long-term and short-term periods. The results showed accurate short-term predictions with a mean absolute error (MAE=0.0077), while long-term predictions also achieved (MAE=0.0775) results. Future work could improve prediction accuracy by using various optimization methods to select the best hyperparameters for training, leading to better outcomes. Furthermore, the collected data could be expanded to include other governorates in Iraq in addition to Baghdad.

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