Improving microgrid energy demand forecasting using convolutional neural networks

M.G.I.U. Karunarathne, P. B. Sudasinghe, H. Weeratunge and Damyanthi Herath

Abstract: Microgrids are localized energy systems that operate independently or in conjunction with the main power grid, integrating various energy sources for a reliable and resilient power supply. Microgrid energy demand refers to the electrical power required to meet consumer needs, influenced by factors such as time, weather, and habits of consumers. Accurate forecasting of energy demand is crucial for efficient microgrid operation, resource management, and optimization. Machine learning offers advantages over traditional methods in forecasting, such as the ability to handle complex relationships, adaptability to changes, and scalability. This paper proposes a Convolutional Neural Network (CNN) based approach to forecast microgrid energy demand.

The study considers a dataset of multi-year power generation, consumption, and storage data in a microgrid and compares different approaches considering the metrics: Mean Squared Error, Mean Absolute Error, and R squared value. The results demonstrate that the CNN model performs well compared to other models. This study seeks to advance the application of machine learning in microgrid management.

Keywords: Machine learning, Energy Demand Forecasting, Microgrid, Convolutional Neural Network

1. Introduction

The surge in carbon emissions and energy demand, propelled by population growth and energy-consuming devices, necessitated a shift toward renewable energy [1]. Centralized grids face challenges such as accommodating distributed resources, transmission losses, grid stability, voltage regulation, etc. [2]. To overcome these problems distributed, or on-site generation, has been proposed as a next-generation smart grid solution. This has more advantages than other methods such as its ability to generate energy locally, which not only reduces energy losses in transmission but also helps to overcome network limitations in integrating RES into the existing grid and enhances grid stability by providing localized control [3]. Therefore, under these circumstances, small-scale grids operating in small areas as fully functioning energy systems have become an interesting solution known as microgrids [4].

Microgrids are localized energy systems that integrate various energy sources and operate independently or in conjunction with the main power grid [5]. A microgrid is a small-scale grid. However, it is fully functional, operating in a limited geographical area. They provide reliable and resilient power supply to specific areas, incorporating renewable energy technologies, energy storage systems, and conventional generators. Microgrids can disconnect from the main grid during outages and emergencies, ensuring uninterrupted power to critical facilities [6].

Microgrid energy demand refers to the amount of electrical power required by a microgrid to meet the energy needs of its consumers within a specific period. It represents the total electricity consumption of the connected loads, including residential, commercial, or industrial facilities related to microgrids.

Forecasting the energy demand of microgrids enhances their efficient operation by managing resources and optimizing systems. This process not only ensures a reliable power supply but also aids in load balancing within the microgrid

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and optimizes the use of generating and storage resources [7].

Existing methods for forecasting energy demand in microgrids often rely on traditional statistical models and simple machine learning algorithms. While these approaches can provide baseline predictions, they frequently struggle with capturing complex patterns and non-linear relationships within the data, leading to less accurate forecasts [8]. There is a clear need for more advanced techniques that can improve prediction accuracy and operational efficiency.

To address this gap, this paper explores convolutional neural networks to forecast the energy demand of microgrids and investigates how forecasted data can be used in optimizing microgrid operations. By understanding and implementing these forecasting methods, microgrid operators can improve the efficiency and reliability of microgrids, encouraging wider adoption of this technology due to its renewable and cost-effective resources. And that economically benefits the country and people.

2. Literature Review

Over the past decade, extensive research has been carried out on microgrids as a promising energy solution for the future [9]. This localized on-site generation method is implemented due to its improved reliability and the ease of inclusion of renewable energy generation.

This revision introduces the concept of energy demand in the context of microgrids, emphasizing the importance of energy strategy for developing countries. The energy demand of a microgrid can vary depending on several factors, including the size of the microgrid, the type of loads it serves, and the availability of renewable energy sources [10]. Peak load demand represents the maximum electricity a microgrid must supply at any given moment, with a typical system experiencing hourly fluctuations [9]. These variations depend on the time of day, season, and weather conditions. Accurately forecasting energy demand is crucial for ensuring a microgrid to meet its peak load requirements.

Energy demand forecasting is one of the most important tools for decision-makers, as it ensures sufficient availability to meet demand and promotes the efficient use of energy resources [11]. Numerous methods are employed to forecast energy demand, ranging from regression and econometric models to neural networks [11]. Among these, the autoregressive integrated moving average (ARIMA), artificial neural networks (ANN), time series analysis, support vector machines, and fuzzy logic methods stand out in studies of electrical energy demand forecasting [12]. Each technique offers unique advantages in analysing and predicting energy consumption patterns.

Machine learning (ML) and deep learning (DL) models have emerged as promising approaches, offering accurate predictions of consumer demands and energy generation from Renewable Energy Sources (RESs) [13].Machine learning techniques have been proven useful for short-term electricity load forecasting, especially in microgrids where a large variety of data should be included in the energy consumption forecast. ML models allow for faster convergence, manipulating big data sets, and solving more complex problems [14]. According to research by D. Mele (2019), it shows that ML was able to produce more accurate forecasts than traditional methods [14].

The literature extensively uses machine learning (ML) methods for forecasting energy demand. Deep learning (DL) is a subset of ML referring to neural networks with many layers. This study utilizes convolutional neural networks (CNNs), a DL technique, to enhance energy demand forecasting for microgrids. D. Mele (2019) reviewed short-term forecasting techniques, such as Support Vector Machines (SVM), k-nearest Neighbors (kNN), Random Forest, and Artificial Neural Networks (ANN), analyzing their performance efficiency, capabilities, and limitations [14]. Subsequently, a range of deep learning (DL) techniques has been proposed, including ANN, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Bidirectional Long Short-Term Memory networks (BLSTM). These DL models are recognized for their ability to effectively learn patterns from customer data and forecast demand where ML models typically rely on feature engineering where they manually select relevant features from the input data to train the ML model. Among the most frequently used DL-based methods are ANN, Deep Neural Networks (DNN), CNN, and RNN [15][13], underscoring their critical role in enhancing the accuracy of demand forecasting.

Research work by Dong et.al (2017) also adapts DL-based methods for load forecasting. There, a hybrid forecasting method is developed by combining the best features of CNN and K-means clustering. The results show that their hybrid CNN–K-means forecasting algorithm has higher accuracy [16]. This literature suggests that DL models have significant potential to improve the accuracy of energy demand forecasting and CNN models are proven to have the ability to capture complex behaviours of time series data more accurately[17], [18].

This research study proposed to use CNN model to forecast energy demand by understanding the existing gaps in the literature.

3. Methodology

3.1 Data Collection and Preprocessing

The data set was sourced from the repository titled 'Open-source multi-year power generation, consumption, and storage data in a microgrid' [19]. It encompasses a detailed power dataset from a segment of the University of California, San Diego's microgrid, featuring various distributed energy resources (DERs) including solar power plants, electric vehicles, and electric and thermal storage systems. This data set primarily consists of 15-minute averages of both real and reactive power demand in microgrid.

The data set includes real and reactive power consumption across two building categories: those with EV charging and those without. It also covers the Trade Street Warehouse microgrid, EV charging stations, Solar PV generation, campus thermal load and storage, demand charge-related data, and the battery energy storage system (BESS). This paper specifically focuses on energy demand forecasting and thus primarily considers the demand charge-related data sets.

This analysis encompasses data sets on Total Campus Load, On-Campus Generation, SDG&E (San Diego Gas & Electric) Import, and Adjusted Demand which is a summation of on campus generation and SDG&E Real Power Import, providing a comprehensive overview of the microgrid's energy demand patterns. Exploratory data analysis was conducted using pandas profiling to identify potential time series patterns within the data. The variation in data over 20 days is illustrated in Fig. 1.

In the data preprocessing phase, NaN (Not a Number) values were replaced with the mean values of their respective columns. Data was then split into 70% training, 20% for validation, and the rest 10% for testing sets. Normalization is done using the standardization method. This gives an equal range to all variables so that no single variable steers model performance in one direction. Therefore, to address uneven data parameters, normalization is necessary. During standardization, each value is first subtracted by the mean of its parameter, and then divided by the standard deviation. In this process, the mean and standard deviation from the training data is used for normalization, ensuring the model does not have access to the values in the validation and test datasets.

The Augmented Dickey-Fuller (ADF) test is a statistical test used to determine whether a time series is stationary or not. The test statistic is compared to critical values at various significance levels, and the null hypothesis of non-stationarity is rejected if the test statistic is less than the critical value.

ADF Statistic: -9.521949
p-value: 0.000000

ADF Statistics being highly negative and the p-value being very close to zero which is less than 0.05 (5% significance level) both suggest strong evidence against the null hypothesis of a non-stationary time series.

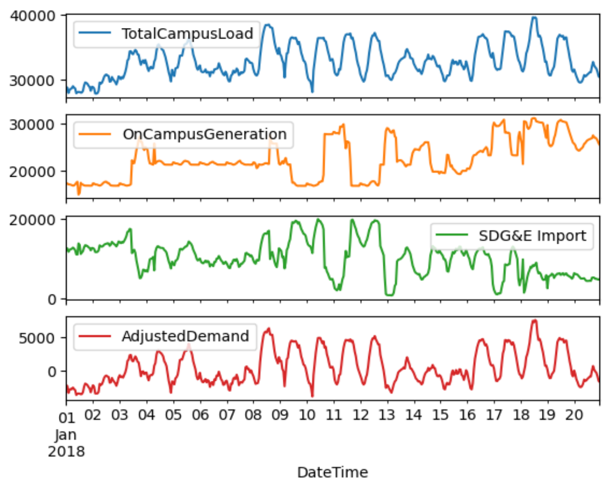

Fig. 1: Feature variations plot for 20 days

3.2 CNN model

The one-dimensional Convolutional Neural Network (1D CNN) is a specialized neural network architecture uniquely designed for handling sequences of one-dimensional data. Using a 1D CNN has the benefit of not requiring human feature engineering because it can automatically extract pertinent features from the sequential input. As they move over the input sequence, the convolutional layers function as local filters that catch up with patterns of various sizes. Pooling layers that come after aid in lowering spatial dimensions, focusing on the most crucial elements and enhancing computing efficiency.

The CNN model is structured with a Lambda layer, selecting the last CONV_WIDTH time steps from the input. Subsequently, a Conv1D layer with 256 filters, ReLU activation, and He normal kernel initialization is applied. Batch Normalization enhances training stability, while a Dropout layer with a 0.2 rate provides regularization. The Dense layer with linear activation and He normal initialization produces an output shape of (OUT_STEPS, num_features).

Finally, a reshaped layer ensures the output format matches the desired shape for effective time series forecasting.

The CNN model shown in Table 1 consists of a lambda layer, followed by a 1D convolutional layer with batch normalization and dropout. It concludes with a dense layer and reshaping, aiming for specific output dimensions (24, 8). In this study, data windowing is used for time series data forecasting. It breaks the time series into windows and allows for the creation of training samples. Each window can be treated as a data point, with the goal of predicting the subsequent values.

Table 1: CNN model architecture parameters

Layer (Type)	**Output Shape**	**Param #**
lambda_1 (Lambda)	(None, 8, 8)	0
Conv1d_1 (Conv1D)	(None, 1, 256)	16640
batch_normalization (Batch Normalization)	(None, 1, 256)	1024
dropout (Dropout)	(None, 1, 256)	0
dense_3 (Dense)	(None, 1, 192)	49344
reshapr_1 (Reshape)	(None, 24, 8)	0

This data window in Fig. 2 consists of 48 data points with 24 input data and 24 label data points.

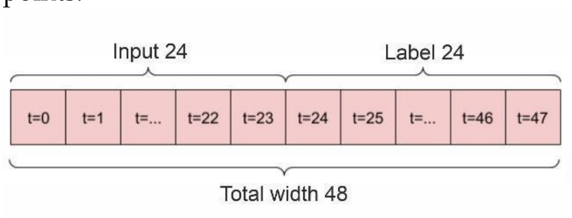

Fig. 2: Data window with input and label data points

CNN model is trained from a training set of 70% from 18900 data and validated from a validation set of 20% from 18900 data. TensorFlow early stopping was applied to avoid overfitting and make a more generalized model. Then the model was tested and these predicted values were compared with actual values using Mean Squared Error (MSE).

3.3 Average naive model (Baseline)

The average naive model defines a simple time series forecasting. In its call method, it calculates the average value along the last axis of the input tensor (assuming it contains time series data).

$$\hat{y}_{T+h|T} = \tilde{y} = (y_1 + \ldots + y_T)/T \quad (1)$$

$\hat{y}_{T+h|T}$ represents the forecasted value of the variable y at the time T+h, based on historical data up to time T. The term $\tilde{y}$ denotes the average of historical values $y_1, \ldots, y_T$. Here, $y_1 + \ldots + y_T$ is denoted by historical data.

This average value is then repeated along the last axis to match the shape of the input. Essentially, the model predicts future values by forecasting the average of the historical values.

3.4 ARMA (Auto Regressive Moving Average) model

The ARMA (Auto Regressive Moving Average) model is implemented as combining autoregressive (AR) and moving average (MA) components for time series forecasting. The autoregressive component captures dependencies in the last order time steps, utilizing a dense layer with no activation and no bias. The moving average component is obtained directly from the entire input sequence. The final prediction is computed by summing the autoregressive and moving average components, offering a concise yet effective approach for forecasting based on historical data patterns.

The performances and model accuracies of demand forecasting in each model is compared with each other to identify the best performing model on demand forecasting.

4. Results

In this study performance evaluation is done by checking Mean Squared Error, Mean Absolute Error, and R-squared values. As well as data visualization has been done to identify patterns.

4.1 Output visualization

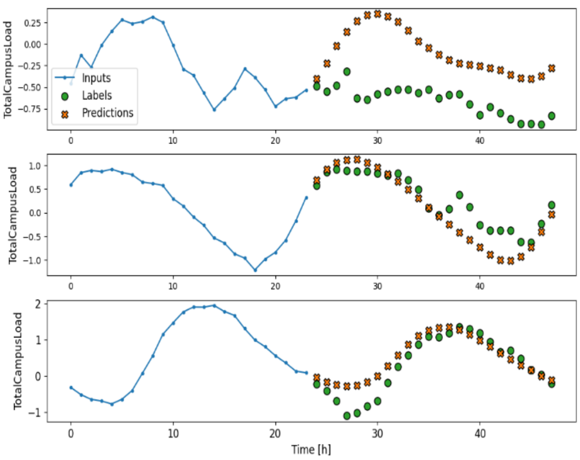

Fig. 3: Actual vs predicted plot for CNN model

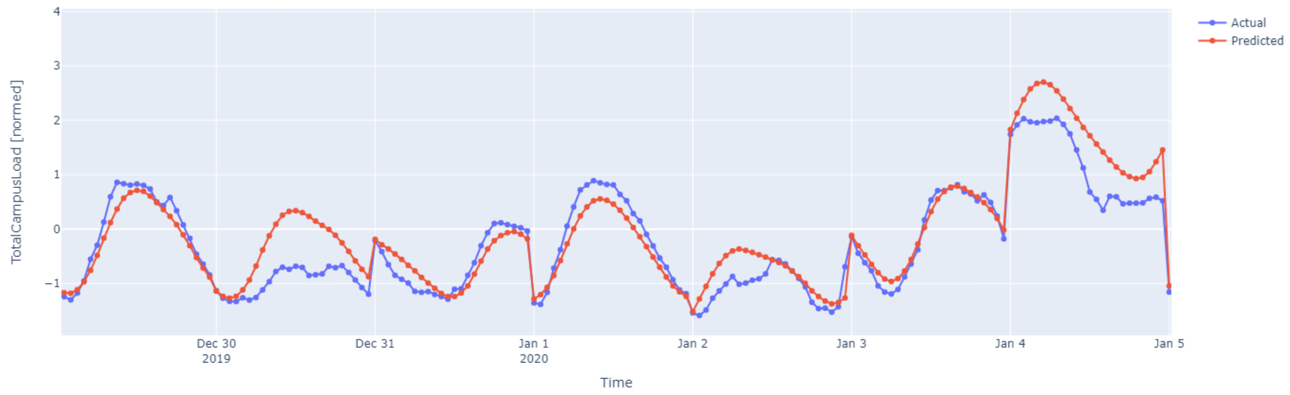

Fig. 4 : Actual vs predicted data of test data set for a week

Plotting actual data vs predicted data involves visually inspecting the alignment of the predicted values with the actual values. Fig. 3 shows 3 plots of 3 random windows of training dataset. Window size is 48 which consists of 24 input data and 24 label data. This plot was obtained using the Total Campus Load data set.

In figure 3, it can see CNN model has identified patterns in the data set for given data window, this can be clearly visualized by plotting actual vs predicted data for all test data sets.

Fig. 4 shows Actual vs predicted data from CNN model of test data for a week. There it has identified patterns of the input data and has predicted values according to that.

4.2 Performance evaluation

In this study performance evaluation is done by checking the Mean Squared Error loss function, MAE, and R squared values.

Plotting training loss and validation loss over epoch gives ideas about overfitting and underfitting of the model which is shown in Fig. 5.

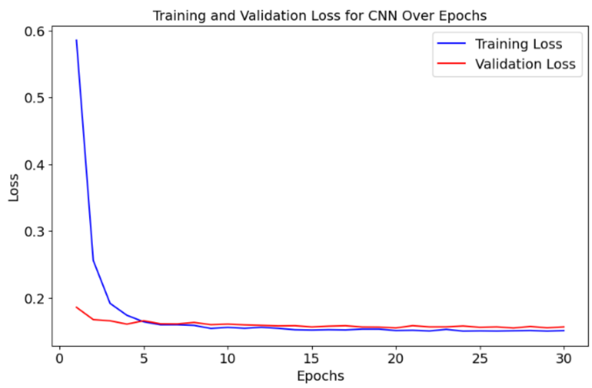

Fig. 5 : Training and validation loss over epochs for "CNN" model

If the gap between training loss and validation loss increases over epoch, the model is overfit. Otherwise, their values are higher; it tells that model is underfit. To overcome overfitting in the model it uses a drop layer. Accuracy of the model over epoch also can be visualized. For that R squared value can be used. In order to do that it has plotted training accuracy and validation accuracy over epoch. as in Fig. 6. There it shows that the increase of epoch accuracy is higher.

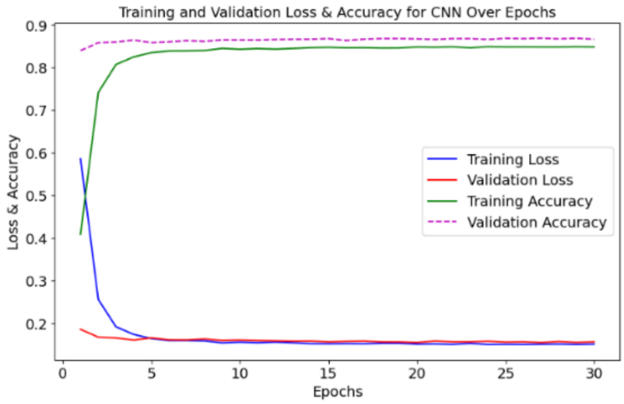

Fig. 6 : Training and validation accuracy over epochs for "CNN" model

Performance evaluation of models on the test data set are summarized in Table 2.

Table 2: Performances of models

	MSE	MAE	R squared
Average naive	0.797	0.755	0.031
ARMA	0.799	0.761	0.028
CNN	o.103	0.150	0.875
CNN_1D	0.108	0.161	0.869

As presented in Table 2, MSE values indicate that both CNN models have lower values compared to other models which means they give more accurate forecasting results. According to Fig. 7, it can see that MAE values for CNN models are lower, which also indicates CNN models give more accurate predictions than other models.

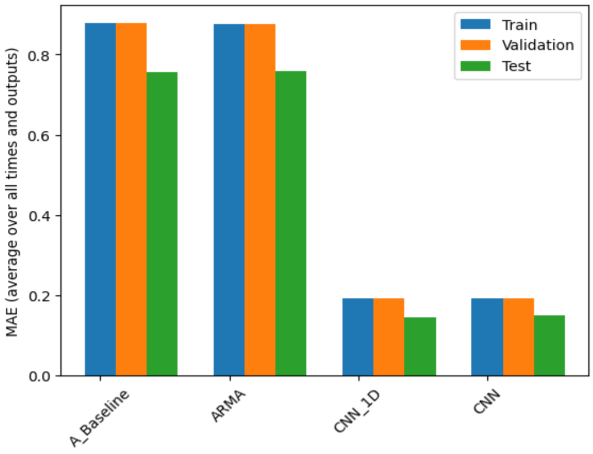

Fig. 7 : MAE values of all the models

R squared value gives ideas about how well-forecasted data fit to the actual value, how well the model fits, or what amount of data can be explained using the model. According to this study, the model explained around 87% of the R squared value for the data from the CNN model while other models show very low values. This means the CNN model is better at forecasting data and its accuracy is around 87%.

4.3 Optimization of Microgrid using demand forecasting

Optimization of microgrid is very important because it brings about various economic, environmental, and reliability benefits. This involves employing various optimization techniques to achieve efficient resource allocation, considering both constraints and objectives. Microgrid optimization techniques also result in significant cost reductions. Operators can reduce operating costs by strategically allocating energy resources according to patterns of demand [20]. Another key benefit is the enhancement of grid resilience.

This study identified four operating processes of microgrids presented in Table 3 and discussed how they operate. Also, there are several optimization algorithms that can be used in this operating process. They can vary with objective functions such as reducing cost, emission etc. To achieve that single objective optimization algorithm or multi objective optimization algorithms are used. As well as assuming forecasted data, accurate deterministic optimization algorithms can be used. If it is uncertain stochastic optimization algorithms are used. Demand forecasting data is dynamic with time. Therefore, dynamic optimization algorithms are also applicable in this case. Other than that linear optimization algorithms are used. Applying forecasted data to optimize microgrid operation is a strategic approach to dynamically adjust energy supply and demand for efficient and cost-effective performance. Optimization model uses forecasted data to adapt the microgrid's energy production, storage, and distribution strategies. For instance, if the forecast predicts a surge in energy demand during specific hours, the microgrid can proactively allocate additional resources or adjust the energy distribution to meet the expected requirements. Conversely, during periods of lower forecasted demand, the microgrid can optimize resource utilization to avoid unnecessary energy generation or storage.

Table 3: Operating process of microgrids

No	Components	Description
1	Include Renewable Energy sources, generators, and battery storage systems. Not connected to the grid.	Energy in microgrids is generated using renewable energy sources (RES) and is not connected to the main grid. Excess energy is stored in batteries, and if there is a deficit, generators are used.
2	Include Renewable Energy sources. Connected to the grid.	Energy generation is done using RES. If there is excess energy, it is sent to the main grid.
3	Include Renewable Energy sources, and battery storage systems. Connected to the grid.	Energy generation is done using RES. If there is surplus energy, they are stored in a battery. As well as if there is more energy than storage they were sent to the main grid. The deficit energy required is taken from the battery and the main grid.
4	Include Renewable Energy sources, generators, and battery storage systems. Connected to the grid.	Energy generation is done using renewable energy sources (RES). Excess energy is stored in batteries or sent to the main grid. During deficits, energy is drawn from batteries, the main grid, or generators based on cost-effectiveness and the situation.

This dynamic adjustment based on forecasted data contributes to several benefits in microgrid operations. Such as reducing energy waste by coordinating output with anticipated demand, makes operations more cost-effective, supports grid resilience and contributes to environmental sustainability goals.

5. Discussion

The results demonstrate that CNN models give more accurate forecasts than other models.
A scatter plot depicting actual versus predicted values provides a visual representation of how well a predictive model performs Fig. 8. Each point on the plot corresponds to an observation, where the x-axis shows the actual values and the y-axis displays the predicted values generated by the model. Ideally, a perfect model would align all points along a 45-degree line, indicating exact predictions. Deviations from this line highlight discrepancies between predicted and actual outcomes Fig. 8. it can be observed its data points are mostly lying around the 45-degree line. Which means actual data values are close with predicted data values. As well as R squared values is also around 0.87 that means 87% of the data are explained by the model.

Researchers have forecasted energy demand data using different ML, DL models considering different architectures. In one study [13], they are using the 2D-ConvLSTM-AE model for forecasting purposes which is claimed to be the best model [13]. They have tried more complex models than this study. In this research study, it uses only 1D CNN model in forecasting the energy demand data. So, according to this study demand forecasting can be done using a simple ML model such as 1D-CNN model and it gives around 87% accurate predicted data. Use of a simple model will reduce the computational cost as well as time.

This forecasted data can be used in different applications. This microgrid data is mainly usable in the optimization of microgrid operations. Applying forecasted data on the chosen algorithm gives the best optimization model for the microgrid.

Integrating energy demand forecasted data into microgrid operations provides various advantages. Accurate predictions of peak demand periods enable microgrid operators to implement effective load-shifting strategies, optimizing energy generation and storage to minimize overall costs; also, it ensures efficient management during periods of peak demand. This capability also facilitates the seamless integration of renewable energy sources.

Knowing day-ahead demand data provides insights into required energy levels, enhancing the credibility of forecasts. By understanding these requirements, microgrid operations can fine-tune their energy generation from solar power and wind turbines, identifying optimal timeframes for energy utilization and assessing surplus generation potential within microgrids. Additionally, operators can determine the optimal amount of energy to export to the main grid. In instances of energy shortages within the microgrid, calculations are made to ascertain the amount of energy required from battery storage systems and the supplementary energy needed from the main grid. All these predictions can be derived based on the anticipated energy demand data forecasted through the proposed CNN model.

This will help in efficiently managing energy storage, incorporating renewable sources, and ensuring reliable operation during grid disruptions. Additionally, microgrid operators can optimize their decision-making by leveraging accurate demand forecasts. This includes making cost-effective choices, strategically planning maintenance activities, and participating more effectively in energy markets.

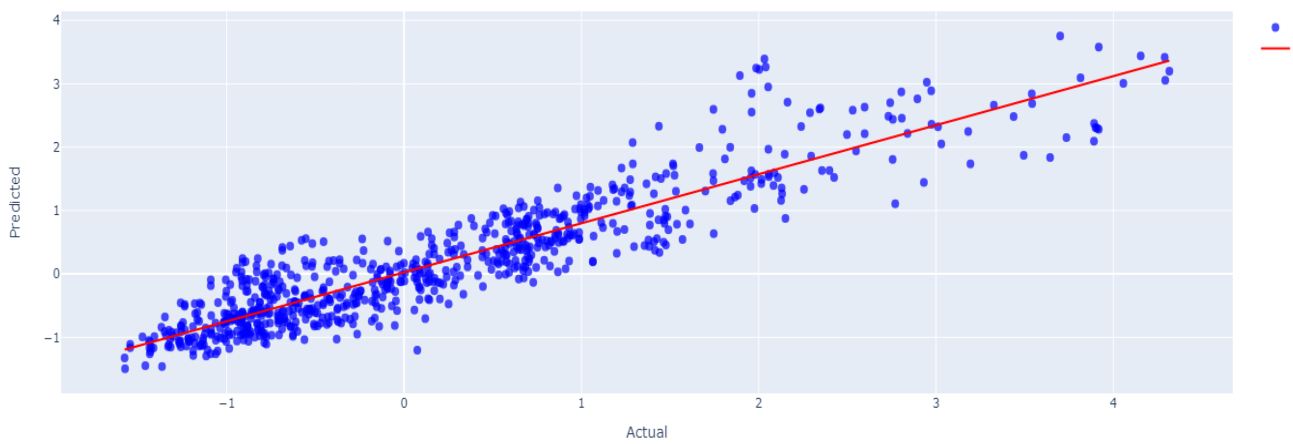

Fig. 8: Actual vs Predicted values considering the test set

As mentioned, forecasting the energy demand of a microgrid is important in different ways. This concept can be applied to local microgrids and using that microgrid operation can be optimized as well as their cost can be reduced and renewable energy resources can be managed efficiently.

6. Conclusions

This study demonstrates that the 1D-CNN model achieves 87% accuracy in predicting energy demand on test data, significantly outperforming the Average naive and ARMA models, which exhibit accuracies below 10%. The computational efficiency and robust predictive capabilities of the CNN model underscore its suitability for energy forecasting applications. These findings have profound implications for microgrid operations, enabling operators to optimize energy management, integrate renewable sources more effectively, and implement cost-saving strategies. Accurate peak demand predictions empower microgrid operators to enhance economic efficiency, improve grid stability, and make informed decisions in energy markets. This study marks a critical advancement towards sustainable and efficient energy management, advocating for the widespread adoption of advanced forecasting techniques like the 1D-CNN model in microgrid environments.

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