MEDIUM-TERM LOAD FORECASTING USING TEMPORAL CONVOLUTIONAL NETWORKS FOR FUEL SUPPLY PLANNING IN A UNIVERSITY CAMPUS

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***Abstract*— Do you want to know how much your university campus consumes energy? In this work, we perform medium-term load forecasting to develop a fuel supply planning for a university campus. Temporal Convolutional Network (TCN) model, an architecture of one-dimensional convolutional kernels layered with pooling blocks and followed by a neural network block, was used to predict the total energy consumption of UBC campus. This model takes a dataset on the daily energy consumption as input, performs convolutional networks, pooling and neural networks to predict the future energy consumption. TCN was evaluated by comparing it to two different models (LSTM and ARIMA) based on different metrics. To perform the comparison the three models were evaluated on a common unseen test set for which the TCN model yielded the best results.**

***Keywords* - Energy Consumption, Medium-Term Load Forecasting, University Campus, TCN, LSTM, ARIMA**

I. INTRODUCTION

Lebanon has experienced very limited and unreliable electricity supply from the national grid [1] [2] that diverted consumers towards private diesel generators [3]. The most prestigious university in Lebanon, the American University of Beirut (AUB) has suffered from utility grid outages and fuel shortages that forced them to shut down critical loads [2] [4].

A common trend in the domain of power systems today is the concept of smart grids. Smart grids today rely heavily on energy management systems. These systems coordinate between different available energy resources to meet the consumer's demand. Demand-side management requires accurate data on the total electric power consumed by users. For a reliable and efficient operation of the power system, load forecasting has been implemented [5]. Types of load forecasting include short-term forecasts ranging from an hour to a week, medium-term from a week to a year and long-term for longer periods [6]. Medium-term forecasting, in particular, can be used for fuel supply planning and could be adopted by AUB to prevent any diesel shortages, through precisely predicting the needed amounts of diesel oil for the upcoming weeks.

Prior work on load forecasting using machine learning utilized Multivariate Auto Regression techniques (ARIMA) [6] [7], Artificial Neural Networks [8] [9], Bagged Regression Trees [9], Long-Short-Term-Memory and Recurrent Networks [10]. Recently, Temporal Convolutional Networks (TCN) have shown their success in forecasting energy consumption for electric vehicle charging stations [10], small-medium enterprises [11] and nation-wide demand [10]. TCNs benefit from lower memory and computational demand and yield more accurate results than conventional models [10].

Given that the nature of appliances used in a university campus varies from the aforementioned loads, this load will acquire a different profile that would need special training. Many models also rely on meteorological data for forecasting [9] which would require the installation of costly infrastructure for weather measurements. Most models focus on day-ahead short-term load forecasting. Very few models have been developed for medium-term forecasting as in [12] while TCNs have found no such application.

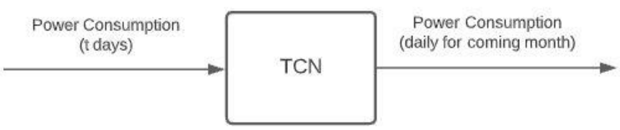


Figure 1. Proposed model

The aim of this work is to develop a multistep time-series forecasting model as shown in figure 1, to predict load consumption over the days in the following month for a university campus, based on power consumption over t days, with each day representing a sample. The long-term objective of this work is to quantify and plan for the total diesel needed for the next month at AUB, eliminating any outages caused by shortages.

The remainder of the work is organized as follows: Section II reports relevant work, then Section III establishes the system Methodology before Section IV reports the outcomes of the conducted experiments. Section V concludes with some ending remarks.

II. RELEVANT WORK

The existing works on load consumption prediction at the level of a university campus focus on short-term forecasting. Shallow models such as ensemble methods were used for that purpose in [13], [14] and [15] and support vector regression in [16], while Artificial Neural Networks have been utilized in [16] and [17]. Medium-term forecasting models were explored in [18],[19] and [20] using Artificial Neural Networks. The performance metric in [18] was the Mean Absolute Percentage

Error (MAPE). Temporal convolutional networks were neither used for university campus nor medium-term forecasting applications. However, it can be shown in [11] and [21] that such models yield more accurate results than conventional models used in load forecasting.

In short, existing work focuses on short-term forecasting, and the few medium-term forecasting models have used at best neural networks. Temporal convolutional networks have shown huge success in such durations of studies. Since fuel supply planning at the level of a university campus requires longer durations of forecasts than those achieved by short-term forecasting, the potential of temporal convolutional networks for that domain is studied in this work.

III. Methodology

The aim of this work is to develop a medium-term load forecasting model to predict electric power consumption at a university campus. The project utilizes a multi-step temporal convolutional network time series model and performs load forecasting on a daily basis. The model takes 7 days as input and predicts power consumption for the upcoming 7 days. The TCN model is an architecture of one-dimensional convolution kernels layered with pooling blocks and followed by a neural network block [23]. In order to evaluate the performance of the model, it is compared with the conventional ARIMA and well-known LSTM models. The work thus consists of the following steps: (1) The data must be gathered for day-by-day power consumption at a university campus. (2) An ARIMA model is built to have an insight into the results that a conventional model can produce when fed complex data such as power demand. (3) An LSTM model is developed to set the benchmark for the TCN model. (4) A TCN model is designed and analyzed. (5) The proposed models are tested based on a list of performance metrics. In the remainder of the section, the steps listed are explored in detail.

A. ARIMA model

An Autoregressive Integrated Moving Average (ARIMA) model basically utilizes time series data to forecast future trends. This model is divided into several parts which include: Autoregression, moving average, and integrated. Autoregression (Equation 1), refers to a model that shows the next periodic value which is found through regressing over the past or previous values. Moving Average (Equation 2) indicates the forecast error as a linear combination of the past value errors. Combining autoregression and moving averages results in an Autoregressive Moving Average Model (ARMA) found in Equation 3. The Integrated step is the differencing of the raw untouched observations (in our case the energy load consumption) to make the time series stationary. This is essential since it can stabilize the mean of the time series which eliminates any trends and seasonality before performing any predictions.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_n Y_{t-n} + \epsilon_1 \quad (1)$$

$$Y_t = \alpha + \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + .. + \phi_q \epsilon_{t-q} \quad (2)$$

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + .. + \phi_q \epsilon_{t-q} \quad (3)$$

A notation for ARIMA normally used is ARIMA(p,d,q) which can identify the ARIMA model by substituting those parameters with integer values. The p is the number of the lag observations also known as the lag order. The d is the number of times the of differencing between our raw observations also known as the degree of differencing. The q is the size of the moving average window also known as the order of the moving average.

B. LSTM model

LSTM is one of the most used artificial neural networks (RNN) architecture. Unlike standard feedforward architectures, LSTM neuron memorize their previous state through feedback connections and use it to identify the importance of new inputs and the impact they have on the next state. The general structure of an LSTM model is found in Figure 2.

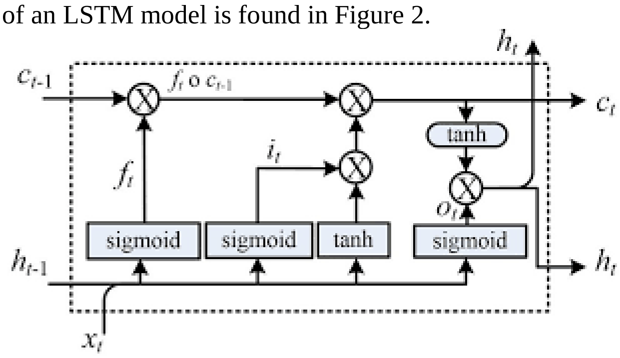
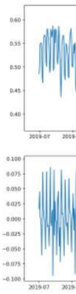


Figure 2. LSTM general structure.



C. TCN model

TCNs are presented as a new alternative to other typical RNN models for time series forecasting. The backbone of this CNN is one-dimensional causal convolution, often dilated, with multiple layers constituting one block and many blocks the model Input and output sizes of such blocks are equal in size.

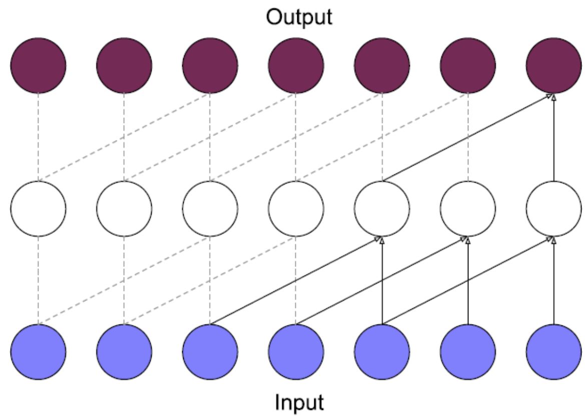


Figure 3. Causal dilated convolutional block with 2 layers, kernel size 2, dilation rate 2 (Lara-Benitez et Al.)

Figure 3 depicts a causal dilated convolutional block with 2 layers, kernel size of 2, and dilation rate of 2. This type of convolution helps capturing temporal features by looking at past values only and extracting the important relationships. We trained our models using Mean Squared Error (MSE) as loss function and the Adam optimizer.

D. Performance Metrics

In order to effectively compare the different models that will be adapted throughout the paper, MAPE or mean absolute percentage error will be adapted as the main Error metric throughout this paper. In addition, sever other metrics will be adapted to further assess the performance of the model. These secondary metrics are MAE (Mean absolute error), MSE (Mean squared error), and Minmax Error.

IV. Experiments & Results

To assess the potential of TCNs in medium-term load forecasting for a university campus load, an experiment was done on a dataset containing daily power consumption for two years for a campus load. First of all, the data preprocessing stage is reported. After that, the results are built up starting with the conventional ARIMA model, passing by the LSTM model, and ending with the TCN model. The evaluation of the TCN model is divided into objective evaluation, guided by a set of performance metrics discussed in Section III, and subjective evaluation based on the shape of the results obtained. The limitations on the experiments are also briefly mentioned.

A. Data collection and preprocessing

Due to the lack of sufficient data at AUB and time limitations imposed by the project, a dataset for the daily energy consumption of the university of British Columbia (UBC) campus from mid-2019 till mid-2021 was used for modeling [23]. A short sample of the load profile is depicted in Figure 4.

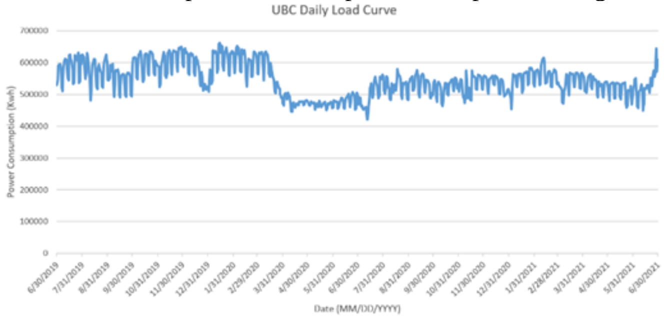


Figure 4. Load curve.

This dataset has been preprocessed so that it becomes convenient and ready for modeling. This was done by filling null values by their corresponding average values (means), finding the total energy consumption of the campus by summing the consumptions of all buildings, generating relevant features such as the day, month, year, day of the month, day of the year, week of the year and holiday. In addition, the dataset has been normalized using the means and the standard deviations of the features leading all columns to have zero mean and unity standard deviation. The final version of the dataset can be seen in Figure 5. Finally, data has been split into 75% training set and 25% test set, meaning that all data before 2021 constitutes the training set while the data corresponding to 2021 belongs to the test set. These sets were structured in a unique way so that our model predicts the next 7 days based on the previous 7 days. The following is a scenario that illustrates the format of the data for 3 instances.

X= [[d1 d2 d3 d4 d5 d6 d7]
[d2 d3 d4 d5 d6 d7 d8]
[d3 d4 d5 d6 d7 d8 d9]]

Y= [[d8 d9 d10 d11 d12 d13 d14]
[d9 d10 d11 d12 d13 d14 d15]
[d10 d11 d12 d13 d14 d15 d16]]

Date	Total Energy Consumption	Holiday	Day	Month	Year	Q	Dayofyear	Dayofmonth	Weekofyear	Temperature
2019-06-30	-0.284580	0	1.499235	-0.150488	2019	-0.453518	181	1.614774	-0.049708	12
2019-07-01	0.040518	1	-1.495144	0.139400	2019	0.441294	182	-1.673324	0.01609	11
2019-07-02	0.912536	0	-0.996081	0.139400	2019	0.441294	183	-1.559942	0.01609	6
2019-07-03	0.988707	0	-0.497018	0.139400	2019	0.441294	184	-1.446559	0.01609	7
2019-07-04	0.974892	0	0.002045	0.139400	2019	0.441294	185	-1.333176	0.01609	6

Figure 5. Preprocessed dataset description.

B. ARIMA results

The ARIMA model was first constructed using an intuition sense. We first plotted the data, where we knew that they needed to be stationary so that the ARIMA model can work. After one differencing, the p-value dropped below 0.05 which means that one differencing is enough. So, we chose d=1. We then plotted the partial autocorrelation graph where we saw 4-5 significant levels above the confidence region. Therefore, we assumed that p=4. Next, the lags of autocorrelation graph indicated that there were at least 5 significant levels above the confidence region, which is why chose q=5. Figure 6 shows the original series and the first differencing. We now have an assumed ARIMA model with parameters (4,1,5).

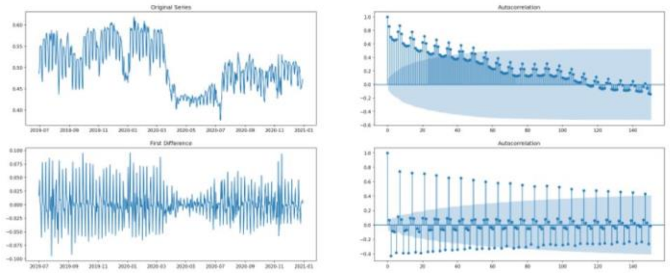


Figure 6. Data distribution after one differencing.

We also got the residuals that portrayed the variance and the mean that was very close to zero as shown in Figure 7.

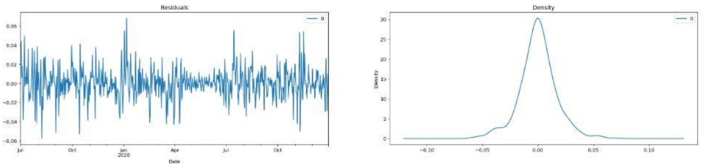


Figure 7. Residuals and density of data after differencing.

However, since we cannot count on manual tuning the parameters, we used a library called "auto_arima", and we were able to obtain the results in Figure 8. Since the concept of validation is not used in the ARIMA model, the figure shows the performance on the test set.

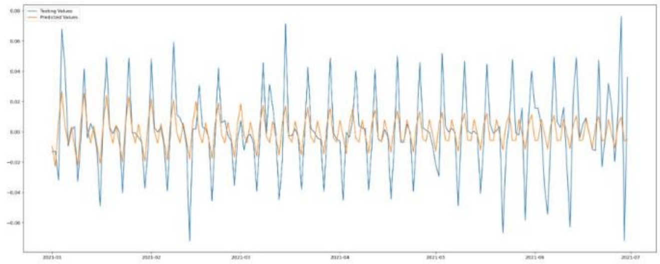


Figure 8. Test data (blue) plotted with forecasted data (yellow).

C. LSTM model

Different from standard LSTM models in which multiple LSTM layers, the LSTM model that was adapted is a primary consistent of one LSTM Layer of 50 neuron followed by 3 Dense layers. In addition, two separate input layers are used to separate between the temporal inputs which are the Energy consumption for each day of the 7 days input and the calendrical features used which are the day of the year, week of the year, and whether any of the dates we want to predict are Holidays. Therefore, one the temporal information will be fed to the LSTM layer. The model's output layer has 7 neuron each associated to one weekday we wish to predict. The detailed proposed structure of the neural network is shown in Figure 7.

The LSTM model proposed was trained and hyper tuned on the validation data. The model was trained for 300 epochs while using an early stopping monitor to prevent overfitting. A mean square error loss function was adapted to train the model. The final validation error reached by model was an MSE of 0.1482 while the average error over 10 run was 0.1466. To further evaluate the model the predicted value of the model on the validation data was plotted compared to the expected values for the first predicted day and the 7th predicted day. The obtained plots are shown in Figures 8 and 9.

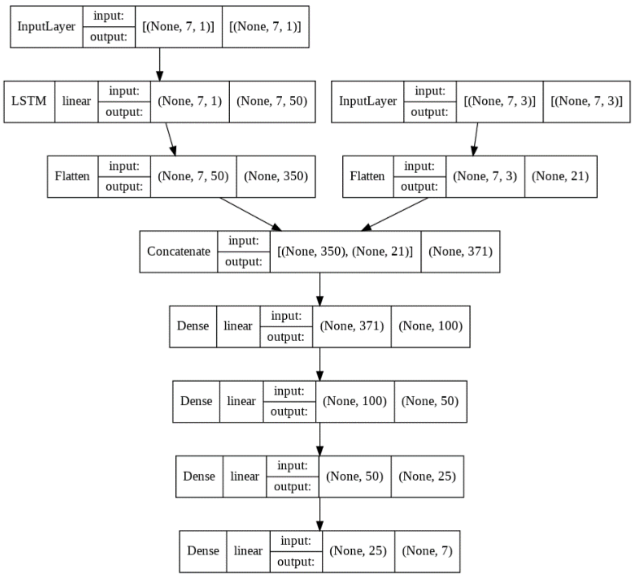


Figure 7. LSTM proposed structure.

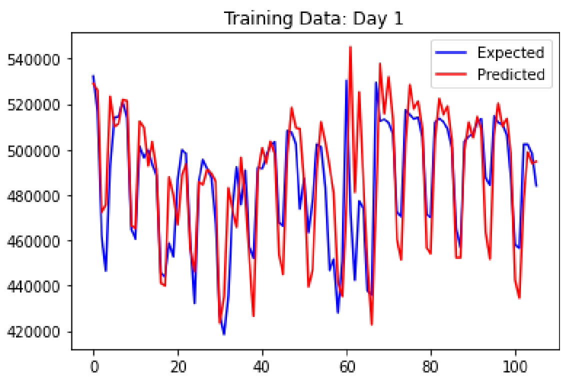


Figure 8. Predicted values comparison with expected values for the first day on validation data.

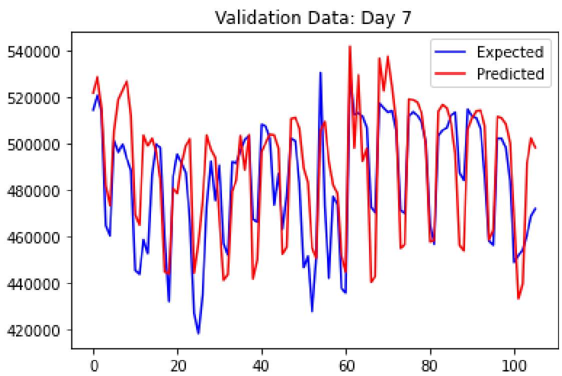


Figure 9. Predicted values comparison with expected values for the seventh day on validation data.

D. TCN model

To better capture trends in forecasting, our model considers the time series data of power consumption, as well as static features relating to the calendrical characteristics of the days, like the day of the year, month, day of the week, day of the month, occurrence of holiday, the year and quartile of the year.

The model uses a TCN architecture that takes the time series data, 7 instances of power consumption, and the output is fed to an ANN block that also takes as input the rest of the static features. Figure 10 below illustrates our complete model.

The TCN stack consists of 1 block with 3 convolutional layers: kernel size of 2, dilation of 5, 3 filters and with linear activation. We noticed that adding a max pooling layer of size 5 and strides of 4 steps improves the model.

The output of the TCN block is concatenated with the static features input and fed into an ANN with 3 hidden layers of 100, 50, 25 neurons per layer and linear activation, and an output layer of 7 neurons, also linear activation.

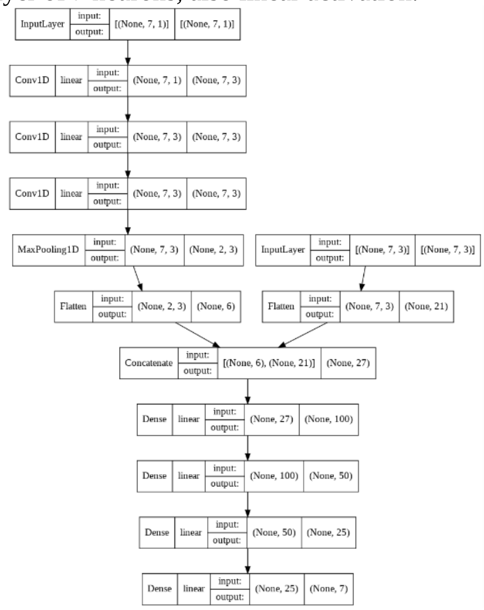


Figure 10. Detailed summary of the TCN-based model.

We tried different learning rates, batch sizes, number of filters, and activation functions (Rectified Linear Unit and Linear). The best combination is summarized in the Table 1.

Table 1. Summary of selected hyperparameters.

Learning Rate	0.001
Batch size	10
Number of filters	3
Activation Function	Linear

Training the model reached a MSE of 0.1368 on validation data, and we plotted the predicted values and the actual values of the training data set. Since the predicted days overlap, we averaged all predictions of the same day and considered this as the power consumption prediction on that day. Figure 11 plots the results.

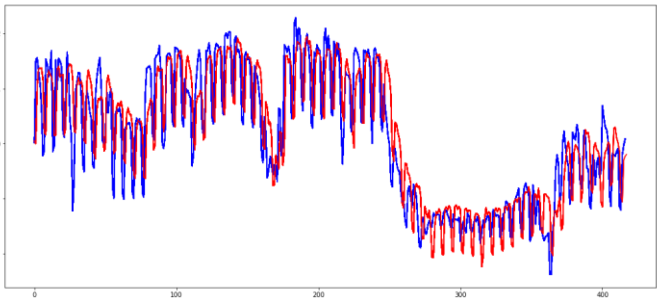


Figure 11. Target (red) and predicted (blue) power consumption (training set).

The red curve represents the target values, and the blue curve represents the predictions. Overall, it looks like the model is able to come close with the approximations, but more comments are presented in a later part of this paper.

The initial version of this model was taking the calendrical characteristics of the previous week, and changing it into features of the target days helped the model slightly, on the order of 0.01 in terms of validation data MSE. Another attempt was feeding the model temperature values of the next week, average temperature as well as minimum and maximum values, however this seemed to have no effect whatsoever. Surely, the correlation between meteorological data and power consumption ranged between -0.05 and -0.2, which are not significant.

E. Objective Evaluation

The three models were all tested on a test set unseen by all models. The results for each model are demonstrated in the table of Table 2. The TCN model performed the best compared to the LSTM and ARIMA model by having the lowest MAPE of approximately 0.026. The ARIMA model preformed very poorly having a much higher MAPE error compared to the other two models. Moreover, the LSTM model performed slightly worse than the LSTM Model. Furthermore, comparing other performance metrics also yield the same result where TCN seem to be outperforming the two other models.

Table 2. Test set prediction evaluation on each proposed performance metric for each model.

Metric	ARIMA	LSTM	TCN
Mean absolute percentage error (MAPE)	3.87	0.028	0.025857
Mean absolute error (MAE)	15326.65	13986.82	12751.4
Mean squared error (MSE)	451210321	348520660.6	316231388.35
Minmax Error	-1.1567	0.0277	0.025

F. Subjective Evaluation

Even though the numerical evaluation of the model shows extremely good results for the LSTM and TCN models, several issues are noticed that can indicate some inaccuracies in these two models. As shown in the plot in figure 4 there is a repetitive cycle of pulses predicted by the TCN model.

Looking more closely, the model seems to be predicting a modified version of the previous week it is fed. This is easily seen from the 3 pulses that begin at around day 100, as shown in a magnified plot in Figure 12. On the first week, the predictions are close to the target, however on the second week the target values suddenly drop overall, while the predictions maintain values closer to the previous target week.

The same issue can be seen for the LSTM model. This uncovers a weakness in the two models, the power consumption levels of previous days along with the calendrical characteristics of the upcoming days are not enough to develop a robust predictor. From this observation, it seems that some other features relating to student behavior on campus may be beneficial for such a model, and an interesting discussion is required to interpret and understand the shape and variability of a university campus load profile. As for the ARIMA model, the model's poor performance can be explained by the non-linearity of the data available for which ARIMA models highly rely on.

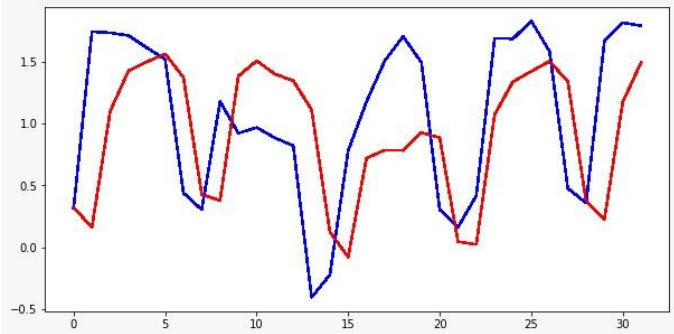


Figure 12. TCN model, to some extent, follows the previous week.

G. Limitations

The results discussed were obtained with a lot of limitations. These include the modest size of the data set that includes only a 2-year period of study. In addition, no clear correlation seems to exist between the power consumption of the studied load and the temperature data, unlike some of the works listed in the literature. Furthermore, the study was missing data relating to the student behavior and university-specific events that can cause special trends in load data unrecognized by this general model. More importantly, the time limitations of the project hindered further studies related to data gathering and preprocessing and model tuning. Future works may be conducted to address these limitations.

V. Conclusion

In this paper, we applied medium-term load forecasting using TCN that accurately predicted the future energy consumption of a university campus. This was achieved by training a TCN model on a dataset that contains the energy consumption of UBC campus and comparing it to other famous models. It was proven throughout this paper that the TCN model performs better than the LSTM and ARIMA models. To Further prove the effectiveness of our model a dataset of the energy consumption at AUB can be collected and by that the proposed TCN model can be tested on whether it generalizes well on different university campuses. Moreover, new data on the energy consumption in UBC are posted on the month of August of every year which can provide more data to further train and test the proposed model. In addition, mechanisms found in the literature for capturing non-linear relations between meteorological data and load consumption, and reducing noise in load data may be utilized. Finally, a hybrid TCN-LSTM model can be explored.

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