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Industrial Electrical Energy Consumption Forecasting by using Temporal Convolutional Neural Networks

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Abstract. In conjunction with the 4th Industrial Revolution, many industries are implementing systems to collect data on energy consumption to be able to make informed decision on scheduling processes and manufacturing in factories. Companies can now use this historical data to forecast the expected energy consumption for cost management. This research proposes the use of a Temporal Convolutional Neural Network (TCN) with dilated causal convolutional layers to perform forecasting instead of conventional Long-Short Term Memory (LSTM) or Recurrent Neural Networks (RNN) as TCN exhibit lower memory and computational requirements. This approach is also chosen due to traditional regressive methods such as Autoregressive Integrated Moving Average (ARIMA) fails to capture non-linear patterns and features for multi-step time series data. In this research paper, the electrical energy consumption of a factory will be forecasted by implementing a TCN to extract the features and to capture the complex patterns in time series data such daily electrical energy consumption with a limited dataset. The neural network will be built using Keras and TensorFlow libraries in Python. The energy consumption data as training data will be provided by GoAutomate Sdn Bhd. Then, the historical data of economic factors and indexes such as the KLCI will be included alongside the consumption data for neural network training to determine the effects of the economy on industrial energy consumption. The forecasted results with and without the economic data will then be compared and evaluated using Weighted Average Percentage Error (WAPE) and Mean Absolute Percentage Error (MAPE) metrics. The parameters for the neural network will then be evaluated and fined tuned accordingly based on the accuracy and error metrics. This research is able create a CNN to forecast electrical energy consumption with WAPE = 0.083 & MAPE = 0.092, of a factory one (1) week ahead with a small scale dataset with only 427 data points, and has determined that the effects of economic index such as the Bursa Malaysia has no meaningful impact on industrial energy consumption that can be then applied to the forecasting of energy consumption of the factory.

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1 Introduction

An accurate electrical energy consumption forecast is vital to manufacturing industries to run their operations via managing and planning of energy policy [1], operational schedules and manufacturing processes as industrial sectors. According to the Malaysian Energy Commission as the industrial sector alone in Malaysia has consumed over 71 million kilowatt-hours in 2017 [2]. One of the main reasons is due to the high cost associated with operating the industrial machines required in the production line which is consuming large amounts of electrical energy and directly translates to higher electricity costs. Hence, the operational times of these machines in the production lines need to be planned in advance to ensure a high efficiency in balancing time, cost and production output [3].Traditionally, common methods for electrical forecasting purposes typically include regression analysis such as Support Vector Machines (SVM) and Least Squares Support Vector Machines (LSVM) as utilized by Kaylez et al.[4] and using (ARIMA) algorithm as built by Nichiforov et al. for electrical forecasting. However, electrical energy consumption as time series data forecast represents a difficult type of predictive modelling problem due to the existence of complex linear and non-linear patterns [5].

Some researchers proposed artificial neural networks for forecasting electrical consumption. Li et.al used Convolutional Neural Networks (CNN) with the time-series data of electrical consumption for energy forecasting without considering external factors such as the weather and economy [6]. However, it is shown that too many input variables by considering of many different external factors can lead to invalid results by complicating the prediction and training process of the neural network [7]. Hence, this research aims to rectify this problem by only selecting economic factors as the sole external factor that will have a significant impact on electrical energy consumption.

Although most of the previously proposed methods for electrical energy consumption forecasting had promising and accurate results but they need to use a large data sets ranging from over 257 thousand records [6] to 1.4 million records [4] for forecasting. Reliable large data sets are only accessible if the data is available through public domain or companies has already built in infrastructures for data collection. As implementing such infrastructures on top of a manufacturing production line is costly, most small-medium enterprises (SME) may not have the capability to implement the data collection and monitoring infrastructure yet or may not even have the capability or financial prowess to maintain the system altogether. Therefore, the current data that has been collected by SME are much more limited compared to large enterprises. Based on the feature extraction performance of CNN [8], shows that it is able extract the features and capture the hidden dynamics of the time-series data and able to generate predictions [9]. As times-series data are sequential and temporal, a method to ensure that there is no leakage of information from future time steps in the sequence is to ensure that the convolutional layers in the network to be causal. Causal convolution is different from standard convolution due to convolutional operation performed to obtain the output does not take future values as inputs [11]. This architecture of CNNs are named as Temporal Convolutional Neural Network (TCN) as it is especially suited to handle temporal time-series data.

Therefore, this research is proposed to create an optimized TCN to forecast the electrical energy consumption of a SME's factory with small data set.

2 Methodology

In this section, the methods to create a Temporal Convolutional Neural Network and optimize the performance of the network with limited training data set will be discussed. Visual Studio Code is used as the main code editing program that is used for this project, while Microsoft Excel is used to tabulate the data of the results.

2.1 Data acquisition & preprocessing

To acquire the data for training, a custom Node.js script is written to download the import the raw data as captured by the sensors in the factory is uploaded to Firestore [12]. Firestore is a NoSQL cloud database to store data and server development from Firebase and the Google Cloud Platform. A Firebase service account is registered with permission from GoAutomate Sdn Bhd, and an authentication token is generated to authorize the manipulation of the database from an external script. The Node.js script implements a custom algorithm to segregate and calculate daily energy consumption from the cumulative raw data in (kWh) kilowatt-hour unit provided by the sensors as the data is sampled every 5 minutes. The downloaded energy consumption data is then normalized with z-score normalization to improve convergence of deep learning neural networks. Z-score normalization is a strategy of normalizing data that avoid any outlier data related issues. The formula for z-score normalization is shown below.

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

Where x is the actual value, μ is the mean and σ is the standard deviation.

The economic index that is chosen for economic factors is the Bursa Malaysia Kuala Lumpur Composite Index or Kuala Lumpur Stock Exchange (KLSE) as it is a daily index that is able to reflect the condition and state of economy of the nation.

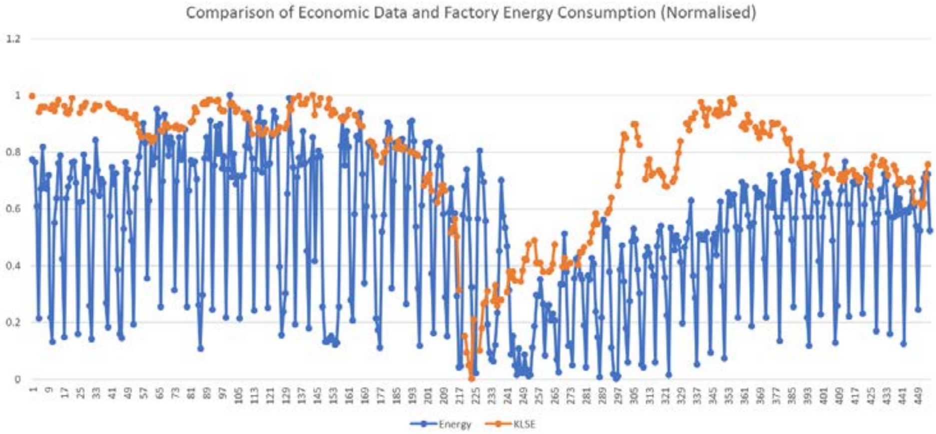


Fig. 1. Normalized comparison of economic index and electrical energy consumption

As seen in the figure above, it can be seen that there are correlation between the trend of the KLSE and electrical energy consumption of the factory.

2.2 Input-output pair sliding window method

As the outcome of the project is to output a multi-time step forecast, that is 7 days of forecasted electrical energy usage, a multi-input multi-output (MIMO) architecture is selected for the network instead of recursive approaches such as forecasting a single timestep, then feedback the last forecast as input for the next forecast as recursive approaches tend to accumulate errors over several forecasts for multi-step prediction [13].

As a result, the training data will be reshaped into the form of a pair input-output sequences. The input-output sequence pairs will follow a sliding window scheme across the entire raw training data to be created. For example, the output sequence in this scenario has a length of 7, while the input sequence is preliminarily chosen as 21. As such, the network will use a lookback window of 21 days as an input to generate a forecast of the next 7 days as output. To help illustrate the sliding window scheme to generate input-output sequence pair, an example figure is shown below.

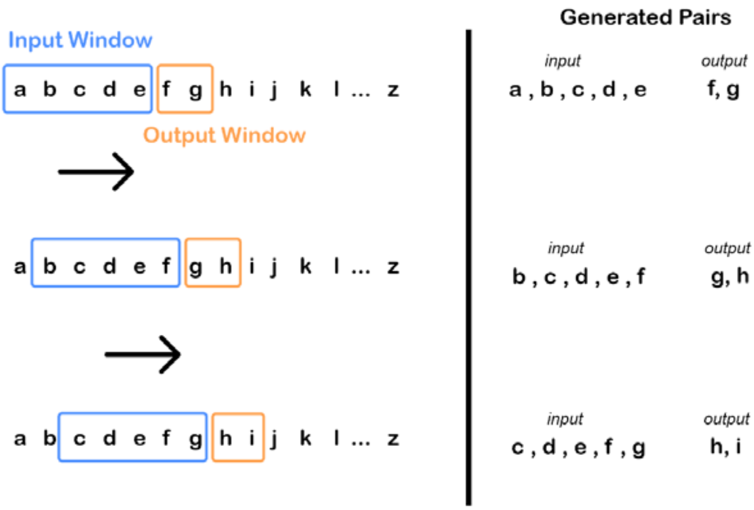


Fig. 2. Example of input-output sequence pair generation with sliding window method.

The training data for the TCN only consists of electrical energy consumption data from August 1, 2019 – September 14, 2020 with a relatively small dataset of only 424 values. The generation of input-output sequence pair with sliding window method is implemented using a script in Python with the utilization of the NumPy library.

2.3 Forecast accuracy metrics

The accuracy of the forecasted values in the output sequence will be evaluated using Weighted Average Percentage Error (WAPE), Mean Average Percentage Error (MAPE) and Root Mean Square Error (RMSE) metrics.

$$\mathrm{WAPE} = \frac{\sum_{i=1}^{n} \left| actual_i - forecast_i \right|}{\sum_{i=1}^{n} \left| actual_i \right|} \tag{2}$$

$$\mathrm{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{actual_i - forecast_i}{actual_i} \right| \tag{3}$$

where n is the length of the network output or forecast window.

3 Results and Discussion

3.1 Temporal convolutional network parameters

To ensure reproducibility and uniformity to the project, a seed for the training process of the neural network is fixed as it is a built-in function of the Keras-TensorFlow library. The TCN is trained with training data as prepared as input-output pair batch size of 7, with starting with and arbitrarily number of 30, then varying epochs/iterations to determine most optimized configuration for most accurate forecasts.

The fixed parameters of the TCN are as follows, dilations layers or *nb_stacks*=1, *padding*='causal', *return_sequences*=False, *dropout_rate*=0.

The optimal network configurations are determined via a series of repeated testing by generating models with different parameters and gauging the accuracy of the forecast using the error metrics of WAPE and MAPE as stated previously. First, it has been determined that an epoch of 38 yields optimum results via a test of several sets of testing data, obtaining the average MAPE and WAPE to determine the optimum model configuration.

Table 1. Average error metrics of forecast with different epochs.

Test Set 1 (Week 1)

Epochs	MAPE	WAPE
30	0.10556	0.098243
38	**0.09390**	**0.08755**
40	0.12070	0.11350
50	0.09666	0.09461
60	0.10668	0.10578

Test Set 2 (Week 2)

Epochs	MAPE	WAPE
30	0.10094	0.09284
38	*0.10058*	**0.09184**
40	0.12984	0.11694
50	0.10640	0.09298
60	**0.09461**	0.09498

Test Set 3 (Week 3)

Epochs	MAPE	WAPE
30	0.10855	0.09406
38	**0.09899**	**0.08821**
40	0.12510	0.10844
50	0.11805	0.10379
60	0.11678	0.09944

Test Set 4 (Week 4)

Epochs	MAPE	WAPE
30	0.11091	0.09996
38	**0.10751**	**0.09402**
40	0.10595	0.09289
50	0.09164	0.07991
60	0.11741	0.10407

As it can be seen in Table 1 (in bold) that training for 38 epochs or iterations yields best overall results for this set of factory electrical energy consumption data.

The optimum ratio for the input, lookback window and output, forecast window has been tested and verified to be at 21:7, that is to have the network using a lookback window of 21 days as an input to generate a forecast of the next 7 days as output. This is verified by repeated testing of 4 different ratios of input-output window for the model with several sets of testing data and comparing the error metrics. The comparison chart is shown below.

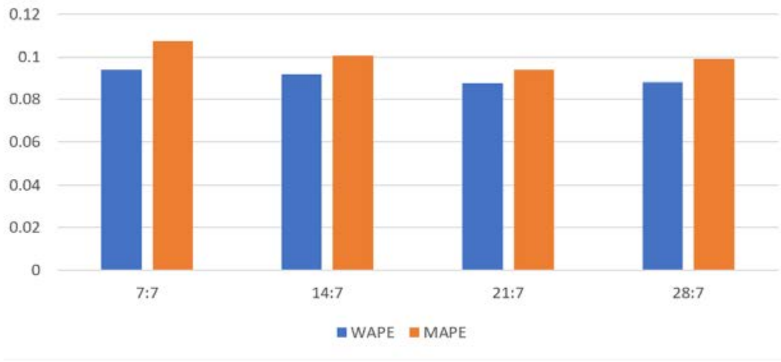


Fig. 3. Comparison of input-output window ratio for network.

Once the optimum basic parameters for the network, that is the ratio of lookback window (input), forecast window(output) and epoch are determined, other parameters to optimize the network based on the MAPE & WAPE scores can be done.
Next, the configurations of 32, 64 and 128 convolutional filters (*nb_filters*) were tested on 4 sets of testing data as stated previously. The optimum number of convolutional filters as tested is at 128. The average value for error metrics is shown in the table below.

Table 2. Average error metrics of forecast for different number convolutional filters.

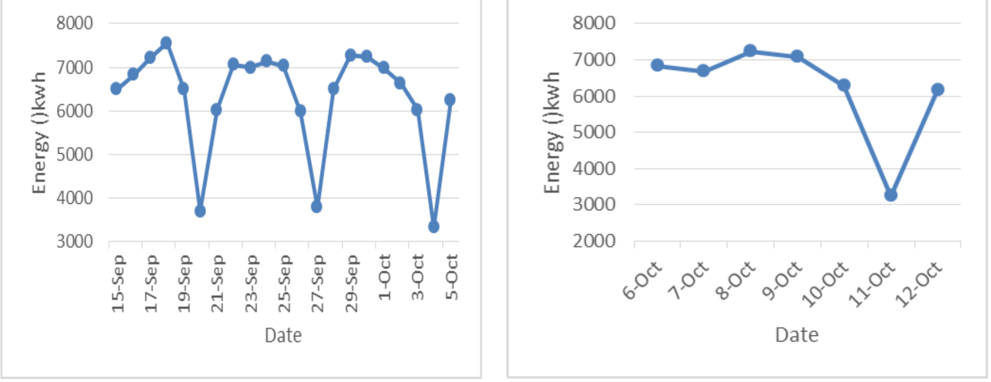
nb_filter	Average WAPE	Average MAPE
32	0.093896506	0.087554652
64	0.116039414	0.103804283
128	0.087554652	0.093896506

The activation function used for the network is the Rectified Linear Unit (ReLU) function in order to overcome the vanishing gradient problem and is commonly used in convolutional neural networks as it enables networks to learn faster. For the optimization function of the neural network, the Adam algorithm instead of a conventional stochastic gradient descent (SGD) function. An optimization function is a function that adjusts and configures the weights of the network after every epoch/iteration during training. The configuration hyperparameters of the Adam are left as default as per Keras-TensorFlow with *learning_rate*=0.001, *beta1*=0.9, *beta2*=0.999, *epsilon*=1e-08. Adam is chosen due to the adaptive per-parameter learning rates based on the average of recent magnitudes of the gradients for the weights.

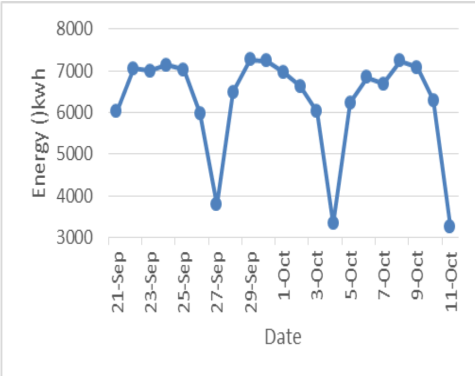
The loss function used for the output is Mean Absolute Error (MAE) is used as it is commonly used for regression problems by comparing absolute error between forecasted and actual values, and works in tandem with the Adam optimizer to readjust the weights and biases in the network.
The padding of the TCN is ensured to be set at *causal* as to prevent any leakage of information from the future to the past, and avoid creating a self-fulfilling forecasting model which does not accurately model the electrical energy consumption of the factory.

After comparison between different major parameters of the TCN, a comparison of the forecasted results of the network trained. The test data consists of an input sequence of 21 days of electrical consumption and output sequence of 7 days. The TCN has not encountered or seen the data before during training. The input sequence is fed into the network to generate the predicted output sequence. The actual and forecasted results by TCN of different configurations are then evaluated and compared.

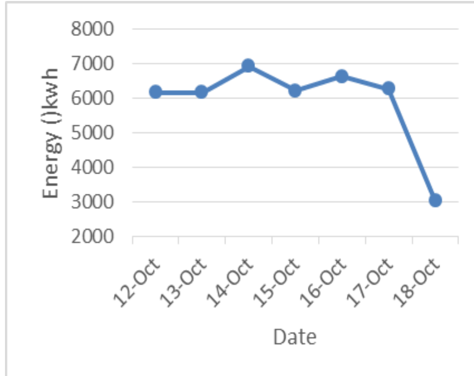
Several sets of test input sequences, that are the electrical energy consumption of the factory of 21 days, will be fed into the network to generate a forecasted output sequence for the next 7 days. The test data sets will be normalized before it is fed into the TCN. The TCN is tasked to generate a forecast for several weeks for the month of October 2020, the testing sequences, input and output will be tabulated below for each week. A visualization of the input-output sequences for all 4 weeks is shown in Figure below.



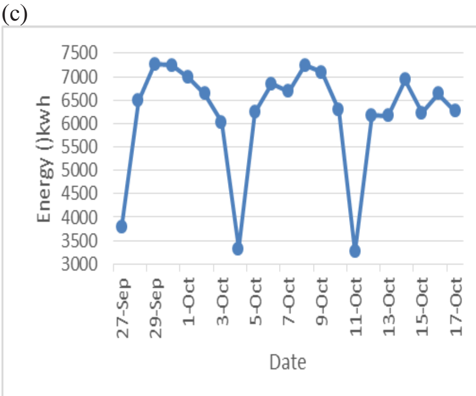
(a) (b)



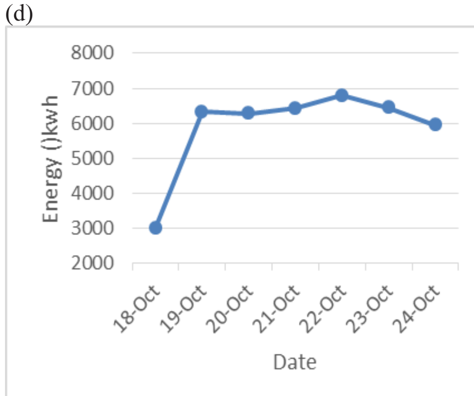
(c)



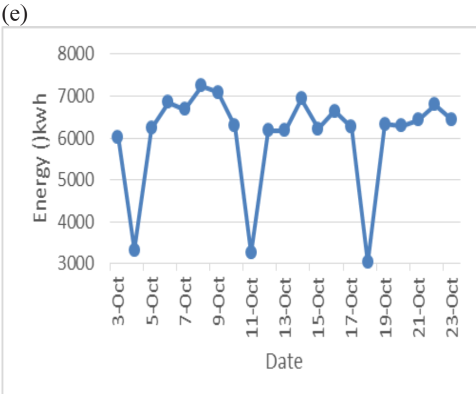
(d)



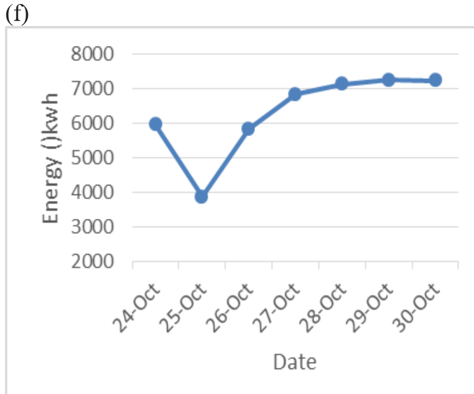
(e)



(f)



(g)



(h)

Fig. 4. Plot of (a) test input sequence, Sep 15 – Oct 5; b) test output sequence, Oct 6 – Oct 12; (c) test input sequence, Sep 21 – Oct 11; (d) test output sequence, Oct 12 – Oct 18; (e) test input sequence, Sep 27 – Oct 17; (f) test output sequence, Oct 18 – Oct 24; (g) test input sequence, Oct 3 – Oct 23; (h) test output sequence, Oct 24 – Oct 30.

Finally, two different kernel sizes and dilations configurations were also compared. The accuracy of the forecast results of the different configurations are tabulated below. The error metrics used for evaluating forecast accuracy are generated with the aid of NumPy library.

Table 3. Error metrics of forecast with kernel size of 2 and dilations of [1, 2, 4, 8, 16, 32, 64].

Week	MAPE	WAPE
1	0.0271148	0.0278651
2	0.149722	0.145305
3	0.076674	0.074936
4	0.122075	0.102113
Average	0.0938965	0.0875547

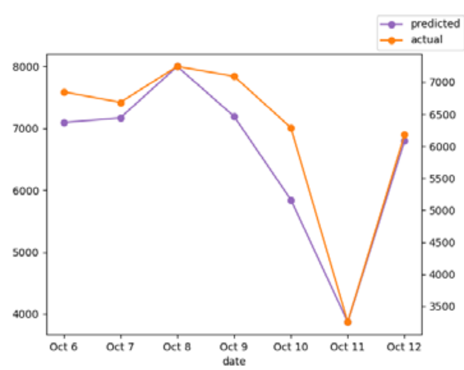
Table 4. Error metrics of forecast with kernel size of 3 and dilations of [1, 5, 7, 14, 28, 56]

Week	MAPE	WAPE
1	0.0836374	0.0747321
2	0.095645	0.101379
3	0.103627	0.088064
4	0.086349	0.066369
Average	0.0923144	0.0826359

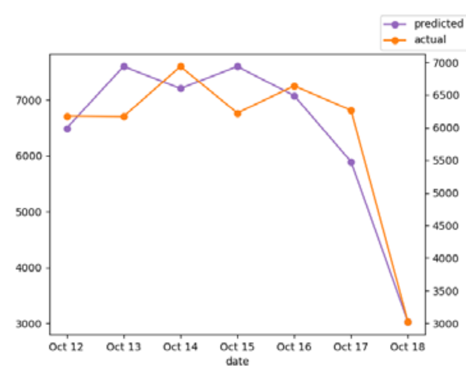
The optimum model, is a TCN that is trained for 38 iterations, with a lookback window of length 21, output window of length 7, with a batch size of 7, kernel size of 3 with dilations of [1 5 7 14 28 56], and with 128 convolutional filters. The average MAPE and WAPE are about 0.0923 and 0.0826 respectively.

The output of the neural network will then be denormalized based on the z-score normalization parameters to obtain forecasted electrical energy consumption values in kWh (kilowatt-hour).

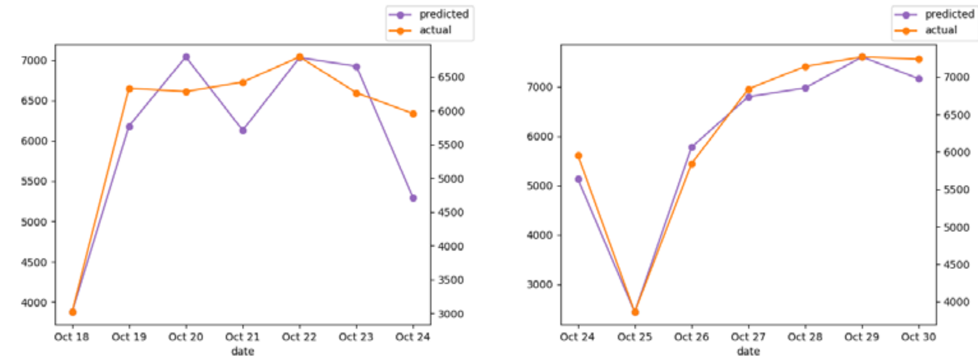
It should also be noted that the networks are able to capture features and trends such as the low energy usage on weekends especially on Sundays, that is on Oct 11 where the TCN is able to forecast as shown in the Figure 5(a), then back to a nominal higher energy usage on Mondays on Oct 12, where weekdays have a higher usage of electrical energy at the factory due to resuming manufacturing operations. This pattern is similarly observed as well in testing sets in other weeks on Oct 18 to Oct 19 and again on Oct 25 to Oct 26.



(a)



(b)



(c) (d)

Fig. 5. Comparison of forecast of the best performing model and actual energy consumption values (a) Week of Oct 6 – Oct 12 (b) Week of Oct 12 – Oct 18; (c) Week of Oct 18 – Oct 24; (d) Week of Oct 24 – Oct 30.

Another feature of interest is that the network is not trained on a strict weekend to weekend fashion, and hence does not rely on a fixed pattern on starting of the week to the end of the week and is able to predict with 90% accuracy from any day chosen in the week to generate a forecast of the next 7 days. This can be seen in the results where all 4 sets of testing data start on different days in Figure 5. The combined plot of forecasted and actual energy usage is shown in Figure 6.

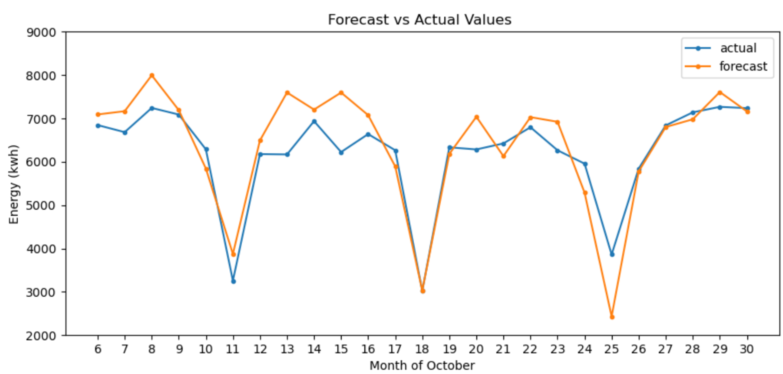


Fig. 6. Combined plot of forecasted & actual energy usage.

3.2 Temporal convolutional network parameters

By factoring in the economic data into the optimum model based on previous testing, that is a neural network that is trained for 38 iterations, kernel size of 3 with dilations of [1 5 7 14 28 56], and with 128 convolutional filters. The KLSE data is merged with the energy consumption data and trained in the exact same parameters and methods. Most numerical operations are performed with the aid of NumPy library.

As the KLSE does not have data on public holidays and weekends, interpolation is performed on the KLSE dataset to obtain parity in data count with the energy consumption data of the factory. Interpolation is performed using Microsoft Excel in Comma Separated Value (CSV) format. It can be observed from the results of the economic it is apparent that the trends and features of the differing weeks in the month of October has been successfully captured but is noticeably similar to the results of the model without the economic factor.

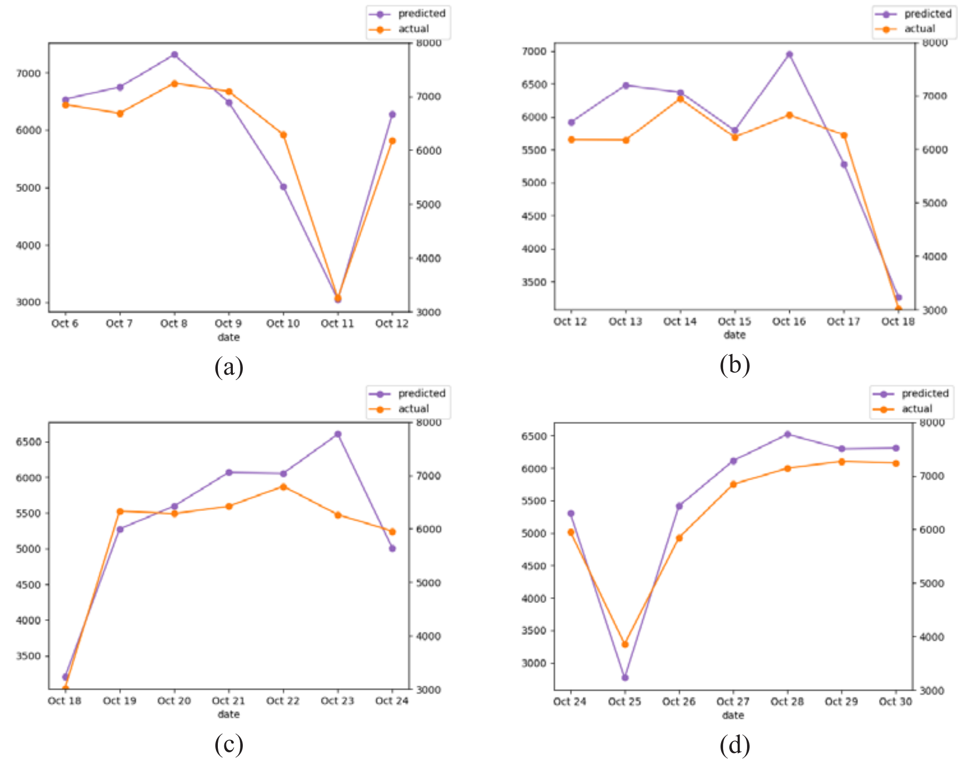


Fig. 6. Comparison of forecast of the best performing model and actual energy consumption values with inclusion of economic factor. (a) Week of Oct 6 – Oct 12 (b) Week of Oct 12 – Oct 18; (c) Week of Oct 18 – Oct 24; (d) Week of Oct 24 – Oct 30.

Table 5. Comparison of error metrics for forecasting energy with economic factor and without economic factor.

	With Economic Factor		**Without Economic Factor**	
Week	**MAPE**	**MAPE**	**MAPE**	**MAPE**
1	0.0619923	0.0605042	0.0836374	0.0747321
2	0.0749508	0.0745891	0.095645	0.101379
3	0.1020385	0.1050175	0.103627	0.088064
4	0.131375	0.1225641	0.086349	0.066369
Average	0.0925893	0.0906687	***0.0923144***	***0.0826359***

Based on the results in Table 5, there is a degradation in both MAPE and WAPE scores as the univariate model without economic factors still upholds the superior position of the optimal configuration.

Although it can be observed that there are similar long term trends when visually and numerically (after normalization) comparing both KLSE and the energy consumption of the factory, the additional external economic factor does not have a huge impact on forecasting accuracy and performance as the fluctuations of the KLSE indicator is too noisy on small scale, such as in this project, to have any meaningful impact to aid in forecasting accuracy even if it exhibits similar trends in comparison.

In terms on computational efficiency, the inclusion of economic data increased the trainable parameters as reported by TensorFlow by 20% as compared to models with only the electrical energy consumption data. The model summary for both models is shown below.

```
Layer (type)                 Output Shape              Param #
================================================================
input_1 (InputLayer)         [(None, 21, 2)]           0

tcn (TCN)                    (None, 128)               543360

flatten (Flatten)            (None, 128)               0

dense (Dense)                (None, 7)                 903

dense_1 (Dense)              (None, 7)                 56
================================================================
Total params: 544,319
Trainable params: 544,319
Non-trainable params: 0
```

(a)

```
Layer (type)                 Output Shape              Param #
================================================================
input_1 (InputLayer)         [(None, 21, 1)]           0

tcn (TCN)                    (None, 128)               542848

flatten (Flatten)            (None, 128)               0

dense (Dense)                (None, 7)                 903

dense_1 (Dense)              (None, 7)                 56
================================================================
Total params: 543,807
Trainable params: 543,807
Non-trainable params: 0
```

(b)

Fig. 7. Comparison of model summaries for each model (a) Model summary inclusive of KLSE; (b) Model summary without economic data.

Table 6. Comparison of time taken to train and generate each model

	Trainable Parameters	**MAPE**	**WAPE**	**Training Time (s)**	**Forecasting Time (s)**
Univariate Model	543, 807	0.0923145	0.082636	54.37	7.71
Model with economic factor	544, 319	0.104595	0.097026	57.98	8.03

In the table above, it can be seen that not only the inclusion of economic factors regressed the accuracy of the model, but it also decreased computational efficiency as the parameters has increased resulting in a slower training and prediction time as tabulated in Table 7. It can be concluded that the inclusion of economic data does not have any positive or meaningful impact on forecasting accuracy for electrical energy consumption. The models are all computed on the same hardware, that is an Intel Core i5-1035G4 CPU without the use of a discrete graphics card. Due to the extra steps of data processing for another set of data to be prepared in order to generate a forecast, it can be concluded that the addition of economic factor decreases computational efficiency and worsens overall performance of the model and is not recommended to be implemented.

4 Conclusion

Temporal Convolutional Neural Networks (TCN) are indeed feasible for forecasting electrical energy consumption even with a limited dataset via causal dilated convolutional layers and resulting in adequate forecasting accuracy with WAPE of 8.3% and MAPE of 9.2%. These results are achieved by using the optimal configurations for the TCN. The optimal configurations for small dataset forecasting modelling are determined to be at trained 38 epochs, with 128 convolutional filters, a kernel size of 3 with 5 dilation layers of [1 5 7 14 28 56]. The inclusion of KLCI economic data did not have a large effect on forecasting accuracy but has in fact regressed the performance of the optimal model with WAPE of 9.7% and MAPE of 10.5% of. It can be concluded that KLCI data, although likely to have correlation, is not suitable as the chosen index that is optimal external factor to improve forecasting accuracy.

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