# Abstract

Having the ability to predict future electricity price proposes an interesting strategy of electricity consumption, optimising the usage to use the most electricity yet pay at the lowest price. However, the lack of correlation of electricity price in Singapore has made predicting it using other known factors a difficult problem. Singapore has only recently opened their electricity retail market to everyone in 2018 and most research done on this market has been using statistical methods. In this project, we will be utilising the Multilayer Perceptron to model the electricity price market and try to forecast the price of the next 10 days. Experient was done to find the most optimised parameters in building the neural network using machine learning libraries in Python. Our neural network model was able to successfully predict the trend of the future price, but more experimentation has to be done to detect outliers and predict a more accurate price value,

# Acknowledgements

# Table of Contents

Contents

[Abstract 1](#_Toc35300608)

[Acknowledgements 1](#_Toc35300609)

[Table of Contents 2](#_Toc35300610)

[List of Tables 3](#_Toc35300611)

[List of Figures 4](#_Toc35300612)

[1. Introduction 5](#_Toc35300613)

[1.1. Background 5](#_Toc35300614)

[1.2. Purpose and Scope 6](#_Toc35300615)

[2. Literature Review 6](#_Toc35300616)

[2.1. Factors Affecting Electric Prices and Trends 6](#_Toc35300617)

[2.2. Methodology in Price Forecasting 7](#_Toc35300618)

[2.2.1. Data Pre-processing and Analysis 7](#_Toc35300619)

[2.2.2. Neural Network 7](#_Toc35300620)

[3. Discussion 8](#_Toc35300621)

[3.1. Data and Analysis 8](#_Toc35300622)

[3.2. Feature Engineering 11](#_Toc35300623)

[3.2.1. Creating the training set 11](#_Toc35300624)

[3.3. Neural Network 13](#_Toc35300625)

[3.3.1. Building the model 14](#_Toc35300626)

[3.3.2. Modelling the future 17](#_Toc35300627)

[4. Conclusion 18](#_Toc35300628)

[5. References 19](#_Toc35300629)

[6. Appendix 20](#_Toc35300630)

# List of Tables

[Table 1. Factors influencing electric prices 7](#_Toc35300771)

[Table 2. Correlation matrix of electric price data 10](#_Toc35300772)

[Table 3. First 8 items of the WEP Timeseries 11](#_Toc35300773)

[Table 4. Supervised data generated from 2019 data 12](#_Toc35300774)

[Table 5. Testing et generated from 2020 data 13](#_Toc35300775)

[Table 6. Software versions used 14](#_Toc35300776)

[Table 7. Model parameters 14](#_Toc35300777)

[Table 8. Model compilation and fit parameters 14](#_Toc35300778)

[Table 9. Results of testing neurons number 15](#_Toc35300779)

[Table 10. Epoch testing results 15](#_Toc35300780)

[Table 11. Batch size testing results 16](#_Toc35300781)

[Table 12. Error metrics in predicting 1-day ahead WEP 17](#_Toc35300782)

# List of Figures

[Figure 1. How the electricity market works 6](#_Toc35300783)

[Figure 2. 2019 Electric Data 8](#_Toc35300784)

[Figure 3. Electric Prices in 2019 9](#_Toc35300785)

[Figure 4. Outliers truncated 9](#_Toc35300786)

[Figure 5. Daily mean price data plotted across the hour of the day over the past 4 years 10](#_Toc35300787)

[Figure 6. Training loss over time 15](#_Toc35300788)

[Figure 7. 1-day forecast results 17](#_Toc35300789)

[Figure 8. Sliding window for predicting 10 days ahead 18](#_Toc35300790)

[Figure 9. 10-day forecast results 18](#_Toc35300791)

# Introduction

## Background

The Energy Market Authority (EMA) is a government entity started to promote competition in Singapore’s energy market and to ensure the energy supplied is reliable and secure.

Power generation companies generate electricity from natural gas and oil and sell them to the wholesale market. Electricity retailers then buy the electricity from this wholesale market and sell to their customers.

Since 2001 [1], EMA has slowly opened the energy retail market to other competitors for business consumers. The high electrical consumption by these businesses means that the cost of electricity plays a big part in their running cost and profits. They will benefit from the increase flexibility and choices when choosing their own retailers who offer different pricing plans for different needs.

Then in May 2019, EMA fully opened the energy market to all households and smaller business accounts. Everyone can now benefit from the flexible plans offered by the numerous retailers.

As of March 2020, there are 3 ways of purchasing electricity for households: Fixed price plans, discounted off the regulated tariff plans and wholesale price.

Fixed price plans are like traditional regulated tariff from SP Group where a fixed price agreed beforehand and calculated per kWh is billed every month.

The discounted off the regulated tariff plans offers a fixed discount of the traditional regulated tariff from SP Group and calculated per kWh for billing every month.

Lastly, any consumers can buy from the energy supplier directly in the wholesale market where half-hourly prices are used to determine the cost at time of usage. However, a 10-day lag is imposed in calculating and releasing of the wholesale price.

Having the ability to forecast future prices is important to both electrical suppliers and consumers during the bidding process. Suppliers can optimise their generation of electricity to prevent wastage and consumers can adjust their usage habits, less during high prices and more during low prices.Thus successful predictions can lead to rewarding monetary returns.

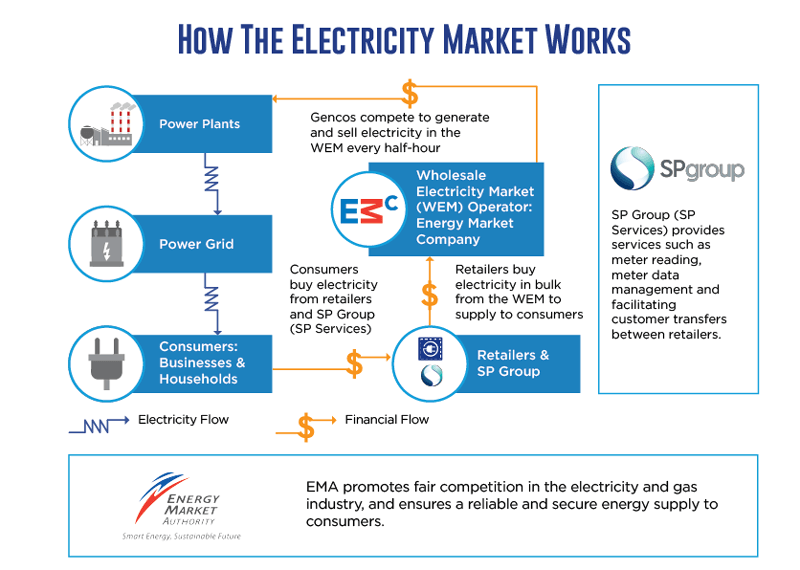


Figure 1. How the electricity market works

## Purpose and Scope

Many researches had been done on predicting future electrical price. Both statistical methods and artificial neural network have both achieved certain rates of success in predicting the future.

Statistical methods like Autoregressive Integrated Moving Average (ARIMA) usually involve solely the historical prices to perform the regression while the artificial neural network can involve both historical prices and other factors that can influence the electrical prices.

For this project, we will be focusing on the artificial neural network method to forecast the Wholesale Electricity Price (WEP) in Singapore. The WEP is the cost charged to the consumer upon the time of use, and ultimately the price that the consumer must pay.

Due to the lag time of 10 days in which the WEP is released to the public, we will need to be able to forecast 10 days in advance for the viability of this project.

# Literature Review

## Factors Affecting Electric Prices and Trends

Sanjeev et al. generalise electric price to contain the following attributes: high volume data with small timesteps, constantly changing mean and variance, highly volatile and outliers are common. They deduce that this is due to the non-tangible aspect of electricity where it cannot be easily stored and there must be an equilibrium between the electric load and generators. Also, demand rarely changes over the small timeframe and the electricity market is commonly oligopolistic. Lastly, both load and generation of electricity can be affected by very unpredictable events. Sudden rain and cloud covers can reduce electricity generated via solar while unforeseen dip in temperature can lead to higher load consumed by heaters. [2]

Sanjeev et al. then categorised the probable factors affecting the price of electricity into 5 classes: market characteristics, nonstrategic uncertainties, other stochastic uncertainties, behaviour indices, and temporal effects.

|  |  |
| --- | --- |
| **Class** | **Input variable** |
| **Market Characteristics** | (1) Historical load f(load), (2) System load rate, (3) imports/exports, (4) capacity excess/shortfall (5) Historical reserves (6) Nuclear, (7) thermal, (8) hydro generation, (9) generation capacity, (10) net-tie flows, (11) MRR, (12) system’s binding constraints, (13) line limits |
| **Nonstrategic Uncertainties** | (15) Forecast load, (16) Forecast reserves, (17) temperature, (18) dew point temperature, (19) weather, (20) oil price, (21) gas price, (22) fuel price |
| **Other Stochastic Uncertainties** | (23) Generation outages, (24) line status, (25) line contingency information, (26) congestion index |
| **Behaviour Indices** | (27) Historical prices, (28) Demand elasticity, (29) bidding strategies, (30) spike existence index, (31) ID flag |
| **Temporal Effects** | (32) Settlement period, (33) day type, (34) month, (35) holiday code, (36) Xmas code, (37) clock change, (38) season, (39) summer index, (40) winter index |

Table 1. Factors influencing electric prices

Using these factors, they further classify them into different input variables used by different researchers with their own predictive models. Specifically, majority of the factors used are those of (1) Historical load, (15) Forecast load and (27) Historical prices in Table 1.

## Methodology in Price Forecasting

### Data Pre-processing and Analysis

According to 2 papers [3] [4], removal of price spikes and outliers gives better accuracy in their neural network models with H.Y. Yamin et al improving their models from 39.89% and 15.47% in mean absolute percentage error (MAPE) of their training and testing sets respectively to 7.98 and 13.7%. Furthermore, instead of simply removing the spikes, a price ceiling was implemented, allowing the model to be trained with these spikes still.

In Singapore context, Shrestha and Qiao was able to determine that the available generation capacity has the greatest influence in determining the price of the electricity [5]. The correlation was only relevant when the mean price was calculated over a time period but the spot price during time of usage is more crucial for end users to optimise their electricity usage and reduce cost.

### Neural Network

Qi and Zhang [6] describe the difficulty faced when building an artificial neural network. To prevent overfitting, the dataset should be split into 3 parts: training, validating and testing. The training set should be used for modelling the network, tuning the parameters estimations with different network configurations. This model is then evaluated with the validating datasets to find the best specifications. Validity is then lastly checked with the testing dataset.

They also decided to use the past observations of their timeseries datasets as the inputs and the future values as the output.

Yilmaz and Kaynar [7] also states that neural network can be a substitute for statistical methods, in solving autocorrelation and regression problems. The artificial network is great for extracting patterns and trends from complex datasets too difficult for humans or other computing methods to recognise. Multilayer perceptron (MLP) and radial basis function (RBF) are found to be widely used for regression and classifications problems.

# Discussion

## Data and Analysis

All data are downloaded and compiled from the Energy Market Company Pte Ltd (EMC) website. They are the middleman between electricity buyer and seller, regulating the market and providing the trading infrastructure for Singapore.

The first five rows of the 2019 data are shown in Figure 2 where the Wholesale Electricity Price (WEP), Uniform Singapore Energy Price (USEP), power demanded, gross power generated, and net power generated are compiled against the datetime index.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **DATE** | **PERIOD** | **WEP ($/MWh)** | **USEP ($/MWh)** | **DEMAND (MW)** | **GROSS INJECTION (MWh)** | **NET INJECTION (MWh)** |
| 1/1/2019 0:00 | 1 | 83.33 | 82.7 | 5201.89 | 2555.1 | 2362.296 |
| 1/1/2019 0:30 | 2 | 83.83 | 82.71 | 5150.461 | 2549.41 | 2357.615 |
| 1/1/2019 1:00 | 3 | 83.19 | 82.7 | 5106.794 | 2519.013 | 2327.042 |
| 1/1/2019 1:30 | 4 | 83.13 | 82.69 | 5075.841 | 2492.473 | 2300.457 |
| 1/1/2019 2:00 | 5 | 83.2 | 82.67 | 5044.147 | 2453.576 | 2261.511 |

Figure 2. 2019 Electric Data

The prices of 2019 in Figure 3 intuitively shows large amount of random price spikes and any trends or seasonality are not immediately obvious within a year.

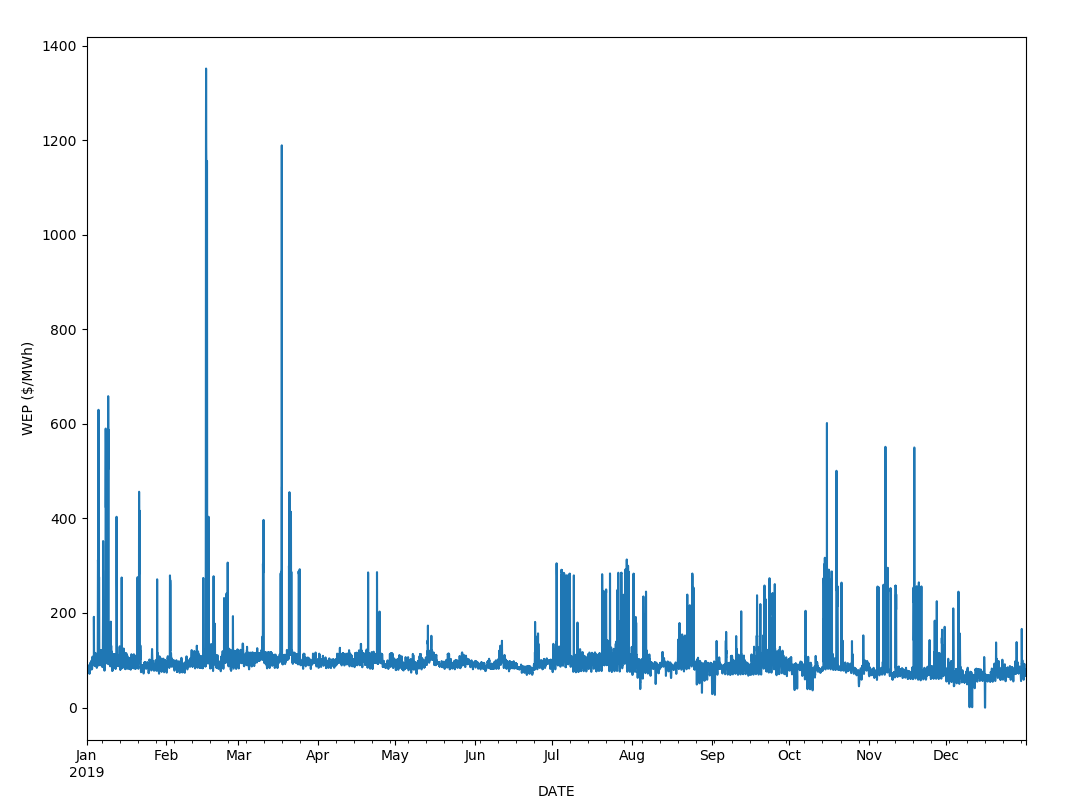


Figure 3. Electric Prices in 2019

In Figure 4, outliers were truncated to within 3 standard deviation from the mean to allow better visualisation of the monthly and daily trends if any.

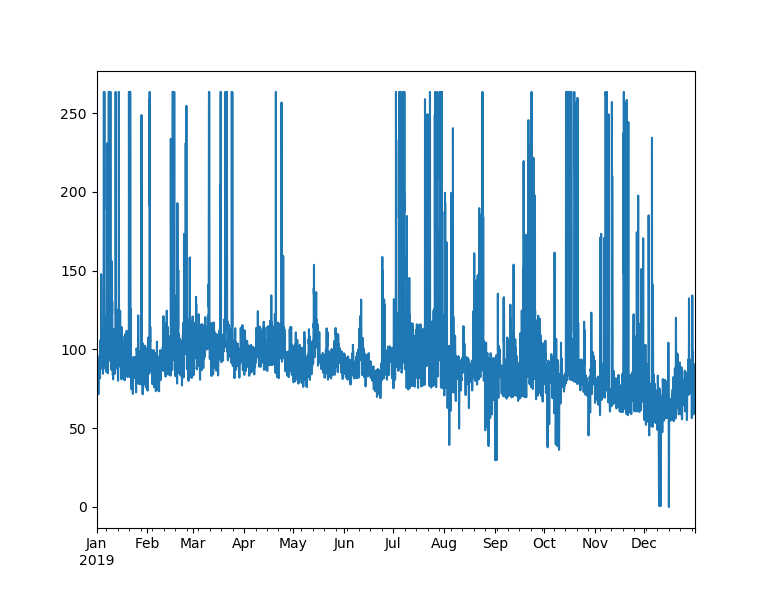


Figure 4. Outliers truncated

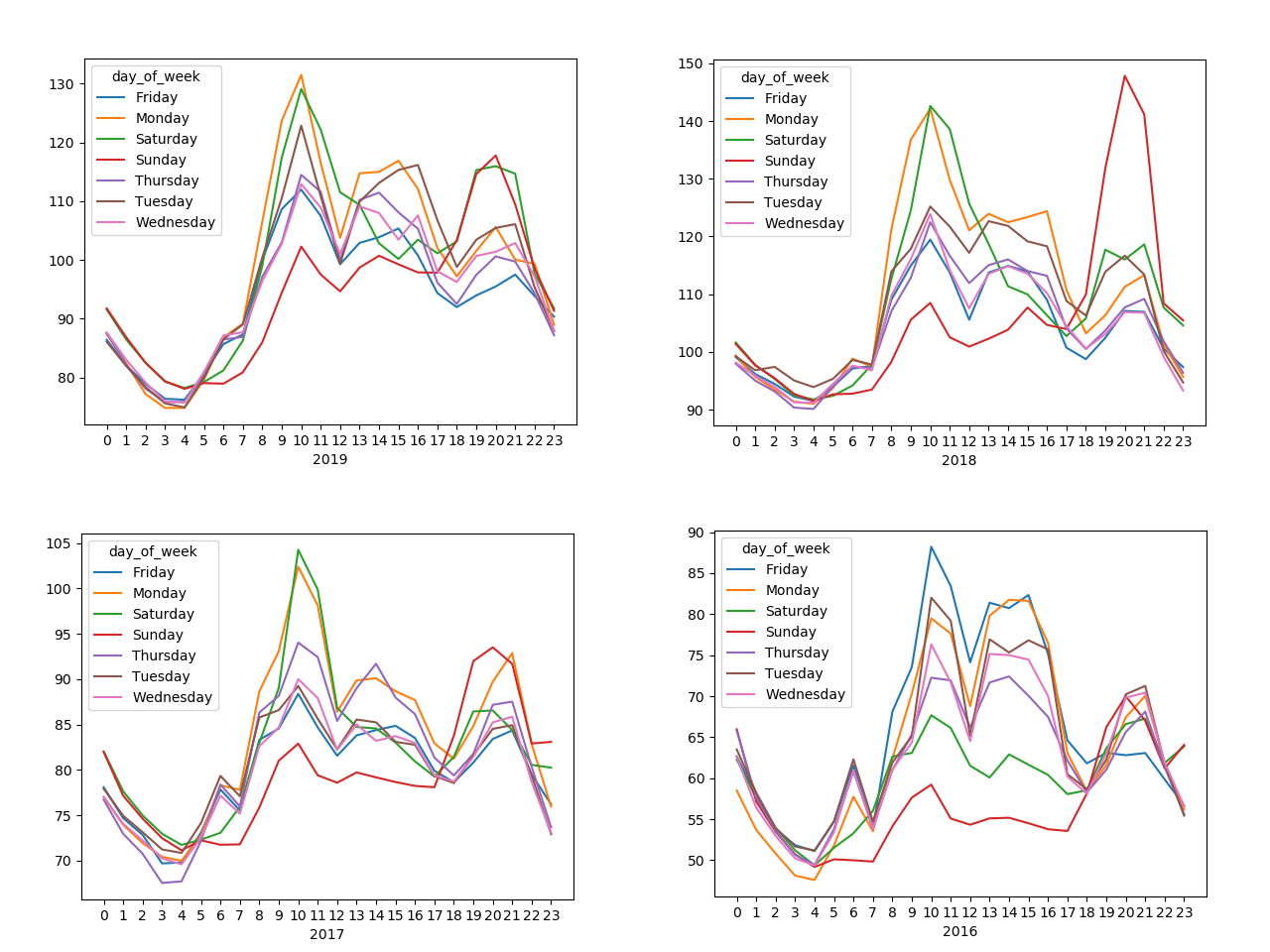
We further analyse the effect of date and time on the WEP in Figure 5. Observation on the daily mean price shows the same trend on the past 4 years of data. The duration between 8 to 10 am and 6 to 9 pm shows large spikes in prices across all the days of the week with Sunday being the lowest during the day but highest during the night. 

Figure 5. Daily mean price data plotted across the hour of the day over the past 4 years

Plotting the correlation matrix in Table 2 shows that neither demand nor supply are highly correlated to the WEP. The high correlation between WEP and USEP is due to WEP being derived from USEP and the different tariffs and administrative costs. From these observations, trying to predict the spot prices simply using demand and supply in Singapore may not be very effective. A timeseries approach will be taken for the prediction.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **PERIOD** | **WEP ($/MWh)** | **USEP ($/MWh)** | **DEMAND (MW)** | **GROSS INJECTION (MWh)** | **NET INJECTION (MWh)** |
| **PERIOD** | 1 | 0.141533322 | 0.143468486 | 0.538817247 | 0.555029534 | 0.56109735 |
| **WEP ($/MWh)** | 0.1415333 | 1 | 0.999900995 | 0.25060302 | 0.256192447 | 0.253536614 |
| **USEP ($/MWh)** | 0.1434685 | 0.999900995 | 1 | 0.254470731 | 0.26015551 | 0.257450558 |
| **DEMAND (MW)** | 0.5388172 | 0.25060302 | 0.254470731 | 1 | 0.995496467 | 0.992566336 |
| **GROSS INJECTION (MWh)** | 0.5550295 | 0.256192447 | 0.26015551 | 0.995496467 | 1 | 0.995956884 |

Table 2. Correlation matrix of electric price data

## Feature Engineering

Since the weekly data shows signs of seasonality and the characteristics of the prices, we propose a 7-day time lag to be used to train and predict the next day price. 7 days of data requires a lag time step of 336 and a day of data needs 48 future time step due to the half-hour pricing in the dataset. Thus, we can create a supervised dataset where the input and output vector will be 336 and 48 respectively, totaling to a size of 384 columns in our training data.

The 2019 WEP price will be used for training and validation while the 2020 WEP price up to March will be used to testing.

### Creating the training set

#### Transform data into timeseries

Generating the training data requires first converting the 2019 data into a timeseries data. The datetime index will help to slice the data during the process of training and validating.

|  |  |
| --- | --- |
|  | WEP |
| 2015-01-01 00:00:00 | 92.055 |
| 2015-01-01 01:00:00 | 90.660 |
| 2015-01-01 02:00:00 | 82.655 |
| 2015-01-01 03:00:00 | 76.625 |
| 2015-01-01 04:00:00 | 75.865 |
| 2015-01-01 05:00:00 | 75.325 |
| 2015-01-01 06:00:00 | 76.685 |
| 2015-01-01 07:00:00 | 77.510 |

Table 3. First 8 items of the WEP Timeseries

#### Building the lag dataset

The first 336 columns *(t-336, t-335, t-334, t-333, …, t-4, t-3, t-2, t-1)* are generated from the price before timestep *t*. The next 47 columns *(t+1, t+2, t+3, t+4, …, t+44, t+45, t+46, t+47)* are generated from the price after timestep *t*.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| DATE | var1(t-336) | var1(t-335) | var1(t-334) | var1(t-333) | … | var1(t+44) | var1(t+45) | var1(t+46) | var1(t+47) |
| 2019-01-08 00:30:00 | 83.83 | 83.19 | 83.13 | 83.20 | … | 115.01 | 103.04 | 93.63 | 105.15 |
| 2019-01-08 01:00:00 | 83.19 | 83.13 | 83.20 | 78.81 | … | 103.04 | 93.63 | 105.15 | 100.07 |
| 2019-01-08 01:30:00 | 83.13 | 83.20 | 78.81 | 78.30 | … | 93.63 | 105.15 | 100.07 | 97.01 |
| 2019-01-08 02:00:00 | 83.20 | 78.81 | 78.30 | 73.55 | … | 105.15 | 100.07 | 97.01 | 97.54 |
| ... | ... | ... | ... | ... | … | ... | ... | ... | ... |
| 2019-12-30 22:00:00 | 80.92 | 75.99 | 71.83 | 67.34 | … | 79.40 | 79.94 | 78.58 | 75.21 |
| 2019-12-30 22:30:00 | 75.99 | 71.83 | 67.34 | 66.62 | … | 79.94 | 78.58 | 75.21 | 72.43 |
| 2019-12-30 23:00:00 | 71.83 | 67.34 | 66.62 | 66.32 | … | 78.58 | 75.21 | 72.43 | 69.58 |
| 2019-12-30 23:30:00 | 67.34 | 66.62 | 66.32 | 58.67 | … | 75.21 | 72.43 | 69.58 | 70.21 |

Table 4. Supervised data generated from 2019 data

#### Building the test dataset

Similarly, the 2020 data must be converted into a supervised dataset but without the need of the 47 future time steps. Only the input vectors will be fed into the model for prediction and the results will be compared to the existing data.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| DATE | var1(t-336) | var1(t-335) | var1(t-334) | … | var1(t-2) | var1(t-1) | WEP |
| 2020-01-08 00:30:00 | 75.50 | 72.69 | 70.36 | … | 65.77 | 53.85 | 69.74 |
| 2020-01-08 01:00:00 | 72.69 | 70.36 | 70.33 | … | 53.85 | 69.74 | 55.00 |
| 2020-01-08 01:30:00 | 70.36 | 70.33 | 69.55 | … | 69.74 | 55.00 | 53.31 |
| 2020-01-08 02:00:00 | 70.33 | 69.55 | 68.62 | … | 55.00 | 53.31 | 52.34 |
| ... | ... | ... | ... | … | ... | ... | ... |
| 2020-03-01 21:30:00 | 79.59 | 76.70 | 73.22 | … | 79.78 | 85.19 | 79.49 |
| 2020-03-01 22:00:00 | 76.70 | 73.22 | 72.83 | … | 85.19 | 79.49 | 73.27 |
| 2020-03-01 22:30:00 | 73.22 | 72.83 | 70.71 | … | 79.49 | 73.27 | 71.14 |
| 2020-03-01 23:00:00 | 72.83 | 70.71 | 70.53 | … | 73.27 | 71.14 | 70.11 |

Table 5. Testing et generated from 2020 data

## Neural Network

An artificial neural network is a system of interconnected nodes or neurons organized in layers, processing information between each neurons and layers. Typically, 3 layers are used to build the network: the input layer, the hidden layer and the output layer.

The input layer consists of neurons corresponding to the input of our data, the 336 historical timesteps from *t*. The hidden layer can consist of 1 or more layers with any number of neurons. The inputted information flowing through this layer are processed and characterized by weights, biases and a pre-set activation function to reach the output data. Lastly, the output layer will contain as many neurons as the number of output data needed, 48 in total for the timesteps we are predicting into the future.

A typical neural network that is built using these layers of neurons is the MLP. MLP requires a supervised learning dataset and backpropagation is used for training. In this project, we will be using the Model object in Keras [6] to sequentially build our network and fit it into a model for prediction.

Finding the optimal configuration for the network and model requires some experimentation. For this project, we will be settling with 4 layers, 1 input layer, 2 hidden layers and 1 output layer, using the mean absolute error (MAE) as the loss function and the mean square error (MSE) to validate.

### Building the model

#### Software environment

|  |  |
| --- | --- |
| Software | Version |
| Python | 3.7.0 |
| Keras | 2.3.1 |
| TensorFlow | 2.1.0 |

Table 6. Software versions used

For this project, we are using Python3 as the scripting language for running and processing the tests used. Keras is a machine learning library written for Python and TensorFlow will be the backend engine for Keras.

#### Building the model

Building a model in Keras can be done in layers using their Sequential model API [9] . The default settings for this project are shown in Table 7 and 8.

1. The input shape, activation function and number of neurons must be declared in the first hidden layer
2. Subsequent hidden layers only need the activation function and number of neurons
3. The output layer needs the output function and the same number of neurons corresponding to the outputs and the
4. The model is compiled with the loss function, optimizer and validation metric.
5. The model is fitted with the dataset split into training and validation set. The epoch size and batch size will determine the training procedure.

The model will be trained 5 times per testing parameters and the lowest mean MSE will be chosen as the optimal option.

|  |  |  |  |
| --- | --- | --- | --- |
| Layer | Parameters | | |
| Hidden layer 1 | Input shape = (336,) | Neurons = 240 | Activation = ReLu |
| Hidden layer 2 | Neurons = 240 | Activation = ReLu |  |
| Output layer | Neurons = 48 | Activation = Linear |  |

Table 7. Model parameters

|  |  |  |  |
| --- | --- | --- | --- |
| Model Compilation and Fit | | | |
| Compile | Loss = MAE | Optimizer = adam | Metrics = MSE |
| Fit | Epoch = 100 | Batch = 48 | Validation split = 0.2 |

Table 8. Model compilation and fit parameters

#### Finding the best neurons number for each layer

We have chosen 6 different iterations of the layers’ neurons for testing and the results are shown in Table9. Our dataset seems to favor high number of neurons during training as the less neurons we used, the higher the MSE during validation. Thus, we decided to use 240 neurons for each of our hidden layers.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Loss Function = MAE, Epoch = 200, Batch size = 48 | | | | | | |
| Neurons (1st layer, 2nd layer) | **(240,240)** | **(240,120)** | **(240,60)** | **(120,60)** | **(120,30)** | **(60,20)** |
| MSE | 532.27 | 552.11 | 600.70 | 660.59 | 730.57 | 757.94 |

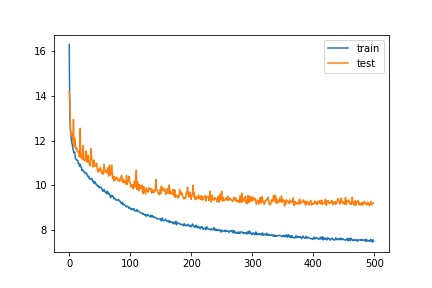
Table 9. Results of testing neurons number

#### Finding the epoch

5 epoch size was chosen for testing and the results are shown in Table 10. We observed that the longer we train, the lower the MSE. Therefore, we decided to go with the highest epoch we tested for our project.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Loss Function = MAE, Layer 1 = 240 neurons, Layer 2 = 240 neurons, Batch size = 48 | | | | | |
| Epoch | **20** | **50** | **100** | **200** | **300** |
| MSE | 721.27 | 669.45 | 593.31 | 536.20 | 531.62 |

Table 10. Epoch testing results



MAE

Epoch

Figure 6. Training loss over time

#### Finding the optimal batch size

During the batch size testing, we observed that a batch size of 64 has the lowest MSE over an average of 5. This can be due to the network being able to see a larger amount of data and detecting the seasonal effect of WEP. Since a weekly season is present in our data, and a week is 48 timesteps, a batch size of 48 and higher should result in faster learning rate and better prediction.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Loss Function = Mean Absolute Error, Epoch = 300, Batch size = 48 | | | | | | |
| Batch size | 4 | 8 | 16 | 32 | 48 | 64 |
| MSE | 704.226965 | 649.406872 | 597.228112 | 512.462744 | 491.711132 | 485.659454 |

Table 11. Batch size testing results

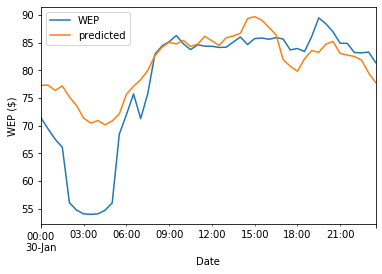
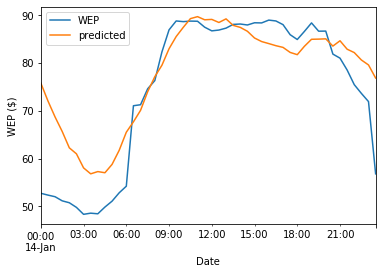
#### Final model configuration

Using an epoch of 500, batch size of 64 and 240 neurons for each hidden layer, a trained model was generated. This model will be used to forecast the next day WEP.

### Modelling the future

The trained model is validated against the 2020 test set for the next day WEP. Similarly to when training the model, the outliers in the test set will be truncated to 3 standard deviation from the mean before being fed into the model. However, when comparing between the predicted and actual, the non-truncated values will be used instead.

#### Forecasting results -1-day ahead - model\_240\_240\_MLP\_300\_64.h5



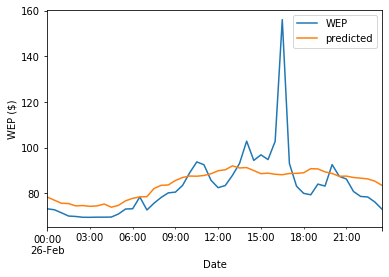
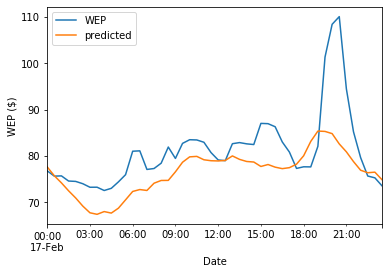


Figure 7. 1-day forecast results

From Figure 6, our model shows capability in predicting the daily trend shown in our test data. The trough between 2 to 4 pm and the gradual increase after that were mostly predicted in the 4 cases. However, it is not able to detect outliers as shown in the peaks in 17 Feb 10pm and 26 Feb 4pm.

|  |  |  |  |
| --- | --- | --- | --- |
| Date | MAE | MSE | MAPE |
| 14-01-2020 | 5.758729528 | 63.07466827 | 9.658947159 |
| 21-01-2020 | 4.930880095 | 54.88411987 | 7.696054389 |
| 17-02-2020 | 5.453149796 | 68.44849557 | 6.195421877 |
| 26-02-2020 | 5.515156008 | 120.1595212 | 5.860455309 |

Table 12. Error metrics in predicting 1-day ahead WEP

#### Forecasting results - 10-day ahead - model\_240\_240\_MLP\_300\_64.h5

Forecasting 10 days ahead requires a sliding window for the inputted values as shown in Figure 7. The newly predicted values of the next day will be used as the latest input for the prediction of the following day.

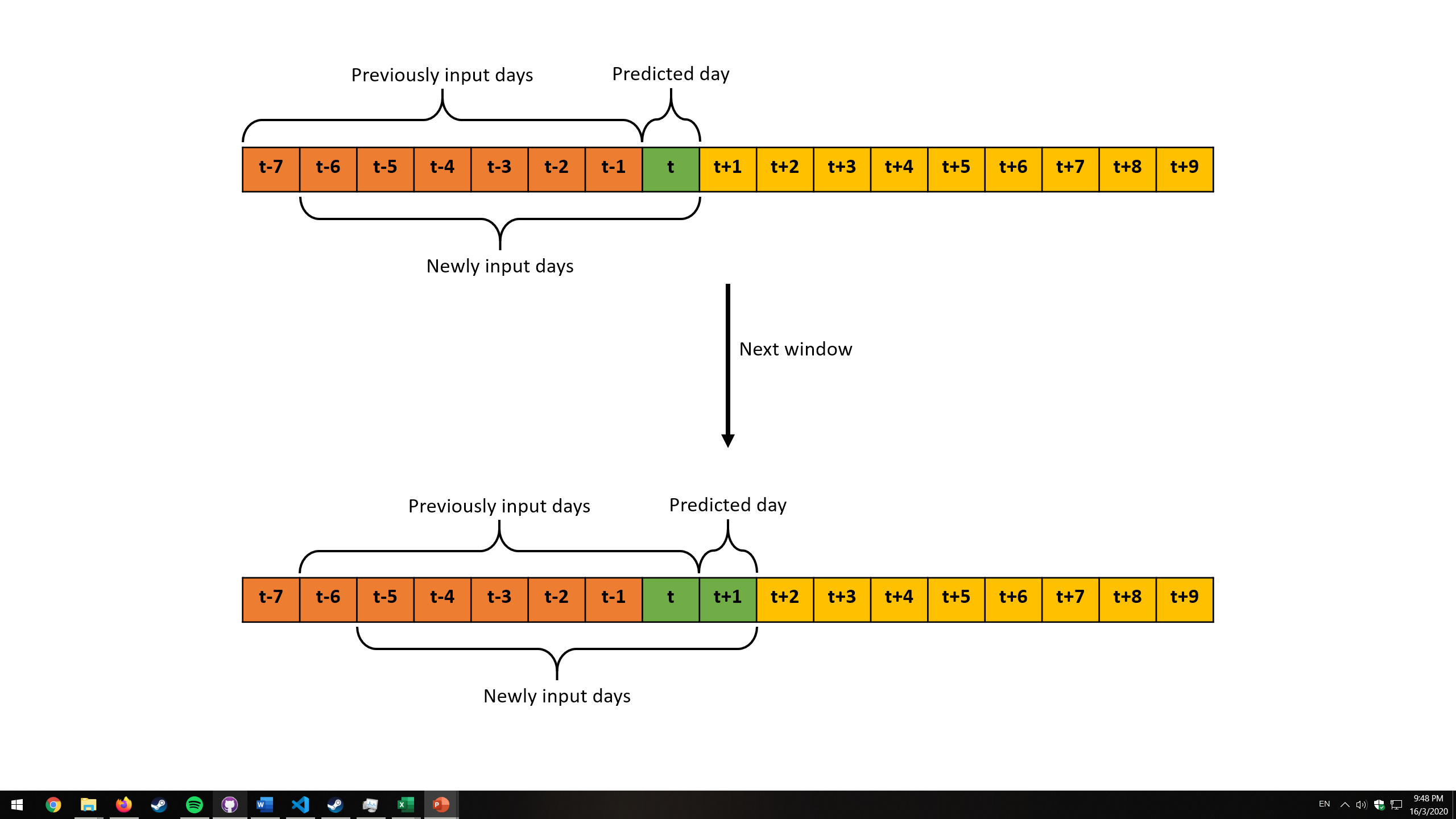


Figure 8. Sliding window for predicting 10 days ahead

Therefore, by sliding the window 10 days forward, our model was able to reproduce the daily trend in the forecast but similarly to the 1-day forecast, not able to predict the large spikes in prices as shown in Figure 8.

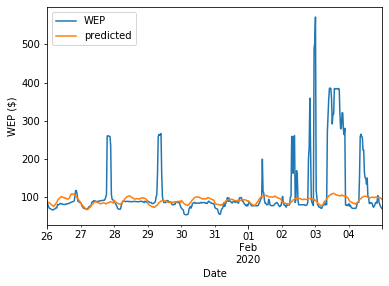
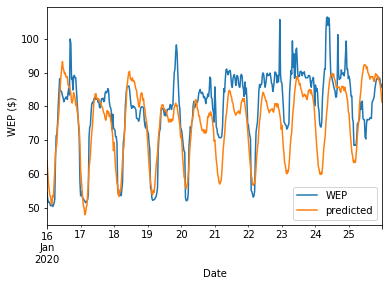


Figure 9. 10-day forecast results

|  |  |  |  |
| --- | --- | --- | --- |
| Date from | MAE | MSE | MAPE |
| 15-01-2020 | 6.8970004644 | 74.60569008 | 8.5715377387 |
| 25-01-2020 | 34.329413709 | 5878.902384 | 19.7400436429 |

# Conclusion

The MLP proves to be effective in predicting future values with seasonal effects. This was shown by the neural network ability to map the weekly, daily and hourly pattern of the historical WEP onto the prediction of the next day prices.

However, due to the unpredictable nature of supplying and distributing electricity in Singapore, where generator and transmission infrastructure might fail suddenly, our model cannot accurately forecast the large spikes in price we have seen in our data. We could only try to remove these outliers and predict for the best case scenario where everything is working as per normal.

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|  |  |
| --- | --- |
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# Appendix

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Predicted WEP for 14 Jan 2020 | | | | | |
| Date | WEP | predicted | MAE | MSE | MAPE |
| 14/1/2020 0:00 | 52.74 | 75.7868576 | 23.0468576 | 531.1576455 | 43.69900949 |
| 14/1/2020 0:30 | 52.36 | 72.04919434 | 19.68919434 | 387.6643736 | 37.60350332 |
| 14/1/2020 1:00 | 52.02 | 68.69690704 | 16.67690704 | 278.1192285 | 32.05864484 |
| 14/1/2020 1:30 | 51.16 | 65.66957092 | 14.50957092 | 210.5276484 | 28.36116287 |
| 14/1/2020 2:00 | 50.76 | 62.24240875 | 11.48240875 | 131.8457108 | 22.62097863 |
| 14/1/2020 2:30 | 49.79 | 60.99349976 | 11.20349976 | 125.5184068 | 22.50150584 |
| 14/1/2020 3:00 | 48.34 | 58.05345917 | 9.713459167 | 94.351289 | 20.09404048 |
| 14/1/2020 3:30 | 48.58 | 56.80533218 | 8.225332184 | 67.65608953 | 16.93151952 |
| 14/1/2020 4:00 | 48.45 | 57.27745819 | 8.827458191 | 77.92401811 | 18.21972795 |
| 14/1/2020 4:30 | 49.86 | 57.03547287 | 7.17547287 | 51.48741091 | 14.39124122 |
| 14/1/2020 5:00 | 51.09 | 58.7821846 | 7.692184601 | 59.16970393 | 15.05614524 |
| 14/1/2020 5:30 | 52.84 | 61.72221756 | 8.88221756 | 78.89378878 | 16.80964716 |
| 14/1/2020 6:00 | 54.22 | 65.50741577 | 11.28741577 | 127.4057548 | 20.81780851 |
| 14/1/2020 6:30 | 71.05 | 67.68184662 | 3.368153381 | 11.3444572 | 4.740539594 |
| 14/1/2020 7:00 | 71.26 | 70.08680725 | 1.173192749 | 1.376381226 | 1.646355247 |
| 14/1/2020 7:30 | 74.6 | 73.98226166 | 0.617738342 | 0.38160066 | 0.828067483 |
| 14/1/2020 8:00 | 76.3 | 77.11875916 | 0.818759155 | 0.670366554 | 1.07307884 |
| 14/1/2020 8:30 | 82.3 | 79.52051544 | 2.779484558 | 7.725534409 | 3.377259487 |
| 14/1/2020 9:00 | 86.92 | 82.96832275 | 3.951677246 | 15.61575306 | 4.546338295 |
| 14/1/2020 9:30 | 88.78 | 85.51706696 | 3.262933044 | 10.64673205 | 3.67530192 |
| 14/1/2020 10:00 | 88.64 | 87.44937897 | 1.190621033 | 1.417578444 | 1.343209649 |
| 14/1/2020 10:30 | 88.75 | 89.26722717 | 0.517227173 | 0.267523948 | 0.582791181 |
| 14/1/2020 11:00 | 88.72 | 89.68289185 | 0.962891846 | 0.927160707 | 1.085315426 |
| 14/1/2020 11:30 | 87.48 | 89.02587128 | 1.545871277 | 2.389718005 | 1.767113942 |
| 14/1/2020 12:00 | 86.71 | 89.10546875 | 2.39546875 | 5.738270532 | 2.762621093 |
| 14/1/2020 12:30 | 86.88 | 88.46233368 | 1.582333679 | 2.503779872 | 1.821286463 |
| 14/1/2020 13:00 | 87.28 | 89.2158432 | 1.935843201 | 3.747488898 | 2.217968837 |
| 14/1/2020 13:30 | 88.06 | 87.86077881 | 0.199221191 | 0.039689083 | 0.226233467 |
| 14/1/2020 14:00 | 88.14 | 87.43497467 | 0.70502533 | 0.497060715 | 0.799892591 |
| 14/1/2020 14:30 | 87.94 | 86.62484741 | 1.315152588 | 1.729626329 | 1.495511244 |
| 14/1/2020 15:00 | 88.4 | 85.21607208 | 3.183927917 | 10.13739698 | 3.601728413 |
| 14/1/2020 15:30 | 88.37 | 84.47099304 | 3.899006958 | 15.20225526 | 4.412138687 |
| 14/1/2020 16:00 | 88.96 | 84.04885101 | 4.911148987 | 24.11938437 | 5.520626109 |
| 14/1/2020 16:30 | 88.78 | 83.60823822 | 5.17176178 | 26.74711991 | 5.825368078 |
| 14/1/2020 17:00 | 88.01 | 83.25314331 | 4.756856689 | 22.62768556 | 5.404904772 |
| 14/1/2020 17:30 | 85.91 | 82.20094299 | 3.709057007 | 13.75710388 | 4.317375168 |
| 14/1/2020 18:00 | 84.9 | 81.73125458 | 3.168745422 | 10.04094755 | 3.732326764 |
| 14/1/2020 18:30 | 86.59 | 83.47579193 | 3.114208069 | 9.698291896 | 3.59649852 |
| 14/1/2020 19:00 | 88.37 | 84.94688416 | 3.423115845 | 11.71772209 | 3.873617568 |
| 14/1/2020 19:30 | 86.64 | 84.98225403 | 1.657745972 | 2.748121707 | 1.913372543 |
| 14/1/2020 20:00 | 86.66 | 85.04170227 | 1.618297729 | 2.618887541 | 1.867410258 |
| 14/1/2020 20:30 | 81.85 | 83.52559662 | 1.675596619 | 2.807624028 | 2.047155307 |
| 14/1/2020 21:00 | 81 | 84.63871765 | 3.638717651 | 13.24026615 | 4.492244014 |
| 14/1/2020 21:30 | 78.52 | 82.87435913 | 4.354359131 | 18.96044344 | 5.54554143 |
| 14/1/2020 22:00 | 75.46 | 82.16723633 | 6.707236328 | 44.98701916 | 8.888465847 |
| 14/1/2020 22:30 | 73.63 | 80.61723328 | 6.987233276 | 48.82142886 | 9.489655407 |
| 14/1/2020 23:00 | 71.92 | 79.58010101 | 7.660101013 | 58.67714753 | 10.65086348 |
| 14/1/2020 23:30 | 56.8 | 76.84832764 | 20.04832764 | 401.935441 | 35.29635147 |
| Mean = | | | 5.758729528 | 63.07466827 | 9.658947159 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Predicted WEP for 30 Jan 2020 | | | | | |
| Date | WEP | predicted | MAE | MSE | MAPE |
| 30/1/2020 0:00 | 71.42 | 77.29811859 | 5.878118591 | 34.55227817 | 8.23035367 |
| 30/1/2020 0:30 | 69.41 | 77.31459808 | 7.904598083 | 62.48267086 | 11.38826982 |
| 30/1/2020 1:00 | 67.53 | 76.37504578 | 8.845045776 | 78.23483479 | 13.09795021 |
| 30/1/2020 1:30 | 66.09 | 77.1813736 | 11.0913736 | 123.0185683 | 16.78222665 |
| 30/1/2020 2:00 | 56.07 | 75.17914581 | 19.10914581 | 365.1594537 | 34.08087357 |
| 30/1/2020 2:30 | 54.72 | 73.61036682 | 18.89036682 | 356.8459586 | 34.52186919 |
| 30/1/2020 3:00 | 54.05 | 71.3480072 | 17.2980072 | 299.2210532 | 32.0037136 |
| 30/1/2020 3:30 | 53.97 | 70.47576141 | 16.50576141 | 272.4401598 | 30.58321552 |
| 30/1/2020 4:00 | 54.06 | 70.91464996 | 16.85464996 | 284.0792254 | 31.17767289 |
| 30/1/2020 4:30 | 54.7 | 70.14792633 | 15.44792633 | 238.6384279 | 28.24118159 |
| 30/1/2020 5:00 | 56.03 | 70.84018707 | 14.81018707 | 219.3416411 | 26.43260231 |
| 30/1/2020 5:30 | 68.46 | 72.1284256 | 3.668425598 | 13.45734637 | 5.358494885 |
| 30/1/2020 6:00 | 71.99 | 75.65962219 | 3.669622192 | 13.46612703 | 5.097405462 |
| 30/1/2020 6:30 | 75.73 | 77.128685 | 1.398684998 | 1.956319722 | 1.846936482 |
| 30/1/2020 7:00 | 71.28 | 78.29644775 | 7.016447754 | 49.23053908 | 9.843501338 |
| 30/1/2020 7:30 | 75.82 | 79.97969055 | 4.159690552 | 17.30302549 | 5.486270841 |
| 30/1/2020 8:00 | 82.92 | 82.66042328 | 0.259576721 | 0.067380074 | 0.313044767 |
| 30/1/2020 8:30 | 84.4 | 84.15851593 | 0.24148407 | 0.058314556 | 0.286118566 |
| 30/1/2020 9:00 | 85.18 | 85.06795502 | 0.112044983 | 0.012554078 | 0.131539074 |
| 30/1/2020 9:30 | 86.29 | 84.77113342 | 1.518866577 | 2.306955679 | 1.760188408 |
| 30/1/2020 10:00 | 84.79 | 85.40447998 | 0.61447998 | 0.377585646 | 0.724708079 |
| 30/1/2020 10:30 | 83.74 | 84.3155365 | 0.575536499 | 0.331242262 | 0.687289824 |
| 30/1/2020 11:00 | 84.61 | 84.72853088 | 0.118530884 | 0.01404957 | 0.140090868 |
| 30/1/2020 11:30 | 84.37 | 86.15753174 | 1.787531738 | 3.195269715 | 2.118681686 |
| 30/1/2020 12:00 | 84.35 | 85.32474518 | 0.974745178 | 0.950128162 | 1.155595943 |
| 30/1/2020 12:30 | 84.14 | 84.49498749 | 0.354987488 | 0.126016116 | 0.421900984 |
| 30/1/2020 13:00 | 84.18 | 85.88800812 | 1.708008118 | 2.91729173 | 2.02899515 |
| 30/1/2020 13:30 | 85.12 | 86.19861603 | 1.078616028 | 1.163412535 | 1.267171085 |
| 30/1/2020 14:00 | 86.03 | 86.69158173 | 0.661581726 | 0.43769038 | 0.769012817 |
| 30/1/2020 14:30 | 84.66 | 89.35404205 | 4.694042053 | 22.0340308 | 5.544580739 |
| 30/1/2020 15:00 | 85.74 | 89.70184326 | 3.961843262 | 15.69620203 | 4.620764243 |
| 30/1/2020 15:30 | 85.84 | 89.06832886 | 3.228328857 | 10.42210721 | 3.760867728 |
| 30/1/2020 16:00 | 85.61 | 87.76815796 | 2.158157959 | 4.657645776 | 2.520918069 |
| 30/1/2020 16:30 | 85.91 | 86.40758514 | 0.497585144 | 0.247590976 | 0.57919351 |
| 30/1/2020 17:00 | 85.66 | 81.92372131 | 3.736278687 | 13.95977842 | 4.361754245 |
| 30/1/2020 17:30 | 83.69 | 80.74328613 | 2.946713867 | 8.683122615 | 3.520986817 |
| 30/1/2020 18:00 | 83.94 | 79.83777618 | 4.102223816 | 16.82824024 | 4.88709056 |
| 30/1/2020 18:30 | 83.39 | 82.07052612 | 1.319473877 | 1.741011312 | 1.582292693 |
| 30/1/2020 19:00 | 86.08 | 83.56552887 | 2.51447113 | 6.322565065 | 2.92108635 |
| 30/1/2020 19:30 | 89.48 | 83.25411987 | 6.225880127 | 38.76158336 | 6.95784547 |
| 30/1/2020 20:00 | 88.41 | 84.73490143 | 3.675098572 | 13.50634951 | 4.15688109 |
| 30/1/2020 20:30 | 86.95 | 85.21205139 | 1.737948608 | 3.020465365 | 1.998790809 |
| 30/1/2020 21:00 | 84.9 | 83.06038666 | 1.839613342 | 3.384177249 | 2.166800168 |
| 30/1/2020 21:30 | 84.87 | 82.75681305 | 2.113186951 | 4.465559089 | 2.489910393 |
| 30/1/2020 22:00 | 83.22 | 82.50476837 | 0.715231628 | 0.511556282 | 0.859446802 |
| 30/1/2020 22:30 | 83.16 | 81.86167908 | 1.298320923 | 1.685637219 | 1.561232471 |
| 30/1/2020 23:00 | 83.29 | 79.53126526 | 3.758734741 | 14.12808685 | 4.51282836 |
| 30/1/2020 23:30 | 81.37 | 77.76493073 | 3.605069275 | 12.99652448 | 4.430464883 |
|  |  |  | 4.930880095 | 54.88411987 | 7.696054389 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Predicted WEP for 17 Feb 2020 | | | | | |
| index | WEP | predicted | MAE | MSE | MAPE |
| 17/2/2020 0:00 | 76.78 | 75.51327515 | 1.266724854 | 1.604591855 | 1.649810958 |
| 17/2/2020 0:30 | 75.64 | 74.44057465 | 1.199425354 | 1.43862118 | 1.585702478 |
| 17/2/2020 1:00 | 75.69 | 73.28771973 | 2.402280273 | 5.770950512 | 3.173841027 |
| 17/2/2020 1:30 | 74.58 | 72.25202179 | 2.32797821 | 5.419482548 | 3.121451073 |
| 17/2/2020 2:00 | 74.5 | 70.21577454 | 4.284225464 | 18.35458783 | 5.750638207 |
| 17/2/2020 2:30 | 74 | 69.20098877 | 4.79901123 | 23.03050879 | 6.485150311 |
| 17/2/2020 3:00 | 73.24 | 68.75177765 | 4.488222351 | 20.14413987 | 6.128102609 |
| 17/2/2020 3:30 | 73.25 | 69.47725677 | 3.772743225 | 14.23359144 | 5.150502696 |
| 17/2/2020 4:00 | 72.54 | 69.93054199 | 2.609458008 | 6.809271095 | 3.597267725 |
| 17/2/2020 4:30 | 73.01 | 70.87276459 | 2.137235413 | 4.567775209 | 2.927318741 |
| 17/2/2020 5:00 | 74.4 | 72.42843628 | 1.971563721 | 3.887063505 | 2.649951238 |
| 17/2/2020 5:30 | 75.95 | 73.2084198 | 2.7415802 | 7.516261994 | 3.609717183 |
| 17/2/2020 6:00 | 81.01 | 74.9044342 | 6.105565796 | 37.27793369 | 7.536805081 |
| 17/2/2020 6:30 | 81.09 | 76.04779053 | 5.042209473 | 25.42387637 | 6.218041032 |
| 17/2/2020 7:00 | 77.08 | 76.12332153 | 0.956678467 | 0.915233689 | 1.241150061 |
| 17/2/2020 7:30 | 77.28 | 76.5246582 | 0.755341797 | 0.57054123 | 0.977409157 |
| 17/2/2020 8:00 | 78.43 | 77.0696106 | 1.360389404 | 1.850659331 | 1.734526845 |
| 17/2/2020 8:30 | 81.91 | 77.90701294 | 4.002987061 | 16.02390541 | 4.887055379 |
| 17/2/2020 9:00 | 79.45 | 79.15449524 | 0.295504761 | 0.087323064 | 0.371938025 |
| 17/2/2020 9:30 | 82.7 | 78.84812927 | 3.851870728 | 14.8369081 | 4.65764296 |
| 17/2/2020 10:00 | 83.49 | 78.5907135 | 4.899286499 | 24.0030082 | 5.868111749 |
| 17/2/2020 10:30 | 83.44 | 77.77625275 | 5.663747253 | 32.07803295 | 6.787808309 |
| 17/2/2020 11:00 | 82.94 | 77.67811584 | 5.261884155 | 27.68742486 | 6.344205637 |
| 17/2/2020 11:30 | 80.71 | 78.29206085 | 2.417939148 | 5.846429723 | 2.995835891 |
| 17/2/2020 12:00 | 79.13 | 76.87358856 | 2.256411438 | 5.091392577 | 2.851524628 |
| 17/2/2020 12:30 | 78.97 | 76.06243134 | 2.907568665 | 8.453955539 | 3.681864841 |
| 17/2/2020 13:00 | 82.63 | 75.87350464 | 6.756495361 | 45.65022957 | 8.176806682 |
| 17/2/2020 13:30 | 82.87 | 75.95046997 | 6.919530029 | 47.87989583 | 8.349861264 |
| 17/2/2020 14:00 | 82.6 | 76.33152771 | 6.26847229 | 39.29374485 | 7.588949504 |
| 17/2/2020 14:30 | 82.45 | 77.19090271 | 5.25909729 | 27.65810431 | 6.378529157 |
| 17/2/2020 15:00 | 87.01 | 76.98509979 | 10.02490021 | 100.4986242 | 11.52154949 |
| 17/2/2020 15:30 | 86.95 | 76.84314728 | 10.10685272 | 102.1484719 | 11.62375241 |
| 17/2/2020 16:00 | 86.29 | 76.4394989 | 9.850501099 | 97.03237189 | 11.41557666 |
| 17/2/2020 16:30 | 83.01 | 75.98291016 | 7.027089844 | 49.37999167 | 8.465353384 |
| 17/2/2020 17:00 | 80.83 | 75.51300049 | 5.316999512 | 28.27048381 | 6.578002613 |
| 17/2/2020 17:30 | 77.3 | 75.6297226 | 1.670277405 | 2.789826609 | 2.160772839 |
| 17/2/2020 18:00 | 77.65 | 76.36603546 | 1.283964539 | 1.648564936 | 1.65352806 |
| 17/2/2020 18:30 | 77.63 | 78.1339035 | 0.503903503 | 0.253918741 | 0.649109241 |
| 17/2/2020 19:00 | 82.07 | 79.48306274 | 2.586937256 | 6.692244366 | 3.152110705 |
| 17/2/2020 19:30 | 101.3 | 80.34714508 | 20.96285492 | 439.4412864 | 20.69179244 |
| 17/2/2020 20:00 | 108.4 | 80.13502502 | 28.24497498 | 797.7786114 | 26.06105829 |
| 17/2/2020 20:30 | 110 | 80.08868408 | 29.94131592 | 896.4823989 | 27.21195666 |
| 17/2/2020 21:00 | 94.45 | 79.00889587 | 15.44110413 | 238.4276966 | 16.3484427 |
| 17/2/2020 21:30 | 85.19 | 79.25183105 | 5.938168945 | 35.26185042 | 6.970499994 |
| 17/2/2020 22:00 | 79.63 | 77.97328949 | 1.65671051 | 2.744689715 | 2.080510499 |
| 17/2/2020 22:30 | 75.66 | 77.72928619 | 2.069286194 | 4.281945352 | 2.734980431 |
| 17/2/2020 23:00 | 75.27 | 76.89289093 | 1.62289093 | 2.633774971 | 2.15609264 |
| 17/2/2020 23:30 | 73.55 | 76.07102966 | 2.521029663 | 6.355590562 | 3.427640602 |
|  |  |  | 5.453149796 | 68.44849557 | 6.195421877 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Predicted WEP for 26 Feb 2020 | | | | | |
| index | WEP | predicted | MAE | MSE | MAPE |
| 26/2/2020 0:00 | 73.28 | 74.7023468 | 1.422346802 | 2.023070424 | 1.940975439 |
| 26/2/2020 0:30 | 72.88 | 72.97664642 | 0.096646423 | 0.009340531 | 0.13261035 |
| 26/2/2020 1:00 | 71.54 | 71.5634079 | 0.023407898 | 0.00054793 | 0.032720014 |
| 26/2/2020 1:30 | 70.12 | 71.4734726 | 1.353472595 | 1.831888066 | 1.930223325 |
| 26/2/2020 2:00 | 69.93 | 70.69032288 | 0.760322876 | 0.578090876 | 1.0872628 |
| 26/2/2020 2:30 | 69.58 | 70.00102234 | 0.421022339 | 0.17725981 | 0.60509103 |
| 26/2/2020 3:00 | 69.56 | 70.83786011 | 1.277860107 | 1.632926454 | 1.837061684 |
| 26/2/2020 3:30 | 69.63 | 73.20445251 | 3.574452515 | 12.77671078 | 5.133494923 |
| 26/2/2020 4:00 | 69.62 | 74.41519165 | 4.79519165 | 22.99386296 | 6.887663962 |
| 26/2/2020 4:30 | 69.67 | 75.00852966 | 5.338529663 | 28.49989896 | 7.662594608 |
| 26/2/2020 5:00 | 71.01 | 77.37699127 | 6.366991272 | 40.53857786 | 8.966330477 |
| 26/2/2020 5:30 | 73.19 | 76.20904541 | 3.01904541 | 9.114635189 | 4.124942492 |
| 26/2/2020 6:00 | 73.31 | 77.99026489 | 4.680264893 | 21.90487946 | 6.384210739 |
| 26/2/2020 6:30 | 78.47 | 79.85567474 | 1.385674744 | 1.920094495 | 1.765865609 |
| 26/2/2020 7:00 | 72.77 | 79.96233368 | 7.192333679 | 51.72966375 | 9.883652163 |
| 26/2/2020 7:30 | 75.76 | 82.35930634 | 6.599306335 | 43.55084411 | 8.710805617 |
| 26/2/2020 8:00 | 78.27 | 83.94229126 | 5.67229126 | 32.17488814 | 7.247082228 |
| 26/2/2020 8:30 | 80.26 | 86.02776337 | 5.767763367 | 33.26709425 | 7.186348576 |
| 26/2/2020 9:00 | 80.59 | 87.41573334 | 6.825733337 | 46.59063559 | 8.469702615 |
| 26/2/2020 9:30 | 83.51 | 87.73495483 | 4.224954834 | 17.85024335 | 5.059220254 |
| 26/2/2020 10:00 | 89.04 | 87.07073212 | 1.969267883 | 3.878015996 | 2.211666536 |
| 26/2/2020 10:30 | 93.8 | 87.12873077 | 6.671269226 | 44.50583309 | 7.11222732 |
| 26/2/2020 11:00 | 92.58 | 88.05893707 | 4.521062927 | 20.44000999 | 4.883412105 |
| 26/2/2020 11:30 | 85.76 | 90.68828583 | 4.928285828 | 24.2880012 | 5.746601945 |
| 26/2/2020 12:00 | 82.52 | 90.17931366 | 7.65931366 | 58.66508574 | 9.281766432 |
| 26/2/2020 12:30 | 83.49 | 91.54270172 | 8.052701721 | 64.84600501 | 9.64510926 |
| 26/2/2020 13:00 | 87.9 | 92.86509705 | 4.965097046 | 24.65218868 | 5.648574569 |
| 26/2/2020 13:30 | 93.15 | 92.41150665 | 0.738493347 | 0.545372424 | 0.792800158 |
| 26/2/2020 14:00 | 102.9 | 93.15382385 | 9.736176147 | 94.79312597 | 9.462704002 |
| 26/2/2020 14:30 | 94.46 | 93.133461 | 1.326539001 | 1.759705722 | 1.404339404 |
| 26/2/2020 15:00 | 96.91 | 92.57108307 | 4.338916931 | 18.82620014 | 4.477264401 |
| 26/2/2020 15:30 | 94.84 | 91.29418182 | 3.545818176 | 12.57282654 | 3.738737006 |
| 26/2/2020 16:00 | 102.8 | 89.67919159 | 13.12080841 | 172.1556133 | 12.76343231 |
| 26/2/2020 16:30 | 156.1 | 88.48421478 | 67.58578522 | 4567.838363 | 43.30478966 |
| 26/2/2020 17:00 | 93.14 | 87.70246124 | 5.437538757 | 29.56682774 | 5.83802744 |
| 26/2/2020 17:30 | 83.19 | 86.67164612 | 3.481646118 | 12.12185969 | 4.185173841 |
| 26/2/2020 18:00 | 80.05 | 85.68740082 | 5.637400818 | 31.78028798 | 7.042349554 |
| 26/2/2020 18:30 | 79.42 | 85.87895966 | 6.458959656 | 41.71815983 | 8.132661365 |
| 26/2/2020 19:00 | 84.1 | 86.02250671 | 1.922506714 | 3.696032065 | 2.285977068 |
| 26/2/2020 19:30 | 83.23 | 84.10671997 | 0.876719971 | 0.768637907 | 1.053370144 |
| 26/2/2020 20:00 | 92.64 | 83.46554565 | 9.174454346 | 84.17061254 | 9.903340183 |
| 26/2/2020 20:30 | 87.5 | 83.35648346 | 4.143516541 | 17.16872932 | 4.735447475 |
| 26/2/2020 21:00 | 86.31 | 82.23656464 | 4.073435364 | 16.59287566 | 4.719540452 |
| 26/2/2020 21:30 | 80.86 | 81.10876465 | 0.248764648 | 0.06188385 | 0.307648588 |
| 26/2/2020 22:00 | 78.7 | 81.38710022 | 2.68710022 | 7.220507591 | 3.414358602 |
| 26/2/2020 22:30 | 78.46 | 80.86585999 | 2.405859985 | 5.788162269 | 3.066352263 |
| 26/2/2020 23:00 | 76.25 | 78.90061951 | 2.650619507 | 7.02578377 | 3.476222304 |
| 26/2/2020 23:30 | 73.12 | 78.69181824 | 5.571818237 | 31.04515847 | 7.620101528 |
|  |  |  | 5.515156008 | 120.1595212 | 5.860455309 |