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Forecasting Electricity Demand from Daily Log Sheet with Correlated Variables

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ABSTRACT

Electricity is one of the most important resources and fundamental infrastructure for every nation. Its milestone shows a significant contribution to world development that brought forth new technological breakthroughs throughout the centuries. Electricity demand constantly fluctuates, which affects the supply. Suppliers need to generate more electrical energy when demand is high, and less when demand is low. It is a common practice in power markets to have a reserve margin for unexpected fluctuation of demand. This research paper investigates regression techniques: multiple linear regression (MLR) and vector autoregression (VAR) to forecast demand with predictors of economic growth, population growth, and climate change as well as the demand itself. Auto-Regressive Integrated Moving Average (Auto-ARIMA) was used in benchmarking the forecasting. The results from MLR and VAR (lag-values=20) and Auto-ARIMA are monitored for five months from June to October of 2019. Using the root mean square error (RMSE) as an indicator for accuracy, Auto-ARIMA has the lowest RMSE for four months except in June 2019. VAR (lag-values=20) shows good forecasting capabilities for all five months, considering it uses the same lag values (20) for each month. Three different techniques have been successfully examined in order to find the best model for the prediction of the demand.

Keywords: *Electricity demands; Forecasting; Multiple Linear Regression; Vector autoregression; Sustainable Cities and Communities.*

1. INTRODUCTION

In Malaysia, the electricity supply industry is monopolistic in nature where utility companies (e.g. Tenaga Nasional Berhad, known as TNB) handles all the generation, transmission, distribution, and sales of electricity in a region. The growth of electricity sectors in Malaysia has shown steady progress over the years with primary energy sources for electricity generation are from coal and natural gas. Other sources also include hydropower, crude oil, and petroleum products. Even if we have seen efforts in harnessing solar energy for more renewable energy sources, Malaysia still has a long way to go before we can procure clean energy that will result in less pollution and global warming emissions. With the rapid growth of the economy in this nation, especially in the industrial and manufacturing sectors, it is no surprise that demand for electricity will keep on growing. Fortunately, with the advancement of technology in today's age and era and the rise of Big Data, forecasting is a viable option. However, overestimation of demand would inevitably lead to wasting resources whereas underestimation would increase the cost for energy suppliers in the country. It may also contribute to future potential blackouts [1]. There has been a significant amount of research done in predicting demand but a large

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number of these research lacked consideration for other contributing factors or predictors that have been theoretically proven to affect energy consumptions. Additionally, most other researches only focus on mainly a predictor of the demand.

This paper presents multiple linear regression (MLR) and vector autoregression (VAR) as techniques to forecast peak demand while using other factors such as economic growth, population growth, and climate change as well as the demand itself as predictors. The VAR proves to be the best method to use in multivariate time series analysis for a 30 days forecast. This paper also presents the result of Auto-Regressive Integrated Moving Average (Auto-ARIMA) to benchmark that those factors do in fact affect demand. The next section elaborates on the related works of literature on electricity and models of prediction, followed by Section 3 that includes the methodology for the modelling and experiments. Section 4 presents the results and discussion, and finally, the conclusion is found in Section 5.

2. LITERATURE STUDIES

2.1 Malaysia Electricity Supply Industry

For the longest time, Malaysia Electricity Supply Industry (MESI) has remained a regulated monopoly [2]. A statutory body under the Commission Act 2001 was established specifically to regulate the energy sector in Peninsular Malaysia [2]. The energy sector in Sarawak is regulated by the state government. In 1992, the Independent Power Producers (IPP) was introduced by the government but their control is limited only within the generation sector [3]. This was all done with the effort to eliminate and prevent a nationwide power outage, series interruptions, and rationing [3]. The initiation of IPP overcame many issues that TNB faced, such as electricity shortage. It also helped to enlarge the energy reserve margin and led a healthy competition among themselves. To this day, the competition is only limited to the generation sector. TNB still has full control over the transmission and distribution sector [2] and MESI applied the single buyer market model [3]. More than 14 IPPs in Peninsular Malaysia sell generated electricity to TNB at a fixed rate based on the Power Purchase Agreement (PPA) with its sole purpose of market risk protection [2]. With the agreement signed and the restructuring supported by the establishment of the Energy Commission, Malaysia managed to overcome the electricity shortage and was able to increase the electrical energy reserve margin.

2.2 Energy Sustainability in Malaysia

When the government decided to adopt the single buyer model and allowed the IPPs to compete in the generation sector, the shortage issues were resolved. Malaysia’s existing electricity generation is mainly divided into five types of sources: oil, coal, natural gas, hydro, and others (biomass, biogas, and solar) [4]. There were efforts taken by the government to reduce the high reliance on natural gas by increasing the use of coal. As a result, the share of coal to the total generation mix increased from 8.8% in 2000 to 21.8% in 2005 [4]. Fuel subsidies are also provided to the producers for oil-based generation, though it does not have the expected reduction in the generation mix. This was mainly due to the subsidies being directed to transportation and it pales by comparison to its share in the power market [5]. There has been without a doubt a significant development in the movement towards less pollution, more environment-friendly, and renewable sources for energy generation. However, by comparing Malaysia to countries like Iceland with almost 100% of its energy coming from renewable

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sources [6], it is safe to assume that Malaysia still has a long way to go with the clean energy approach even though it is definitely heading in the right direction.

2.3 Factors Affecting Electricity Consumption

There are numerous factors that affect the demand for electricity. Identifying and studying these factors that contribute the most to the increase (peak) or decrease in demand would be advantageous in trying to forecast demand. Four main factors are; climate change, economic growth, population growth, and the electricity price.

i. Climate Change

The concern for climate change arose when the production, distribution, and use of energy were revealed to be detrimental to public health. The existing power system might be inefficient and become a threat to several parts of the environment. It emits greenhouse gases (GHG) which will result in climate change. According to the statistics released by World Health Organization (WHO), indirect and direct impacts of climate change have led to 160,000 deaths per year and it is estimated to double by the year 2020 [7]. Hence, climate change might be one of the factors that could relate to the demand for electricity. Changes in the intensity and pattern of extreme weather events, and sea-level rise, are expected to affect both energy supply and demand [8]. This is due to fairly simple reasons; when the temperature rises, there is a higher demand for cooling, and a drop in temperature implies higher demand for heating. The relationship between temperature and demand is not something new and has been already investigated in many works focusing on European countries [9]. Moreover, the increased use of air conditioning indoors on hotter days with the addition to the improvement of the living standards had further enforced and made it more pronounce of the correlation between electricity demand and temperature above the threshold level [10].

ii. Economic Growth and Population Growth

There are studies conducted that focused on nationwide aggregation or state-level data in estimating the energy demand elasticity. One study found that growth in private expenditure caused electricity consumption to rise especially in the residential sector [11]. Another study was conducted in Italy to see if there is a causal relationship between electricity consumption to economic growth factors which are the gross domestic product (GDP) and labor force [12]. A statistical test was done in Bahawalpur to investigate the impact of population growth on domestic electricity consumption. Positives values of regression coefficients were obtained for all corresponding dependent variables which indicate a positive dependence of all variables on population growth [13].

iii. Electricity Price

Price control by sector, region, and time has widely been adopted as a short-term solution for anticipating changes in electricity demand [14]. The study in [14] has investigated the causal relationships between electricity prices, demand, and effects on the manufacturing output. The research hypothesized that as the price rises, the demand for electricity would decline and this reduction of demand for electricity would have an unfavorable effect on manufacturing output [14]. A single modelling framework was later used to study the relationship between electricity prices, demand, and manufacturing output. At the end of the study, the hypothesis that an

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increase in electricity price will decrease demand was proven to be true. There was an increase of 2% for the annual electricity price between 2013 and 2022 and the demand showed a decline to about 10%. Subsequently, the manufacturing output also showed a decrease to around 4.5%, proving their initial hypothesis to be valid [14]. Some utilities even go as far as to provide monetary incentives for private consumers so that they can shift their operations to a more favorable timing [15].

2.4 Forecasting Techniques

There are several forecasting techniques used in predicting demand:

i. Multiple Linear Regression (MLR): According to Kenton [16], the technique is the easiest to implement as it is able to visualize the trends and does not consider the seasonality of the time series. Linear relationships imply that any changes to the independent variables (x) will constantly affect the dependent variable (y) [17].

$$Y = m + a_1 X_1 + a_2 X_2 \dots a_k X_k \tag{2}$$

Y is the dependent variable (demand) and m is the intercept. Each of the X_k is the value for each of the exogenous variables and a_k is the coefficient for each of the explanatory variables. k is simply the number of exogenous variables considered in this study. MLR is modeled with the assumption that there is a linear relationship between the dependent variable (demand) and independent variables and that each of the independent variables is not highly correlated with each other. For example, variable A that is derived from the summation of two other variables B and C would mean that they are highly correlated. Variable A would be excluded from the equation.

ii. Vector Autoregression (VAR): According to [18] and [19], VAR has a good forecasting capability that incorporates exogenous variables in the modelling process. In this process, the dependent variable is forecasted using its own past (lag) values as well as the lag values of exogenous factors.

VAR requires the dataset to satisfy three conditions.

- There are at least two variables (time series) in the system.
- The variables are associated with each other.
- The time series should be stationary.

If there is more than one variable in the system, thus the first condition is satisfied. Granger's Causality Test is done to test causation between the variables [20]. This is because the basis of autoregression models is that each variable in the time series should influence (associated with) each other. Based on the test, Granger's Causation Matrix is produced. *P*-values of each attribute in relation to each other is checked. However, since the main focus is to forecast demand, only the *p*-values that denote the relation between each attribute and the demand will be prioritized. If the *p*-value is less than 0.05 (significance level), then the corresponding *X* series causes the *Y* series. If the *p*-value is more than 0.05, the *X* series does not cause the *Y* series and the attribute will be discarded. VAR models also require the time series to be stationary. Stationary time series are time series with mean, variance, and covariance that do not change over time. In simple terms, a stationary time series should not exhibit a trend. To

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check the stationarity for each time series, the Augmented Dickey-Fuller (ADF) test is executed. If the test statistic is less than the critical values, the null hypothesis is rejected which means that the series is stationary. If the values are greater than the critical values, then the series is not stationary. Non-stationary series can however be transformed into stationary ones using a method called differencing. Differenced series are checked for stationarity again. Once all of the series are stationary, the series (variables) can then be included in the model.

iii. Auto-ARIMA is a univariate method for forecasting, so it only considers the lags of itself. Auto-Arima also figures out the combination of the parameters on its own according to the Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) generated [21]. Since this paper only focuses on multivariate time series, an in-depth explanation is not provided.

iv. Simple Exponential Smoothing (SES): SES gives priority to the most recent observations and very useful for prioritizing recent trends that would lead to a more accurate prediction [20]. The technique is best used for short-term forecasting with data availability and the performance is decreased when the time series pattern has a sudden or drastic course of action.

Based on the available works of literature found, this study proceeded to experiment with two forecasting techniques; MLR and VAR with Auto-ARIMA as a benchmark using a set of variables namely weather, economic, and population data with historical demand information. Since the price of electricity was consistent for several years, hence it was excluded from the study.

3. METHODOLOGY

There are three (3) main phases in this paper: problem understanding, data collection and preparation, model construction, and evaluation. The problem understanding was discussed in Introduction and Literature Studies. Meanwhile, the second phase is data collection and preparation. The data required for the project was obtained through several means. The data is obtained from two sources; the first is from Suruhanjaya Tenaga (ST) website [3] and the second from the Grid System Operator (GSO) website [22]. GSO provides historical demand data and can be downloaded straight from https://www.gso.org.my/. However, GSO's data only span a few years back till 2017. On the other hand, the ST website provides reports in the form of a Daily Log sheet (DLS). These are the archived reports from TNB which means that it is stretched for over several years back until 2011. After the reports were collected, it went through a series of data cleaning process. Missing values are imputed or removed and are resampled. The outcome of this phase is a clean cohesive dataset, as shown in Figure 1. Economic and population data are downloaded from Bank Negara Malaysia [23], and weather data for 15 locations all around Peninsular Malaysia is downloaded from Raspisaniye Pogodi Ltd. [24] which includes several states such as Selangor, Perlis, Pulau Pinang, Kelantan, Pahang, Kuala Terengganu, Melaka, Johor, and Perak.

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Year	Month	Day	Total Generated (MW)	Maximum Demand (MW)	Load Factor (%)	SR at Peak Demand (MW)
2015	1	1	17453	12252	87.7	1017
2015	1	2	17729	13740	86.91	1010
2015	1	3	18009	12985	87.87	918
2015	1	4	18594	12681	87.05	1064
2015	1	5	18030	15515	83.81	574

Figure 1: Sample of Extracted Data from Daily Logsheets obtained from ST

The predictors were tested for correlation using the Pearson coefficient of correlation (R_2) value, as shown in Table 1. R_2 values are calculated by finding the best fit line for two variables and squaring the difference between the predicted values from the fitted line and the actual values. This is to test for linear correlation between variables. A higher R_2 score means there is a correlation between the two variables. Table 1 shows the factors that are most correlated economic factors with demand; Electricity, Gas and Water with a score of 0.42, Transport, Storage and Communication with a score of 0.43, and Other Services with a score of 0.43. Population and employment also gained a high score of 0.95, while the temperature of various locations shows a correlation to electricity demand.

Table 1: Factors and Score R_2 value

Factor	Score value
Economic (sectors)	Electricity, Gas and Water (0.42) Transport, Storage and Communication (0.43) Other Services (0.43)
Population and employment	Scores are at 0.95
Temperatures during AM & PM	Various locations with more than 0.50

The third phase is model construction and evaluation as shown in Figure 2. The data was trained and evaluated through the hold-out method where the dataset is split into two sets; one for training and one for testing. The dataset was collected from the year 2011 till 2017. There are five iterations and for each of the iterations, the model tries to forecast one month ahead for five months in total. The rest of the dataset prior to the start of the month is the testing set.

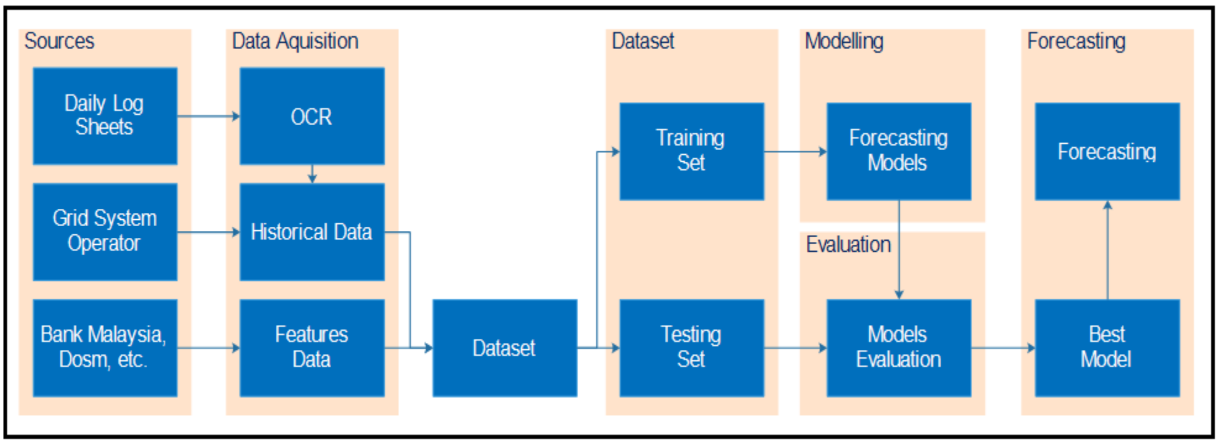

Figure 2: Modeling Framework

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The three models developed were based on MLR, VAR, and Auto-ARIMA. Each model was judged by several metrics after they have gone through a series of experiments. The AIC, BIC, and the Root Square Mean Error (RMSE) metrics were used to check the performances of regression models. AIC adds a penalty that increases the error when additional variables are included. BIC is just a variant of AIC but adds a stricter penalty to additional variables. RMSE on the other hand is the average error performed by the model. A lower AIC, BIC, and RMSE results indicate better models.

4. RESULTS AND DISCUSSION

The implementation of the MLR model was done quite straightforward by setting a set of factors as the attributes and *y* is the electricity demand. For VAR, several tests were done (as described in section 2.4) and the results show that the dataset has more than two variables with time-series pattern and Granger's Causality Test shows that each time-series has influenced each other with the *p*-values less than 0.05 (*X* variables toward demand as *Y*). VAR also requires that the series are stationary (the third criteria). Stationary time-series are important for the accuracy of forecasting. The stationarity of a time series can be examined through an ADF test. Based on the test, "*demand*" is stationary with the temperatures for 14 locations and the rest attributes are non-stationary, as shown in Figure 3.

```
 Augmented Dickey-Fuller Test on "demand"
 -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
Test Statistic        = -4.2507
No. Lags Chosen       = 24

Critical value 1%     = -3.434
Critical value 5%     = -2.863
Critical value 10%    = -2.568
=> P-Value = 0.0005. Rejecting Null Hypothesis.
=> Series is Stationary.
 Augmented Dickey-Fuller Test on "National Accounts Current Prices"
 -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level    = 0.05
Test Statistic        = -1.3025
No. Lags Chosen       = 0

Critical value 1%     = -3.434
Critical value 5%     = -2.863
Critical value 10%    = -2.568
=> P-Value = 0.628. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.
 Augmented Dickey-Fuller Test on "Agriculture"
 -----------------------------------------------
```

Figure 3: Example Results of Dickey-Fuller Test (ADF)

VAR is modelled with few experiments in finding the best lag-values for five months in 2019. It is important to find the optimum lag-values to prevent model overfitting. To avoid that, the hold-out method was used to compare performances between different lag-values. The RMSE of VAR is shown in Table 2 based on *lag-values=10*, *lag-values=20* and *lag-values=30*.

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Table 2: Results of RMSE for VAR models for different lag values

Lag Values	10	20	30
Jun-19	1767.8158	**1694.4243**	1876.8498
Jul-19	771.1707	**762.1748**	962.7452
Aug-19	771.1707	**762.1748**	962.7452
Sep-19	**1253.011**	1483.8721	1377.9323
Oct-19	**769.3844**	843.6717	1040.9678

Table 3 shows the records of performance (RMSE) between MLR, VAR (*lag-values=20*), and Auto-ARIMA for five months in 2019. Auto-ARIMA is univariate forecasting, which means it only uses its own past values to predict future values. Auto-ARIMA remodelled for every iteration, so its lag-values vary for each month. This is done to evaluate the best possible results to act as a benchmark for the univariate (VAR) and MLR. The implementation of this technique is rather straightforward in Python. A function *.fit()* is called and the training set is passed to it.

Table 3: Results of RMSE for VAR(20), MLR and Auto-ARIMA

	VAR(20)	MLR	Auto-ARIMA
June-19	1694.4243	1738.73	1715.1933
Jul-19	762.1748	793.54	691.8856
Aug-19	1090.8916	1006.88	747.8186
Sep-19	1483.8721	1131.59	1432.1288
Oct-19	843.6717	1060.2252	658.4388

Based on the RMSE values, it is clear that Auto-ARIMA exhibits a good forecasting capability. Though in June, VAR (*lag-values=20*) managed to surpass Auto-ARIMA's performance which served as the benchmark value. For the rest of the months, Auto-ARIMA had the best performance whereas VAR (*lag-values=20*) was not far behind in terms of performance. MLR was not able to compete with both models which were as expected. There are months that both models perform rather poorly such as in September and June. Overall, VAR showed a decent performance and is deemed as capable of forecasting. VAR (*lag-values=20*) is then embedded into the dashboard to forecast demand for the next 30 days of each month. Figure 4 shows an example of the dashboard.

The dashboard displays several things such as the current daily demand, forecasted daily demand, standard reserve margin (30%), and proposed reduced reserve margin (15%) of the highest forecasted daily demand. The figures will appear when the cursor hovers above it. The difference between the actual reserve margin (30%) and the reduced margin (15%) are also displayed along with the accuracy of the forecasting according to the available data for that particular month. The dashboard will also display current hourly demand from GSO website, highest recorded demand, total installed capacity, and the highest energy recorded as shown in Figure 4. At the start of a new month, the graph will reset where a blank graph with only the forecasted demand and proposed a reduced margin for that particular month is shown. Once the day ends, the dashboard will scrap the hourly demand from the GSO website, calculate the mean, and store it in *sqlite* where it will appear on the graph on the next day. This continues until the end of the month.

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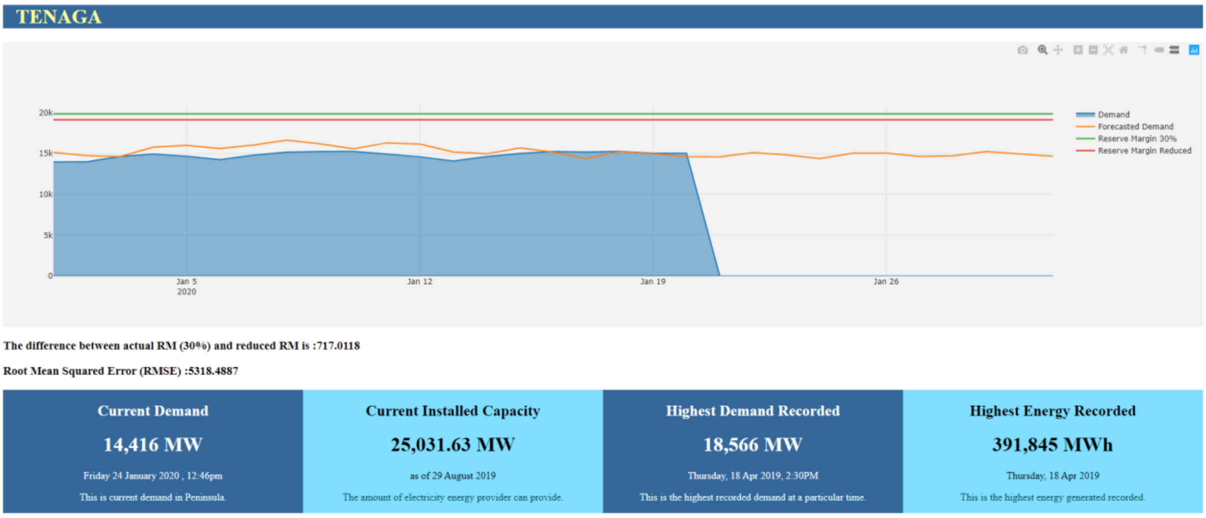

Figure 4: Example of the Forecasting Dashboard (Tenaga)

5. CONCLUSION

This research achieved its first objective by listing the factors that affect the demand for electricity. Subsequently, this research has narrowed down the four main factors namely economic growth, price, population growth, and climate change. Based on these factors, a series of attributes were derived. It was a challenge to acquire all the data required for this research since the data came from multiple sources. Three different techniques have been successfully examined in an effort to find the best model for the task. MLR and VAR showed their potential and reliability while Auto-ARIMA and VAR were very close performance-wise. Lastly, a dashboard was developed for a real-time tool that was able to forecast electricity demand a month ahead. The dashboard was successfully developed using the dash framework that allowed the integration of Python and Web. A scheduler was also embedded into the dashboard to do the scheduled scraping. The dashboard has few limitations which include the need for a scraping script that will scrap real-time data from GSO. However, this can only be done once a day due to the way data was formatted on the website. Furthermore, the dashboard can only be used in Peninsular Malaysia because the data used for training comes from Peninsular Malaysia only. Early on, the price factor was mentioned as one of the factors that affect electricity demand. But since the price factor is constant and most probably not going to change any time soon, it was left out. In the future, techniques such as Genetic Algorithm or any kind of searching algorithms can be implemented to find the best combination of factors for this kind of combinatorial problem.

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