Hybrid vector autoregression–recurrent neural networks to forecast multivariate time series jet fuel transaction price

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Abstract. Fuel cost is the most contributed component in the operational cost of all transportation modes. In the aviation industry, jet fuel cost contributed to a percentage of 33.33% of the total airline operational costs. To increase efficiency in operational costs and the airline should have jet fuel price monitoring systems that can forecast the future price and give some strategy recommendations to airlines. In this research, we propose many multivariate time series-based predictive analytics as a tool for the airline to monitor and forecast the jet fuel price transaction based on jet fuel transaction price. We consider the global crude oil price and also global and local jet fuel prices in each airport. We also consider additional variables for the economical aspect that applied differently for each airport location. We examine two Recurrent Neural Network (RNN) algorithm, Long Short Term Memory (LSTM) and Gate Recurrent Units (GRU). For minimizing the weakness of LSTM and GRU, we combine each methods with Vector Autoregression (VAR). After forecasting results using VAR-LSTM and VAR-GRU, we get forecasting accuracy of 98.98% and 99.40% respectively.

1. Introduction
Nowadays, business competition in an information technology era drive all company to develop their business using the internet. The company can use the internet to get a blue ocean business, monitor the competitors, making a new strategy to compete in the market, etc. that will improve the usage of the internet. Increasing the usage of the internet can lead to an increase the number of data and bring us into a big data era [1]. To get the information from data and make a decision or new strategy, we can use data mining [2]. Data mining is a process to extract the information or knowledge from big data using many statistical techniques. Many techniques of data mining such as: (1) descriptive analysis, (2) estimation, (3) prediction, (4) classification, (5) clustering, and (6) association [3]. Data mining is already used in many industrial sectors like manufacturing, pharmacy, finance, transportation, etc.

In the transportation industry, one of the areas that data mining can applied to monitor and forecast the market price of each operational cost component that might help management to develop the strategy of business efficiency. According to a report submitted by Martino, et al. [4], Fuel cost is the most contributed in many transportation vehicles. Fig. 1 presents that for sea transportation, fuel cost is 50% of all operational costs. For air transportation, fuel cost is 33.33% of all operational costs. International Air Transport Association (IATA) as a world organization of airline reported in 2014 that fuel cost is contributed 33.3% from airline cost structure as shown in Fig.2 [5]. By using the Pareto theory, if we improve in the biggest component, we can get a significant impact on our goals. So, to give a significant
impact to airline operational cost, we should make an efficiency strategy in jet fuel management system by using monitoring systems to estimate or forecast the jet fuel price, so the airline can make an efficiency strategy such as selecting the time and location to into-plane the jet fuel based on the forecasting results.

![Figure 1. Fuel cost vs other operational cost in many types of vehicles [4]](image1)

According to many studies before, research about fuel price forecasting is common to forecast crude oil price or basic price of the derivative product of crude oil (such as Petrol, Diesel, LPG, Kerosene, Jet Fuel, etc.). The similarities of both prices is fluctuated in a time frame and standardized by an organization. The differences in crude oil prices can be applied worldwide, but derivative product price depends on locations refer to policy that applied by local authority [6].

For example, for jet fuel basic price, the several previous studies showed that jet fuel basic price is correlated with crude oil price and depends on its historical price [7] [8]. The Fig. 3 presents the comparisons of crude oil price (using Brent Spot Price) and jet fuel price (using MOPS Posting Price) prepared by Platts, Singapore in May 2013 until May 2020 that relatively have the same trends [9].

![Figure 2. Airline cost structure [5]](image2)

![Figure 3. Jet fuel & crude oil price comparisons in usd/bbl [9]](image3)

Based on the real case in the airline industry, the airline should pay to a fuel supplier, not in jet fuel basic price, but the airline will negotiate for the scheme of jet fuel transaction price that different for each location [8]. For example, in Soekarno-Hatta International Airport, Indonesia (CGK), there are two price equations that can be applied by airline: (1) MOPS Posting Price + Differential Price, and (2) Pertamina Posting Price + Discount Price. The Pertamina Posting Price is the base price that already set by Pertamina as a fuel manufacturer in Indonesia for each airport in Indonesia [10]. So, the jet fuel transaction price will different, but depends on crude oil price and jet fuel basic price.
Considering that jet fuel transaction price is different in each location, it’s possible to state that local economic conditions such as the exchange rate of local currency and the local inflation rate will affect jet fuel transaction price fluctuation. This is done considering the price of fuel transactions that are also influenced by currency hedging conducted by the airlines and fuel providers as well as the political-economic conditions that are applied in Indonesia. Where the political-economic decisions determined by the government will usually affect and be influenced by currency exchange rates and inflation rates. As well as stated in the IATA website presented in Fig. 4 that the trend of jet fuel price in USD and Euro that relatively have the same trends [9].

![Jet Fuel Price Currency Comparison](image)

**Figure 4.** Jet fuel price comparison in USD and Euro [9]

Considering the characteristics of crude oil price and jet fuel price is time series plotted, the previous studies using time-series forecasting-based predictive analytics to build monitoring and estimating tools. Khan et al. [6], that research price predictions for 4 petroleum products, namely Petrol, Diesel, LPG, and Kerosene in India, using ARIMA and Neural Network techniques using historical data of each petroleum products and crude oil prices as independent variables. For jet fuel price prediction, previous research has been conducted by Atems, et al. [7] by making a predictive analytics model of jet fuel price using the Vector Autoregressive (VAR) technique with the independent variable is crude oil prices and also using jet fuel historical data. For research on forecasting aircraft fuel transaction prices, previous research has been conducted by Firmansyah [11], where the independent variable used is Crude Oil Price (Brent Posting Price), Price from local suppliers (Pertamina Posting Price), and Basic Jet Fuel Price (MOPS Posting Price) and using multiple linear regression analysis with an accuracy of 93.68%.

One of the studies in forecasting oil prices that has a fairly high degree of accuracy is a study conducted by Guo [12], research conducted with deep learning methods, namely Long Term Short Memory (LSTM) and Gated Recurrent Unit (GRU) with a forecast accuracy level of 98.45% was obtained, but the research was only conducted using historical data (univariate). However, LSTM and GRU still have some weakness as the absence of a structured model and can be directly used for forecasting. In addition, in the LSTM there is an output gate that makes some stored data removed because it is considered too long or too far away. Whereas in the GRU there is no output gate, but calculations using all the data are very potential for bias [13].

Based on these explanations, this study will examine how predictions can be made using deep learning methods, LSTM and GRU, which according to prior research on time series forecasting can produce a sufficient level of accuracy. However, to minimize the risk of LSTM and GRU weakness, the optimum amount of historical data will be sought in advance to be entered into the model. One technique that can be used is to add a regression technique for multivariate time series data, the Vector Autoregressive (VAR) method. VAR used as a method in the feature selection process prior to the LSTM and GRU process because it can build a structured forecast model and can determine the optimal number of lags (historical data). In addition, this study will add several variables that have not been considered in previous studies but which affect jet fuel transaction price, namely inflation and local currency rates. The additional variable is expected to increasing forecast accuracy.
2. Research Methodology
In this research, we will discuss about jet fuel pricing, data collection and pre-processing, and forecast using many algorithm and combinations.

2.1. Jet Fuel Pricing
Fuel is the refinery product from crude oil and used by all transportation modes as the main material for the combustion and ignition systems in the engine and causes the transportation mode to move [8]. Fuel is an important component in the operation of a vehicle, not least in the aviation industry, which must use to good, quality, and standard because it involves aviation safety and security [4].

One of type of fuel product is Avtur (Aviation Turbine Fuel), or also known as Jet Fuel, which is a fuel with an external combustion system based on turbine gas or jet engines used by many commercial aircraft. One type of Avtur that is most often used by Indonesian airlines is the Avtur Jet A-1 series because it has an excess freezing point of up to -470C and this is needed when aircraft fly at cruising altitudes of 30,000 to 40,000 feet [11].

As stated in previous research that fuel costs are one of the biggest cost components of airlines [4] [5], one reason is the price of fuel which is very volatile. Compiled from several sources, except from political factors, fuel fluctuations can be caused by the following factors: (1) Crude oil price trends (2) Fueling location (crowds / frequency of flights, location of oil refineries, currency exchange rates, inflation), and (3) Fuel manufacturer monopoly.

Fuel manufacturer usually set the base price that applied in many locations in their country, then airline paying the fuel cost to supplier using manufacturer’s base price that added by differential prices. For example, at Soekarno-Hatta International Airport, Indonesia (CGK), there are two price equations that can be applied by airline: (1) MOPS Posting Price + Differential Price, and (2) Pertamina Posting Price + Discount Price. The Pertamina Posting Price is the base price that already set by Pertamina as fuel manufacturer in Indonesia for each airport in Indonesia [10].

2.2. Data Collection
In this research, we will examine forecasting of jet fuel transaction price at CGK Airport in Tangerang, Indonesia. We will use data in the period January 2017 until April 2020 each dataset with details below:

| Table 1. Dataset collection |
|-----------------------------|
| Variable | Description | Variable Type |
| WTI | Crude Oil Price issued by West Texas Intermediate (US Approach) | Independent |
| Brent | Crude Oil Price issued by Brent (European Approach) | Independent |
| Gulf | Basic Jet Kerosene Fuel Price issued by Arabian Gulf Coast | Independent |
| MOPS | Basic Jet Kerosene Fuel Price issued by Platts Singapore | Independent |
| Pertamina | Local jet fuel supplier price in CGK Airport Indonesia | Independent |
| JISDOR | Indonesia Exchange Rate by Bank Indonesia | Independent |
| Inflation | Indonesia Inflation Rate by Bank Indonesia | Independent |
| Transaction | Indonesian Airline Jet Fuel Transaction Price | Dependent |

The data used in this research we used 8 variables that are grabbed from 5 different sources as follows:
- Crude oil price dataset, we will use WTI Spot Price and Brent Spot Price from open data source that updated every business days [14].
- Basic jet fuel price dataset, that will use Gulf Coast Kero Jet Fuel Spot Price and MOPS Posting Price from Platts’s website that updated every business days [15].
- Local jet fuel supplier posting price that in CGK airport will use Pertamina Posting Price from Pertamina’s website that updated every 2 weeks in date 1st and 15th every month [10].
• Local economic aspect, using currency exchange rate, JISDOR rate from IDR to USD and local inflation rate from Bank Indonesia website as the Indonesian economic condition that updated every business days [16].
• Jet fuel transaction price of one of Indonesian airline dataset from their internal data source that updates every days.

2.3. Data Pre-processing

2.3.1. Data Integration
As data grabbed from 5 different sources with time series order, it is necessary to integrate all data into a coherent dataset. Data is integrated and adjusted in date order to become a database. So the database consists of 8 columns.

2.3.2. Data Cleansing and Selection
After integrating the data taken from several sources that has different dimensions, so it needs to be cleaning data to become a database that is ready for use. Stages of cleansing and selection of data carried out are as follows:
• Data selection with the shortest dimension, namely Pertamina Posting Price, which is valid from January 1, 2017. So, the data used is data from January 1, 2017 to April 30, 2020.
• Remove the data for international holidays, national holidays, and Saturdays and Sundays (non working days).
• Estimating incomplete data / has a value of 0, Refer to the characteristics of the data, if there is no price update, then the price in the previous period is still valid. So, for incomplete data will be filled with data in the previous period.

2.3.3. Data Transformation / Data Scaling
After cleansing and selecting the data, the transformation process is conducted by changing the scale of the data into the range of 0 to 1 per column. The 3 rows of already processed data shown in Table 2.

| Date        | WTI  | Brent | Gulf  | MOPS  | Pertamina | JISDOR | Inflation | Transaction |
|-------------|------|-------|-------|-------|-----------|--------|-----------|-------------|
| 03-01-17    | 0.7810 | 0.5969 | 0.5773 | 0.6098 | 0.1350    | 0.0923 | 0.5       | 0.4193      |
| 04-01-17    | 0.7889 | 0.5906 | 0.5773 | 0.5968 | 0.1350    | 0.0903 | 0.5       | 0.4021      |
| 05-01-17    | 0.7933 | 0.5961 | 0.5825 | 0.5946 | 0.1350    | 0.0602 | 0.5       | 0.3953      |

After get the ready to processed data, data is divided into 2 groups. Data training is 80% of total amount data from first period dated from January 3rd, 2017 until August 29th, 2019 to build model. Then, next 20% data dated from August 30th, 2019 until April 30th, 2020 is grouped into data testing that used for validation and performance evaluation.

2.4. Data Processing
In this section, we proposed a novel model to forecast the jet fuel transaction price which is the hybrid of traditional multivariate time series forecasting method, Vector Autoregression (VAR) with two recurrent neural networks (RNN) algorithm, Long Short Term Memory (LSTM) and Gated Recurrent Units (GRU). The mapping of process flow will be shown in Figure 5.

In Figure 5, we can show that we will apply VAR as an optimization method for parameter and input before the LSTM and GRU process. VAR will optimize the parameter, build a model based on training data, and estimate the data as a feature selection process. So, it will be 2 steps of the training process. As a comparison, we will also forecast the jet fuel transaction price using LSTM (3 layers), GRU (3
layers), and VAR separately. In this research, the models of VAR, LSTM, GRU, VAR-LSTM, and VAR-GRU are operated in Python 3.5 via Google Collaboratory platform with the function tool of Keras and Tensorflow.

2.5. Evaluation process
In assessing the performance of each algorithm, it is necessary to evaluate the level of accuracy of the predicted results. The following are some evaluation criteria that can be used to evaluate the performance of prediction accuracy [17]:

a. Mean Absolute Deviation (MAD):

\[
MAD = \frac{1}{N} \sum_{i=1}^{N} |y_t - \hat{y}_t|
\]

(1)

b. Root Mean Square Error (RMSE):

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_t - \hat{y}_t)^2}
\]

(2)

c. Mean Absolute Percent Error (MAPE):

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100\%
\]

(3)

3. Results and Discussion

3.1. LSTM and GRU process
First, we will process using LSTM and tried for several epoch parameter configurations in the range of 500 to 1,000. For the input of neurons used is n = 70, and the batch size used is 128. The results of accuracy will be shown in Table 3.

| Epoch | MAD    | RMSE   | MAPE   | Accuracy |
|-------|--------|--------|--------|----------|
| 500   | 202.38 | 187.99 | 0.1673 | 85.27%   |
| 600   | 593.72 | 989.95 | 0.1307 | 86.93%   |
| 700   | 411.16 | 298.41 | 0.1824 | 83.76%   |
| 800   | 498.95 | 371.40 | 0.1755 | 84.45%   |
| 900   | 446.57 | 217.56 | 0.1839 | 83.61%   |

Figure 5. Hybrid algorithm process flow
For next step, we will process using GRU and tried for several epoch parameter configurations in the range of 500 to 1,000. For the input of neurons used is \( n = 70 \), and the batch size used is 128. The results of accuracy will be shown in Table 4.

### Table 4. Performance evaluation of GRU 3 layer

| Epoch | MAD    | RMSE   | MAPE   | Accuracy |
|-------|--------|--------|--------|----------|
| 500   | 573.44 | 833.29 | 0.1245 | 87.55%   |
| 600   | 541.86 | 806.93 | 0.1196 | 88.04%   |
| 700   | 513.29 | 794.27 | 0.1097 | 89.03%   |
| 800   | 374.27 | 842.51 | 0.1281 | 87.19%   |
| 900   | 385.91 | 795.10 | 0.1393 | 86.07%   |
| 1000  | 458.16 | 786.18 | 0.1498 | 85.02%   |

In processing data using LSTM and GRU, the forecasting results are obtained by plot and performance results as can be seen in sections Table 2 and Table 3. It can be seen that forecasting results with the best accuracy are obtained when the LSTM model is used with 3 layers and as many as 600 epochs which produce an accuracy of 86.93%. For forecasting with the GRU model, the best accuracy when the model is used with 3 layers and epoch is 700 which results in an accuracy of 89.03%. Figure 6 below shows a comparison graph plot between the forecasting done by the LSTM and GRU algorithm.

#### Figure 6. Graphical plot forecasting using LSTM 3 layer and GRU 3 layer

### 3.2. VAR, VAR-LSTM, and VAR-GRU process

In VAR process, we should determine the optimum lag number that will applied to LSTM and GRU in future steps. The determination will calculated by Akaike information criterion (AIC) and the results is in maximum lag order 2, with AIC number 2.255. Next, with maximum lag order 2, we can generate mathematics model like regression with VAR(2) as follows:

\[
\text{Trans}_t = 1.04 - 1.36\text{WTI}_{t-1} - 1.75\text{Brent}_{t-1} + 41.29\text{Gulf}_{t-1} - 7.26\text{MOPS}_{t-1} + 0.20\text{Pertamina}_{t-1} - 0.04\text{JISDOR}_{t-1} + 2278.67\text{Inf}_{t-1} + 0.06\text{Trans}_{t-1} - 4.72\text{WTI}_{t-2} - 0.28\text{Brent}_{t-2} + 347.27\text{Gulf}_{t-2} - 0.62\text{MOPS}_{t-2} + 0.12\text{Pertamina}_{t-2} - 0.05\text{JISDOR}_{t-2} - 11347.37\text{Inf}_{t-2} - 0.05\text{Trans}_{t-2} + \varepsilon_t
\]

Next, we will continue to LSTM and GRU process with input from VAR estimation. Figure 7 below shows a comparison graph plot between the forecasting done by the VAR, VAR- LSTM and VAR-GRU algorithm.
The performance measurement for this 5 models as follows:

| Algorithm     | MAD     | RMSE   | MAPE   | Accuracy  |
|---------------|---------|--------|--------|-----------|
| LSTM-3layer   | 593.72  | 989.95 | 0.1307 | 86.93%    |
| GRU-3layer    | 513.29  | 794.27 | 0.1097 | 89.03%    |
| VAR           | 141.13  | 164.82 | 0.0252 | 97.48%    |
| VAR-LSTM      | 68.21   | 81.52  | 0.0102 | 98.98%    |
| VAR-GRU       | 40.50   | 62.53  | 0.0060 | 99.40%    |

In processing data using VAR-LSTM and VAR-GRU, the forecasting results obtained by plot and performance results can be seen in Table 4. It can be seen that forecasting results with the best accuracy are obtained when the VAR-LSTM model produces an accuracy of 98.98%. For forecasting with the VAR-GRU model, the best accuracy when the model produces an accuracy of 99.40%. Based on the graph plot shown in Figure 6 and 7, it can be seen that the experimental results for forecasting aircraft fuel transaction prices are better than the LSTM and GRU outputs. Even outputs are consistent from the beginning to the end of the testing data. The outputs of VAR-LSTM and VAR-GRU can also follow a downward trend in extreme conditions due to the Covid-19 pandemic that occurred twice, namely in February and mid-March 2020. By combining the VAR algorithm with the LSTM and / or GRU, causing instability experienced by forecasting LSTM and GRU can be minimized so that it can produce more accurate outputs with actual values.

Furthermore, if we look at the output of the VAR, the shortcomings can be seen that is along with the progress of the period, the wider bias is generated against the actual data. This turned out to also be minimized by combining VAR-LSTM and VAR-GRU so that the output produced would be more accurate. In addition, the level of performance of VAR-LSTM and VAR-GRU, the outputs become more convergent, which has a minimum difference between epoch accuracy. This proves that the instability of the LSTM and GRU which causes the output value to always change when running can be minimized by using a merge with the VAR method, although it has not been fully structured.

For comparisons of performance evaluation, based on Table 4, it can be seen that the best performance for all evaluation criteria is obtained by the VAR-GRU algorithm with total accuracy of 99.40%. This is because of the VAR-GRU algorithm has advantages over the other 3 algorithms as follows:

a. Has the advantage of LSTM, which has a memory cell in the forecasting process.

b. It has the advantage of GRU, that is, no information is released on the lag or previous period stored in the LSTM memory cell, so that the best value can be produced as an output.

c. Has the advantage of VAR, which is knowing the optimum amount of lag that is used, so that the data process will be more concise and optimum.
4. Conclusions
In this paper, we studied hybrid between Vector Autoregression (VAR) and Long Term Short Memory (LSTM) or Gated Recurrent Unit (GRU), to predict the multivariate time series problem, there is a jet fuel transaction price. We use jet fuel transaction price as a dependent variable that forecasted in time series using 7 independent variables such as 2 crude oil price, 2 basic jet fuel posting price, local supplier posting price, local currency exchange rate, and inflation rate. This is done considering the price of fuel transactions that are also influenced by currency hedging conducted by the airlines and fuel providers as well as the political-economic conditions that are applied in Indonesia. Where the political-economic decisions determined by the government will usually affect and be influenced by currency exchange rates and inflation rates. In addition to these two variables, the variables that are still being used are world crude oil prices and aircraft fuel prices that apply in the world and at every airport location.

The method that has been tried to improve the forecasting accuracy of 2 (two) RNN methods, namely Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) in this study is to combine the Vector Autoregression (VAR) method as a feature selection process method. so that it can produce forecasting results with a higher degree of accuracy. Where for VAR-LSTM produces forecasting with an accuracy of 98.98%, while VAR-GRU produces forecasting with an accuracy of 99.40%. Especially with the Covid-19 pandemic which caused a significant decrease in the period from February to April 2020, VAR-LSTM and VAR-GRU remain sensitive to these changes and can produce forecasting with small bias.

For future research, we suggest developing a model with the addition of the variables which certainly can influence decisions when negotiations are carried out by airlines with fuel providers, such as planned a number of flights, a flight duration of each aircraft, and location of filling/intoplane. For example, with the implementation of Large-Scale Social Distancing during the Covid-19 pandemic in Indonesia, the demand for aircraft fuel will be low and automatically the price of aircraft fuel will go down as the number of flights decreases. For the methods on multivariate time series using neural network algorithms, it can also be combined with a metaheuristic algorithm to get a more optimal feature selection process.

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