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Article

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Forecasting Gasoline Demand in Indonesia Using Time Series

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ABSTRACT

Fuel is an essential commodity in both the economy and society. Indonesian fuel demand continues to increase annually, whereas fuel production has decreased. Gasoline accounts for more than 50% of fuel consumption for transportation. A reliable gasoline product demand forecast is required to plan the gasoline supply. The objective of this study is to forecast the demand for total gasoline and its three components, which are gasoline 88, gasoline 90, and gasoline 92. This study compared the Holt–Winters additive model and autoregressive integrated moving average for the time-series data for the 2017-2019 period. Because the Holt–Winters additive model generates more accurate results, it was applied to predict the total demand for gasoline during 2020-2022. The results of the combination of the Holt–Winters model and a neural network to forecast gasoline 92 demand had lower errors than the individual Holt–Winters method. The forecast results show that total gasoline demand is forecasted to increase, but the components indicate a different trend. Gasoline 92 and gasoline 88 decreased, but gasoline 90 increased.

Keywords: Forecasting, Time Series, Gasoline Demand, Holt-Winters, Neural Network
JEL Classifications: Q4, Q47

1. INTRODUCTION

The petroleum industry plays an essential role in the world economy, and disruptions in its supply chain have significant impacts on the economy and society (Lima et al., 2016). Over the years, oil consumption in Indonesia has increased significantly, but oil production had been decreasing. As a result, Indonesia has become an importer of crude oil and refined oil products (Sa'ad, 2009). Among the factors that influence the escalation in petroleum demand, population and economic growth receive significant attention (Zhang et al., 2009). Indonesia's population was 211 million in 2000, which increased to 267 million in 2018. Moreover, the country's economic growth over the years has trended upward. Indonesia's GDP was US$165 billion in 2000, increasing to US$1042 trillion in 2018 (World Bank, 2018). These statistics indicate a tendency for a widening gap between oil demand and domestic supply capabilities that requires attention.

Forecasting gasoline demand, which is part of the energy, plays an essential role in gasoline supply planning (Zhao and Chen, 2014). Accurate forecasting assists decision-makers in understanding the volume of and trends in gasoline demand for supply system planning (Ghalehkhondabi et al., 2017). Demand forecasting errors result imbalances in supply and demand, which negatively affects operating costs, network security, and service quality (De Felice et al., 2013).

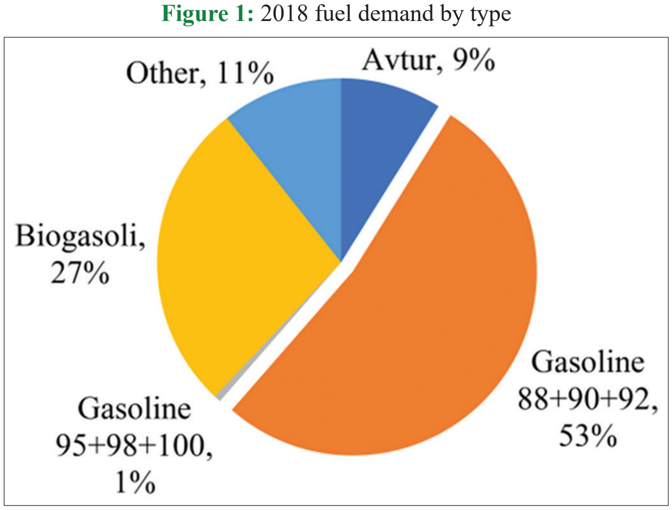
Transportation as a backbone of the economy is strongly dependent on petroleum, which is why the sector received significant attention (He et al., 2005; Chai et al., 2016). The transportation sector records the highest petroleum consumption in Indonesia. In 2018, the transportation sector accounted for 45.06% of energy consumption, industry 33.51%, households 14.765% and commercial establishments 4.82%. Fuel accounted for 37.78% of energy consumption, followed by electricity 18.07%, biofuel 13.11%, coal 11.58%, natural gas 11.01%, and other 7.44% (Ministry of Energy and Mineral Resource Republic of Indonesia, 2018).

Issues in the transportation system, especially fuel demand have become concerns of the government (Zhang et al., 2009). Given this importance, we forecast the fuel demand for transportation or gasoline and its components for 2020-2022 using a case study on the Indonesian state oil company. Gasoline is a fuel used in road transportation—primarily vehicles. The components of gasoline to be studied are gasoline 88, gasoline 90 and gasoline 92. They gasoline types have certain RON (Research Octane Number) levels. In this study, gasoline 88, gasoline 90, and gasoline 92 refer to gasoline with RON 88, 90, and 92, respectively. Higher RON numbers indicate higher quality. Gasoline with RON 88 and RON 90 is medium grade, whereas gasoline with RON 92 or higher is premium grade (US Energy Information Administration, 2019). These three types of gasoline are consumed the most by vehicles in Indonesia. Figure 1 provides 2018 fuel demand by type and indicates that these three gasoline components account for 53% of the total fuel provided for transportation, including air and railway transportation. The other types of gasoline, namely gasoline 95, gasoline 98, and gasoline 100, account for only 1% of all fuel used.

Few studies analyzed Indonesia's petroleum demand. Dahl and Kurtubi (2001) analyzed petroleum product demand and price elasticity, Sa'ad (2009) studied total gasoline and diesel demand and price elasticity, and Akhmad and Amir (2018) analyzed the supply and demand of kerosene, solar, and total gasoline. However, no study has forecasted component gasoline demand or has identified an appropriate model for the demand of gasoline products of the Indonesian state oil company. Hence, this study is the first on component gasoline forecasts in Indonesia.

Companies use product demand forecasts for tactical planning such as production planning, and for inventory strategic planning to determine the necessity to build a new plant (Chopra and Meindl, 2016). Therefore, the component demand forecast for gasoline is very important in determining inventory levels for each product, production, and imports.

Figure 1: 2018 fuel demand by type



Source: Ministry of Energy and Mineral Resource Republic of Indonesia, 2018

This paper is organized as follows: Section 2 presents an overview of Indonesia's gasoline supply, demand, and policies. Section 3 presents related studies. Section 4 discusses the contribution made by this study, and Section 5 presents a theoretical description of the method for energy forecasting models such as Holt-Winters' additive, autoregressive integrated moving average (ARIMA), linear regression, and neural networks. Section 6 provides the data description and Section 7 presents the analysis. Section 8 presents the forecasting results and a discussion. The findings and subsequent studies are provided in Section 9 as the conclusion.

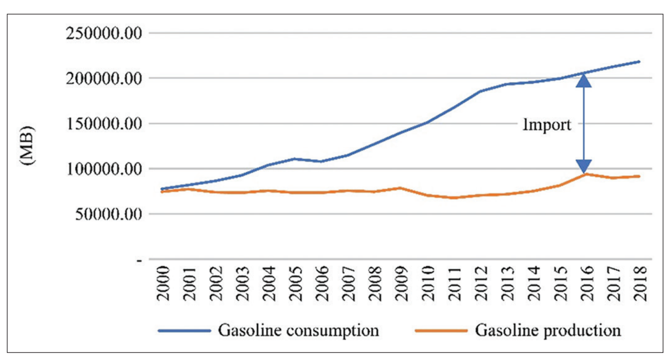
2. OVERVIEW OF INDONESIA'S GASOLINE SUPPLY, DEMAND, AND POLICY

The transportation sector is the primary consumer of gasoline. From 2000 to 2018, the average gasoline consumption increased by 5.6% per year, with a maximum increase of 10.83% and a minimum of 1.35%. However, Indonesia's gasoline production does not show a significant increase. The average annual production was 76,905 MB with a maximum of 91,640 MB and a minimum of 67,642 MB. Since 2000, Indonesia's gasoline consumption has exceeded its domestic supply, resulting in an imbalance between supply and demand. As Figure 2 indicates, the difference between supply and demand widened. The shortage caused Indonesian gasoline imports to increase over the years.

Initially, retail fuel sales may only be carried out by national oil companies owned by the government. In 2000, Indonesia liberalized its oil and gas businesses by passing an oil and gas law that allowed foreign companies to sell gasoline in its country.

Gasoline 88 is a product under government supervision, and companies are required to sell it without exceeding the specified sales quota determined by the government. Every price change for all gasoline products must be approved by the government. Specifically for gasoline 88, the government issued a "one price" policy that mandated that this product be sold at the same price throughout Indonesia. The government bears the costs of transporting these products. Although the policy reduces the burden on gasoline consumers in remote areas who initially had to buy gasoline at higher prices than other regions, it certainly had the consequence of increasing the government's financial burden.

Figure 2: Gasoline consumption and production in Indonesia, 2000-2018



Source: Ministry of Energy and Mineral Resources Republic of Indonesia, 2008 and 2018

3. LITERATURE REVIEW

Reliable gasoline demand forecasting is essential for petroleum supply chain planning. Many studies of various scopes have been conducted on energy demand forecasting, including energy as a whole (De Vita et al., 2006; Sözen and Arcaklioglu, 2007; Lee and Tong, 2012; Barak and Sadegh, 2016; Rehman et al., 2017; Ozturk and Ozturk, 2018; Wang et al., 2018; Wang et al., 2019; Li and Zhang, 2019), electricity (González-Romera et al., 2008; Maçaira et al., 2015; Hussain et al., 2016; Ryu et al., 2017; Oliveira and Oliveira, 2018; McNeil et al., 2019; Jiang et al., 2020), petroleum (Houri and Baratimalayeri, 2008; Sa'ad, 2009; Azadeh et al., 2010; Ma et al., 2012; Melikoglu, 2013; Barde, 2014; Chai et al., 2016; Akhmad and Amir, 2018; Sapnken et al., 2018; Oliskevych et al., 2018), natural gas (Szoplik, 2015; Akpinar and Yumusak, 2016; Karabiber and Xydis, 2020), or solar and wind energy (Alsaedi et al., 2019).

Although energy demand prediction is an important issue in all countries, limited gasoline demand forecasting studies exist on Indonesia. Sa'ad (2009) analyzed the demand for petroleum used for transportation with econometric techniques that forecast per capita petroleum consumption. The study concluded that petroleum demand would increase. Akhmad and Amir (2018) used an econometric method with simultaneous equation to predict the supply and consumption of fuel and the factors influencing supply and demand. These authors concluded that the demand, price, and import of fuel oil would increase, and the influencing factors of fuel consumption are fuel price and the previous year's fuel consumption. To the best of our knowledge, no research exists on gasoline component demand forecasting in Indonesia.

Researchers have paid significant attention to studies on the demand for fuel transportation, which commonly used the time series analysis approach (Houri and Baratimalayeri, 2008). A variety of energy demand forecasting methods have been applied over the years. Studies on the forecasting method revealed that no one best method exists for all conditions (Ghalehkhondabi et al., 2017). The most common models in the energy-related demand forecasting area are time series models, regression-based formulations, and artificial neural network (ANN) (Kuster et al., 2017; Wang et al., 2018). Time series forecasting is a forecasting method in which past data for the variable are analyzed to generate a model (Zhang, 2003; Akpinar and Yumusak, 2016). The method is widely used to predict energy needs. A linear regression model also had been used in gasoline consumption forecasting (Sapnken et al., 2018) as well as ANN (Lai et al., 2014).

ARIMA methods are widely used in time series data analysis (Suganthi and Samuel, 2012). However, Holt–Winters, an extension of exponential smoothing, is also broadly used to predict energy consumption and remains a reliable approach (Kays et al., 2018). Taylor (2003) used the Holt–Winters method to forecast electricity demand. Jónsson et al. (2014) predicted a real-time electricity market using the Holt–Winters method. Jiang et al. (2020) applied the enhanced Holt–Winters exponential smoothing to predict electricity consumption in China and concluded that this method generated accurate results with few sample data points. In contrast, Ediger and Akar (2007) used ARIMA and seasonal ARIMA (SARIMA) to forecast energy demand in Turkey. Another energy consumption forecasting method was conducted by Ozturk and Ozturk (2018) using the ARIMA model. Many authors used a combination of ARIMA and other models to forecast energy demand, such as ARIMA and ANFIS (Barak and Sadegh, 2016), ARIMA and ANN (Babazadeh, 2017), ARIMA and MGM (Wang et al., 2018), and ARIMA and NMGM (Li and Wang, 2019). They concluded that a combination model provides better results than a single model.

In forecasting, using a shorter period of data provides a more accurate result than a longer period of data (As'ad, 2012). Although ARIMA is widely used for demand forecasting, it does not always generate more accurate results than simpler methods such as linear regression, a logistic model (Melikoglu, 2013), or a quadratic regression (Li et al., 2010). Chai et al. (2016) revealed that the exponential smoothing and the ARIMA prediction results were very close but that the exponential smoothing result was more accurate than the ARIMA result. Akpinar and Yumusak (2016) concluded that ARIMA error rates decrease as the computation complexity of the method increases.

Many authors compared the Holt–Winters method and ARIMA. Li et al. (2010) compared various time series methods to forecast petrol demand in Australia and concluded that the quadratic and linear regression methods outperformed other methods, including Holt–Winters and ARIMA, and that ARIMA provided a better result than Holt-Winters. Taylor (2003) applied the Holt–Winters method to forecast electricity demand and concluded that the method outperforms ARIMA (Hussain et al., 2016). Oliveira and Oliveira (2018) conducted a study of electricity consumption in several developed and developing countries by comparing ARIMA with exponential smoothing. ARIMA showed better results for developing countries cases, such as Brazil and Mexico, whereas exponential smoothing performed well for Canada, France, and Italy.

The neural network or ANN is another forecasting method that is based on the machine learning approach and can accommodate nonlinearity and linearity models. This methodology predicts the causal effect of variables (Chattopadhyay et al., 2019). Many forecasting studies used the neural network (NN) method because it generates accurate prediction results (Ryu et al., 2017). Although the NN has many advantages relative to the multiple regression method, it has limitations. Some of these limitations are that the model parameters cannot be identified, meaning that the functional relationship between variables is unrevealed (Detienne et al., 2003). Moreover, to obtain the minimum error, trial and error must be exercised many times (Ayyoub and Riaz, 2017).

Although accurately forecasting demand is not possible, several studies have been successful. Therefore, researchers always make their best attempts to minimize forecast errors (Hussain et al., 2016). Table 1 presents a summary of the energy forecasting studies using time series and their accuracy measurement results.

4. CONTRIBUTION OF THIS STUDY

This study fills the gap in the research on component gasoline demand forecasting in Indonesia. Moreover, most petroleum or

Table 1: Time series energy demand forecasting studies during 2007-2019

Author	Country and type of energy	Method	Variable	Accuracy
Ediger and Akar (2007)	Turkey Primary energy (Oil, coal, natural gas, other energy)	ARIMA and SARIMA	Yearly energy consumption 1950-2004	MSE 2,840,285
Sa'ad (2009)	Indonesia Gasoline and diesel	Structural Time- Series Model and Unrestricted Error Correction Model	Per capita consumption 1973-2007	n.a
Li et al. (2010)	Australia Gasoline	Linear Quadratic Exponential Holt Linear (HL) Holt-Winter (HW) Partial Adjustment (PA) ARIMA	Quarterly gasoline demand 1977−2006	MAD Linear: 3.68% Quadratic: 3.63% Exponential: 3.8% HL: 5.36% HW: 6.09% PA: 3.92% ARIMA: 5.53%
Melikoglu (2013)	Turkey Natural gas	Linear regression Logistic	Yearly natural gas demand per capita 1987−2011	RMSE logistics 2.348
Barde (2014)	Nigeria Fuel oil, diesel, gasoline, kerosene, LPG	Structural Time Series	Yearly consumption 1980-2010	n.a
Akpinar and Yumusa (2016)	Turkey Natural gas	Holt-Winters ARIMA Time series decomposition	Energy consumption Jan 2014-Dec 2014	MAPE Time series decomposition: 19% Holt-Winters: 14.01% ARIMA with differencing log 12: 12.9%
Barak and Sadegh (2016)	Iran Electricity	ARIMA and ANFIS	Population, GDP, import, export	MSE 0.00035
Hussain et al. (2016)	Pakistan Electricity	Holt-Winters ARIMA	Yearly electricity consumption in various sectors	MAPE ARIMA 84.3% Holt-Winters : 3%
Rehman et al. (2017)	Pakistan Various energy	ARIMA Holt-Winter Long-range energy alternate (LEAP)	Demand per capita	n.a
Oliveira and Oliveira (2018)	Canada, Italy, France, Japan, Brazil, Mexico, Turkey. Electricity	ARIMA Holt-Winters	Consumption 2015−2016	MAPE: ARIMA 2.277%-4.359% Holt–Winters: 2.035%-3.174%
Ozturk and Ozturk (2018)	Turkey Oil, natural gas, coal, renewable energy	ARIMA	Yearly consumption 1970−2015	n.a
Wang et al. (2018)	China and India Total Energy	Hybrid MGM- ARIMA	Yearly energy consumption in China and India 1990−2016	MAPE MGM-ARIMA China: 2.571% India : 0.804%
Wang et al. (2019)	Middle Africa Total energy	MGM, MECM, ARIMA, BP (ANN)	Yearly energy demand 1994−2017	MAPE MGM: 2.41% MECM: 4.8% ARIMA 1.91% ANN: 0.88%
Li and Wang (2019)	India Oil	NMGM–ARIMA NMGM–BP (ANN)	Yearly oil production and consumption 1995−2017	MAPE NMGM-ARIMA: 1.598% and 1.31% NMGM–BP: 1.874% and 1.751%
McNeil et al. (2019)	Indonesia Electricity	Bottom-up Energy Analysis System	Hourly load	n.a

gasoline demand forecasting in a time series analysis used previous demand or consumption as a time series variable. The contribution of this study is that forecasting gasoline is performed using a ratio variable. The following four methods are studied: Holt–Winters' additive, ARIMA, linear regression, and NN. The NN method is applied to model the correlation between the ratio of gasoline 92 to total demand and the price difference between gasoline 92 and gasoline 90. Demand forecasts for gasoline 90 and gasoline 88 are carried out using the variable for the demand ratio of gasoline 88 to gasoline 90.

5. METHODS

Gasoline demand forecasting was carried out using a top-down approach through which aggregated gasoline was first predicted. The components of gasoline demand were then calculated using their predicted demand ratio. This approach was applied because aggregate demand forecasting was more reliable than the summation of the individual component predictions (Ediger and Akar, 2007).

In this study, we used the Holt–Winters additive, ARIMA, linear regression, and NN methods. Holt–Winters additive and ARIMA are the time series methods that are widely used in demand forecasting because they can capture trends and seasonality. These two popular tools are used by researchers and practitioners to forecast studies (Xu et al., 2018). NN can predict nonlinear correlation among variables (Sharma and Chopra, 2013).

The Holt–Winters additive and ARIMA model are compared, and the best one is selected to apply the appropriate model to forecast gasoline demand. We analyzed the linear regression and NN to select the most accurate model to be applied to model the correlation between the price difference and the demand ratio. A combination of the Holt–Winters' additive prediction result and the forecasting result based on the correlation between the price difference and the demand ratio model is used to predict the component gasoline demand.

This study used IBM SPSS version 26 software to apply the Holt–Winters additive, ARIMA, linear regression, and NN model.

5.1. Holt–Winters Method

Holt–Winters is an exponential smoothing development that includes trends and seasonal data. Exponential smoothing assigns a different weight to each observation. Previous period data are given higher weights than older period data (Xu et al., 2018).

The Holt–Winters method uses three equations for level, trend, and seasonal. The seasonal component can also be treated additively in the formulation. The formulation includes α, β, and γ as smoothing parameters. The Holt–Winters additive method is as presented in equations (1), (2), (3), and (4) (Chase, 2013):

$$\text{Level: } L_t = \alpha\,(Y_t - S_{t-s}) + (1-\alpha)\,(L_{t-1} + b_{t-1}) \tag{1}$$

$$\text{Trend: } b_t = \beta\,(L_t - L_{t-1}) + (1-\beta)\,b_{t-1} \tag{2}$$

$$\text{Seasonal: } S_t = \gamma\,(Y_t - L_t) + (1-\gamma)\,S_{t-s} \tag{3}$$

$$\text{Forecast: } F = L_t + b_t m + S_{t-s+m} \tag{4}$$

where L_t = the level of the series
s = length of seasonality (e.g., number of the month in a year)
b_t = trend
S_t = seasonal component
F = forecast for m periods ahead
Y_t = actual demand in period t
α = constant between 0 and 1
β = constant between 0 and 1
γ = constant between 0 and 1.

5.2. Linear Regression

The linear regression is commonly used method in fuel demand studies (Li et al., 2010). This study compared the linear regression and NN methods to examine the correlation between the price difference and the demand for gasoline 92.

The regression analysis method estimates the parameter of the relationship between two or more variables. Typically, the modeler seeks to discover the cause and effect of one variable on another (Chase, 2013), such as the effect of the price difference between two products on sales.

The linear relationship between variables Y and X is given in equation (5):

$$Y = c + bX \tag{5}$$

where Y = dependent variable
c = intercept
b = slope of a line
X = independent variable

5.3. Autoregressive Integrated Moving Average (ARIMA)

ARIMA models were developed by Box and Jenkins (Gujarati and Porter, 2014). The requisite for applying ARIMA is that the data must be stationary. Stationary means that the data have constant mean and constant variance, and it can be determined using a graph. If no trend exists, then the time series is stationary. The way to remove the nonstationary data is by differencing, which is done by applying the differences among the observations (Li et al., 2010).

ARIMA is a combination of (1) auto regressive (AR), (2) integrated average (IA), and (3) moving average (MA). The IA is used to make the series stationary. In ARIMA (p, d, q), p expresses the number of autoregressive terms, q is the number of lagged forecast errors and d is the number of nonseasonal differences. The autocorrelation function (ACF) and the partial autocorrelation function (PACF) should be analyzed to determine the order of p and q (Brown and Rozeff, 1979; Fan and Yao, 2003; Gottman, 1981; Hussain et al., 2016).

Three steps are involved in applying ARIMA: (1) model identification, (2) parameter estimation, and (3) model diagnostics and forecasting (Ediger and Akar, 2007; Asuamah and Ohene, 2015; Barak and Sadegh, 2016). If seasonality is contained in the ARIMA model, SARIMA is used. SARIMA is represented as ARIMA (p, d, q) (P, D, Q), where P is the number of the seasonal autoregressive (SAR), D is the number of the seasonal differences and Q is the number of the seasonal moving average (SMA) (Debnath and Mourshed, 2018; Oliveira and Oliveira, 2018).

Bayesian Information Criterion (BIC) is a criterion for ARIMA models selection. The model to be selected is the one with the lower BIC value (Clement, 2014). The formula used to compute BIC is:

$$\mathrm{BIC} = n\,\{\ln(\sigma_e^2) + k\left\{\ln\left(n\right)\right\} \tag{6}$$

where k = the number of free parameters to be estimated
n = the number of observations
σ_e^2 = error variance

$$\sigma_e^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{7}$$

Under the normality assumption, the following formula may be more tractable (Clement, 2014):

$$\mathrm{BIC} = x^2 + k\{\ ln(n))\} \tag{8}$$

The general form of ARIMA forecasting is:

$$Y_t = c + a_1 y_{t-1} + a_2 y_{t-2} + \ldots\ldots + a_p y_{t-p} + \varepsilon_t - b_1 \varepsilon_{t-1} - \ldots - b_q \varepsilon_{t-q} \tag{9}$$

where: Y_t = value of variables
c = constant
a = coefficient of AR
b = coefficient of MA
ε_t = disturbance term (Rachev et al., 2007).

5.4. Neural Network

The NN is a prediction method that resembles the work of the human brain in processing information. NN form a specific structure consisting of several process units called neurons. This structure helps neurons solve problems by communicating with one another. Neurons are the fundamental operational unit of a NN. Each neuron performs the following tasks: receive signals from other neurons, signals are multiplied by a certain weight, the results of the multiplication of neurons with each weight are added up, the sum is transferred by the transfer function, and the number of transformations is sent to other neurons.

The neuron typology consists of three layers. The first layer is the input layer, the last layer is the output layer and a hidden layer is between the input and output layers. The input layer contains predictive variables. A network of neurons must have at least one independent variable as a factor. The data provided are called the values of the input variable.

The hidden layer consists of nodes that function as "black boxes" of NN. The value of each node is the result of the activation function, which is the sum of the input weights and biases. The output layer is the target variable. A minimum of one dependent variable exists as a target variable with nominal, ordinal or scale categories. (Ayyoub and Riaz, 2017). The neuron is a real function of input vector (x_j, ..., x_k). The output is obtained as

$$y_k = \varphi\left(\sum_{j=1}^{m} w_{kj} x_j + b_k\right) \tag{10}$$

where x_j represents the jth input to the kth neuron, w_{kj} is the weight of the neuron k and its jth input, y_k is the neuron output, and b_k is a bias constant (Haykin, 2005). The activation function ϕ is usually sigmoid (Sharma and Chopra, 2013).

A graphical presentation of a neuron is provided in Figure 3.

The sum square error (Szoplik, 2015), which measures the network error is calculated using the following formula:

$$\text{Sum square error} = \sum_{i=1}^{n}\left(d_i - z_i\right)^2 \tag{11}$$

where d_i = real value
z_i = value calculated by NN

5.5. Forecast Evaluation

The root mean square error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE) are commonly used to measure the accuracy for goodness of fit. The formula to compute RMSE, MAPE, and MAE are as follows (Hussain et al., 2016):

$$\mathrm{RMSE} = \sqrt{\frac{\sum (Y_t - F_t)^2}{N}} \tag{12}$$

where Y_t = actual value in time period t
F_t = forecasted value in time period t
N = total number of observations

$$\mathrm{MAPE} = \frac{1}{N} \times \sum\left[\frac{F_t - Y_t}{Y_t}\right] \times 100\% \tag{13}$$

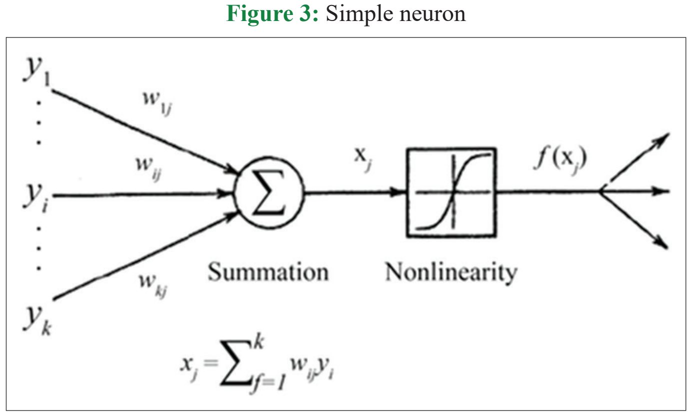
where Y_t = actual value in time period t
F_t = forecasted value in time period t
N = total number of observations

$$\mathrm{MAE} = \frac{1}{N} \times \sum\left[\frac{F_t - Y_t}{Y_t}\right] \tag{14}$$

All the parameter descriptions are the same as for MAPE. MAE and MAPE are similar, MAE is the absolute error and MAPE is the error in percentage.

The scale of judgement based on MAPE criteria developed by Lewis (Melikoglu, 2013) given in Table 2.

Figure 3: Simple neuron



Source: Sharma and Chopra (2013)

Table 2: Forecast accuracy scale

MAPE%	Evaluation
<10%	High accuracy
10% <MAPE <20%	Good forecast
20% <MAPE <50%	Reasonable forecast
>50%	Inaccurate forecast

The R square value is used to measure the goodness of fit of a model. R square is the squared correlation between the forecast variable Y and the estimated value $\hat{Y}$. The formula is:

$$\text{R square} = \frac{\sum_{i=1}^{n}\left(\hat{Y}i - \bar{Y}\right)^2}{\sum_{i=1}^{n}\left(Yi - \bar{Y}\right)^2} \tag{15}$$

where Y_i = actual value in i
$\hat{Y}_i$ = predicted value in i
$\bar{Y}$ = mean value (Chase, 2013).

R square values are between 0 and 1, and an R square of 1 indicates a perfect fit. When using time series data, an R square higher than 0.75 indicates a fairly good model fit (Chase, 2013).

P-values describe the exact significance level associated with an explanatory variable. If the P-value is 0.05 or less at a 95% confidence level, the explanatory variable is significant in predicting variable Y (Chase, 2013).

6. DATA DESCRIPTION

Figure 4 is a plot of the monthly gasoline total and gasoline 92 demand from January 2015 to December 2019 and indicates that trend and seasonality are present in the series.

The mean of total gasoline demand was 17,477 MB with a standard deviation of 1059, a minimum of 14,842 MB, and a maximum of 19,487 MB. The mean of gasoline 92 demand was 424 MB, the standard deviation was 768, the minimum was 1180 MB, and the maximum was 3671 MB. The mean ratio of gasoline 92 demand to total gasoline is 13.86%.

Figure 5 provides a plot of the ratio of gasoline 88 and gasoline 90 demand and indicates a downward trend in this ratio. At the beginning of 2017, gasoline 88 demand was about 1 times that of gasoline 90 demand—approximately the same. However, at the end of 2019, gasoline 88 demand was approximately 0.5 times that of gasoline 90 demand. This ratio is modeled to forecast the demand for these two products.

7. ANALYSIS

This section consists of five stages. The first stage compares two forecasting methods—the Holt-Winters additive and ARIMA. The second stage is to construct a model of gasoline 92 demand on the basis of the relationship between gasoline 92 and gasoline 90 price differences with the ratio of gasoline 92 demand to total gasoline.

Figure 4: Time series plot of monthly gasoline demand (in MB)

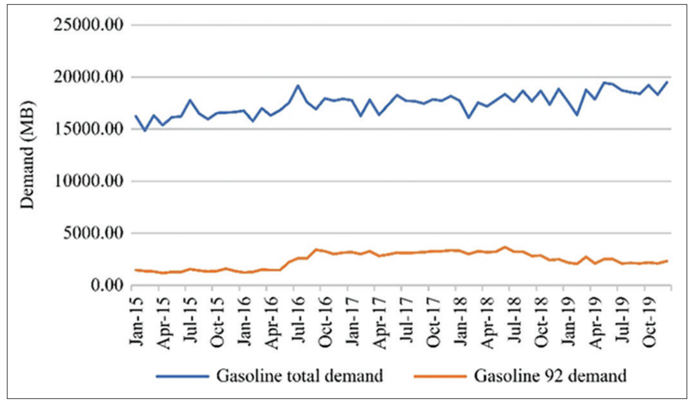
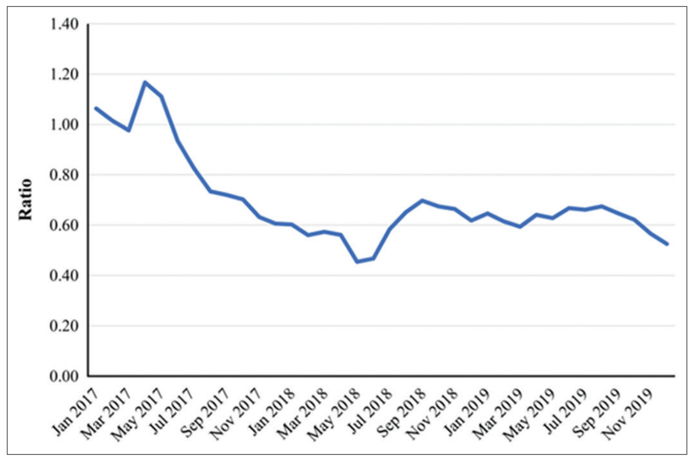


Figure 5: Time series plot of gasoline 88 and gasoline 90 demand ratio



The third, fourth, and fifth stages forecast the total gasoline, gasoline 92, gasoline 90, and gasoline 88 demand, respectively.

7.1. Stage 1

At this stage several time series methods are compared to determine which method is the most suitable for forecasting gasoline demand. The methods compared are Holt-Winters additive and ARIMA. In addition, the forecasting accuracy is compared between two periods: 2015-2019 and 2017-2019.

Table 3 shows the accuracy measures of the prediction model using the Holt-Winters additive. The results show that forecasting using 2017-2019 data is better than forecasting using 2015-2019 data. For the gasoline total and gasoline 92, data from the 2017 to 2019 period are more accurate than those from 2015 to 2019. MAPE's gasoline total from the 2017 to 2019 period is 1.472, whereas that from the MAPE 2015 to 2019 period is 1.807. Similarly, for gasoline 92, MAPE of the 2017-2019 period data is 4.322, and MAPE of the 2015-2019 period data is 7.411. Gasoline 90 was produced in the middle of 2016. Therefore, the forecast model was produced for 2017-2019. The MAPE of the ratio of gasoline 88 to gasoline 90 demand is 5.591.

Table 4 provides a comparison between the two ARIMA models for total gasoline demand, gasoline 92 demand, and the ratio of

Table 3: Accuracy measures of Holt-Winters additive using 2015-2019 and 2017-2019 data

Period	Variable	Accuracy measures	Holt-winters additive model
Based on demand data period 2015-2019	Gasoline total	RMSE	432.295
		MAPE	1.807
		MAE	319.087
		R square	0.839
	Gasoline 92	RMSE	226.752
		MAPE	7.411
		MAE	160.248
		R square	0.916
Based on demand data period 2017-2019	Gasoline total	RMSE	338.522
		MAPE	1.472
		MAE	262.989
		R square	0.854
		P value	0.149
	Gasoline 92	RMSE	150.898
		MAPE	4.322
		MAE	119.967
		R square	0.904
		P value	0.001
Based on demand data period 2017-2019	Ratio of gasoline 88 and gasoline 90	RMSE	0.056
		MAPE	5.591
		MAE	0.038
		R square	0.903
		P value	0.057

Generated by IBM SPSS Software

Table 4: Accuracy measures of ARIMA model of gasoline demand based on data period 2017-2019

Variable	Accuracy measures	ARIMA (0, 1, 1) (1, 1, 0)	ARIMA (1, 1, 0) (1, 1, 0)
Gasoline total demand	RMSE	558.122	558,018
	MAPE	2.108	2.258
	MAE	384.499	412.415
	R square	0.645	0.645
	BIC	12.922	12.921
	P value	MA (1): 0.000	AR (1): 0.005
		SAR (1): 0.347	SAR (1): 0.256
		ARIMA (1, 1, 1) (1, 0, 0)	ARIMA (1, 2, 0) (1, 0, 0)
Gasoline 92 demand	RMSE	228.216	278.104
	MAPE	6.663	7.297
	MAE	179.353	197.526
	R square	0.777	0.677
	BIC	11,064	11,463
	P value	AR (1): 0.009	AR (1): 0.000
		SAR (1): 0.138	SAR (1): 0.005
		ARIMA (11.1.0) (1, 0, 0)	ARIMA (2, 1, 0) (0, 0, 0)
Ratio of gasoline 88 and gasoline 90 demand	RMSE	6.974	6.316
	MAPE	5.796	6.308
	MAE	4.091	4.427
	R square	0.886	0.864
	BIC	5.205	3.991
	P value	AR (11): 0.051	AR (2): 0.230
		SAR (1): 0.001	C: 0.196

Generated by IBM SPSS Software

gasoline 88 to gasoline 90 demand. For the total gasoline demand, both ARIMA models have almost the same RMSE, R square, and BIC parameters; however the MAPE of ARIMA (0, 1, 1) (1, 0, 0) is smaller than ARIMA (1, 1, 1) (1, 0, 0), at 2.108 and 2.258, respectively. Moreover, the MAE of ARIMA (0, 1, 1) (1, 0, 0) is also smaller than ARIMA (1, 1, 1) (1, 0, 0), at 384.499 relative to 412.415. The best ARIMA model for gasoline 92 demand is ARIMA (1, 1, 1) (1, 0, 0). The MAPE of ARIMA (1, 1, 1) (1, 0, 0) is 6.663, the RMSE is 228.216, and the BIC is 11.064, whereas ARIMA (1, 2, 0) (1, 0, 0) generates MAPE, RMSE, and BIC equal to 7.297, 278.104 and 11.463 respectively. The R square of ARIMA (1, 1, 1) (1, 0, 0) is also higher than ARIMA (1, 2, 0) (1, 0, 0), which is 0.777 relative to 0.6777. For the ratio of gasoline 88 to gasoline 90 demand, the ARIMA (11, 1, 0) (1, 0, 0) is better than ARIMA (2, 1, 0) (0, 0, 0). The MAPE of the ARIMA (11, 1, 0) (1, 0, 0) is 5.796, whereas ARIMA (2, 1, 0) (0, 0, 0) is 6.308. The R square of ARIMA (11, 1, 0) (1, 0, 0) is also higher than ARIMA (2, 1, 0) (0, 0, 0), at 0.886 relative to 0.864.

A comparison of the Holt-Winters additive model and the ARIMA model shows that Holt-Winters is more accurate than ARIMA. The MAPE of the Holt-Winters additive model for all variables is lower than the ARIMA model. For the total gasoline demand, the MAPE of Holt-Winters additive model is 1.472 whereas ARIMA (0, 1, 1) (1, 1, 0) is 2.108, and the R square is also higher at 0.854 compared to 0.645. The similar holds for gasoline 92 demand and the ratio of gasoline 88 to gasoline 90 demand. The MAPE of the Holt-Winters additive model for gasoline 92 demand is 4.322 while MAPE of the ARIMA (1, 1, 1) (1, 0, 0) is 6.663. Similarly, for the ratio of gasoline 88 to gasoline 90 demand, the MAPE of the Holt-Winters additive model is 5.591 and of ARIMA (11, 1, 0) (1, 0, 0) is 5.796. The R square of the Holt-Winters additive model for these two variables is also higher than the ARIMA model.

7.2. Stage 2

In this stage, the correlation between the price difference and the demand ratio is calculated. The price difference is between gasoline 90 and gasoline 92, whereas the demand ratio is the ratio of gasoline 92 demand to total gasoline demand. The price of gasoline 90 and gasoline 92 increased periodically, and the price difference over time between the two products increases. Figure 6 indicates that if the price difference is IDR 1000, then the gasoline consumption is approximately 18% of total consumption. In contrast, if the price difference is IDR 2200, then the gasoline 92 consumption is 11%-14% of total consumption. Therefore, the larger the price difference between gasoline 90 and gasoline 92 the smaller the ratio of gasoline 92 demand to total gasoline demand. In other words, the larger the price difference between the two products, the more consumers will switch to products at lower prices.

The correlation between the price difference of the two products and the ratio is examined using two models. The first model is a linear regression, and the second model is a NN. The model with the lower MAPE will be selected.

The process of modeling the relationship between the price differences and the ratio of gasoline consumption 92 to total gasoline is carried out as follows:

1. Data are processed to determine the linear regression equation. The independent variable is price difference and the dependent variable is the ratio of gasoline 92 demand to total gasoline demand.
2. The dependent variable value is calculated using a linear regression formula with parameters generated by the software.
3. The data are processed to find a model for the relationship between price differences with the ratio of gasoline 92 consumption to total gasoline using the NN method.
4. The data processing for NN modeling is carried out by iteration to obtain the smallest error generated by the software. In each iteration the MAPE is calculated and compared one to another. The input layer variable is the price difference, and the output layer variable is the consumption ratio as the dependent variable. After several trials, the sigmoid activation function is chosen because it produced a lower error than the other activation function
5. The MAPE of the linear regression model and NN model is calculated and the results are compared.

Table 5 provides a summary of the linear regression model, and Table 6 provides the result of the linear regression model.

Then, the formula of the linear regression model for the correlation of the differences in prices and consumption is as follows:

$$Y = 21.229 - 0.004 * X$$

where Y = percentage of gasoline 92 consumption to total gasoline consumption

X = price difference between gasoline 92 and gasoline 90.

Figure 6: Correlation between price difference and ratio of gasoline 92 demand to total gasoline demand

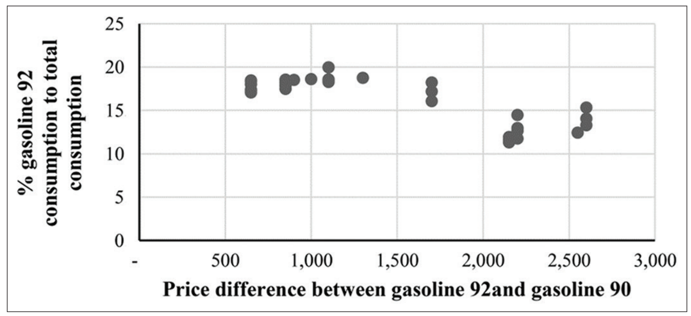


Table 5: Model summary of linear regression

Period	Parameter	P value
R square	0.726	0.000
Coefficients ß	−0.004	0.000
Constant	21.229	0.000

Generated by IBM SPSS software

Table 6: Results of linear regression

Correlation between price difference and ratio of gasoline 92 to total gasoline demand			
Price difference	Ratio of gasoline 92 to total gasoline (%)	Price difference	Ratio of gasoline 92 to total gasoline (%)
700	18.43	1700	14.43
750	18.23	2150	12.63
900	17.63	2200	12.43
1000	17.23	2550	11.03
1100	16.83	2600	10.83
1300	16.03		

Table 7: Summary of NN model

Model summary	Training	Sum of square error	0.144
		Relative error	0.117
	Testing	Sum of square error	0.065
		Relative error	0.090
Case processing summary	Training	22	61.1%
	Testing	14	38.9%

Generated by IBM SPSS Software

After several iterations of the NN, the model with the lowest error is obtained. The summary is as provided in Table 7, and the correlation between the price difference and the ratio of gasoline 92 demand to total gasoline demand is provided in Table 8.

The results of the linear regression model and the ANN model are compared. Table 9 shows that the predicted and the actual demand ratio of gasoline 92 using the ANN model is more accurate than the linear regression. The MAPE of the ANN model is 4.89% whereas the linear regression model is 8.48%. Therefore, the ANN model will be applied to forecast gasoline 92 demand using its ratio to total gasoline demand.

Table 8: Correlation between price difference and ratio of gasoline 92 demand using ANN method*

Price difference	Ratio of gasoline 92 to total gasoline (%)	Price difference	Ratio of gasoline 92 to total gasoline (%)
700	18.24	1550	18.24
750	18.24	1700	17.20
900	18.24	2150	12.64
1000	18.24	2200	12.63
1100	18.24	2550	12.63
1300	18.24	2600	12.63

*Generated by IBM SPSS software with sigmoid activation function

7.3. Stage 3

In this stage, total gasoline demand is forecasted using Holt-Winters additive as a suitable method. The result is shown in Figure 7.

As Figure 7 indicates, the trend in the demand for total gasoline, which comprises gasoline 88, gasoline 90, and gasoline 92, increased.

7.4. Stage 4

At this stage, gasoline 92 is forecasted on the basis of the combined weight calculation of 20% of the calculation using the ANN model in Table 8 plus 80% of the calculation using the Holt-Winters additive. The results of these analyses are presented in Figure 8.

Table 9: Prediction and actual correlation between price difference and gasoline 92 demand

Period	Price difference	Ratio gasoline 92 demand to total demand - actual	Linear regression model: Ratio gasoline 92 demand to total demand - predicted	Linear regression model: % Error	ANN model: Ratio gasoline 92 demand to total demand - predicted	ANN model: % error
January-17	700	18.04	18.43	2.16	18.24	0.95
February-17	700	18.47	18.43	0.24	18.24	1.42
March -17	700	18.37	18.23	0.34	18.24	0.85
April-17	750	17.39	18.23	4.80	18.24	4.69
May-17	750	17.08	18.23	6.75	18.24	6.64
June-17	750	17.28	18.23	5.51	18.24	5.41
July-17	750	17.49	18.23	4.22	18.24	4.12
August-17	750	17.88	18.23	1.95	18.24	1.85
September-17	750	18.21	18.23	0.10	18.24	0.01
October-17	750	18.24	18.23	0.07	18.24	0.17
November-17	900	18.57	17.63	5.05	18.24	1.91
December-17	900	18.52	17.63	4.81	18.24	1.67
January-18	1000	18.63	17.23	7.50	18.24	2.22
February-18	1300	18.75	16.03	14.52	18.24	2.89
March-18	1100	18.58	16.83	9.44	18.24	2.00
April-18	1100	18.47	16.83	8.88	18.24	1.39
May-18	1100	18.28	16.83	7.94	18.24	0.38
June-18	1100	19.98	16.83	15.77	18.24	8.86
July-18	1700	18.24	14.43	20.89	17.20	5.88
August-18	1700	17.20	14.43	16.11	17.20	0.20
September-18	1700	16.09	14.43	10.30	17.20	6.71
October-18	2600	15.34	10.83	29.41	12.63	17.67
November-18	2600	14.06	10.83	22.96	12.63	10.15
December-18	2600	13.30	10.83	18.59	12.63	5.04
January-19	2550	12.44	11.03	11.33	12.63	1.54
February-19	2200	12.65	12.43	1.74	12.63	0.12
March-19	2200	14.48	12.43	14.16	12.63	12.75
April-19	2200	11.77	12.43	5.62	12.63	7.35
May-19	2200	12.92	12.43	3.83	12.63	2.25
June-19	2200	12.97	12.43	4.14	12.63	2.57
July-19	2200	11.32	12.43	9.78	12.64	11.61
August-19	2200	11.66	12.43	6.55	12.64	8.33
September-19	2200	11.40	12.43	9.05	12.64	10.88
October-19	2200	11.53	12.43	7.78	12.64	9.58
November-19	2200	11.41	12.43	8.96	12.64	10.78
December-19	2200	11.93	12.43	4.16	12.64	5.90
			MAPE	8.48		4.89

Figure 7: Total gasoline demand forecast

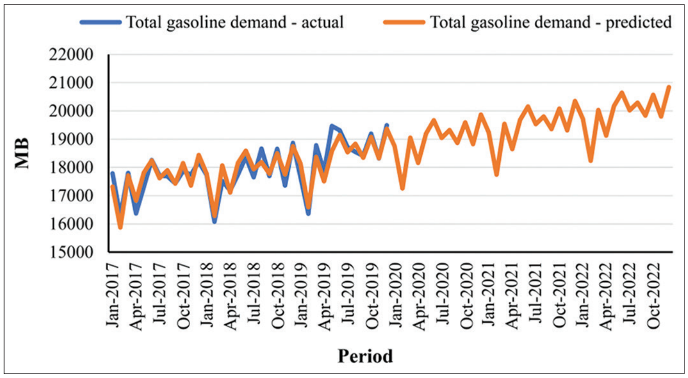
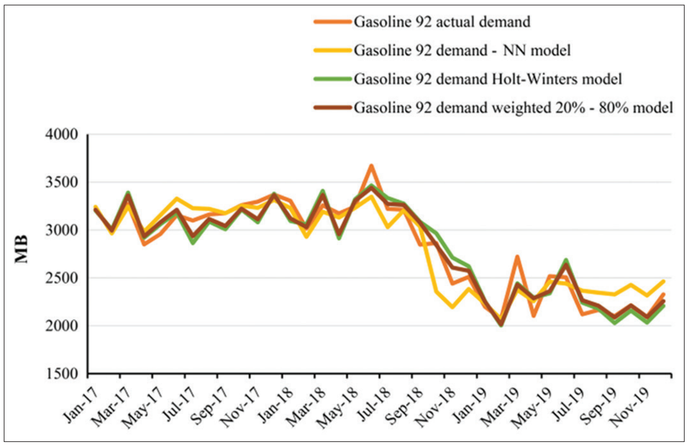


Figure 8: Gasoline 92 demand model



The combined model is more accurate than the standalone Holt-Winters additive method. The MAPE result of this combined model is 3.45, whereas the MAPE of the Holt-Winters additive model is 4.322.

Gasoline 92 demand is forecasted using the combined model. The forecast is done using certain assumptions of the price difference between gasoline 92 and gasoline 90, as listed in Table 10.

7.5. Stage 5

In this stage, gasoline 90 and gasoline 88 are forecasted. The steps to generate a forecast are as follows:
1. Forecast the ratio of gasoline 90 and gasoline 88 demand using the Holt-Winters additive method.
2. Compute the demand of gasoline 90 plus gasoline 88, and then calculate the gasoline 90 and gasoline 88 demand forecasts using the previous ratio.

Step 1

As Figure 9 indicates, the demand for gasoline 88 at the beginning of 2017 was 1.06 times that of gasoline 90.

During the observation period, the ratio of the demand for the two products decreases. At the end of 2019, gasoline 88 demand becomes 0.53 times that of gasoline 90 and continues to decline. The prediction is that, at the end of 2022, gasoline 88 demand is predicted to be 0.14 times that of gasoline 90.

Figure 9: Ratio of gasoline 88 to gasoline 90 demand

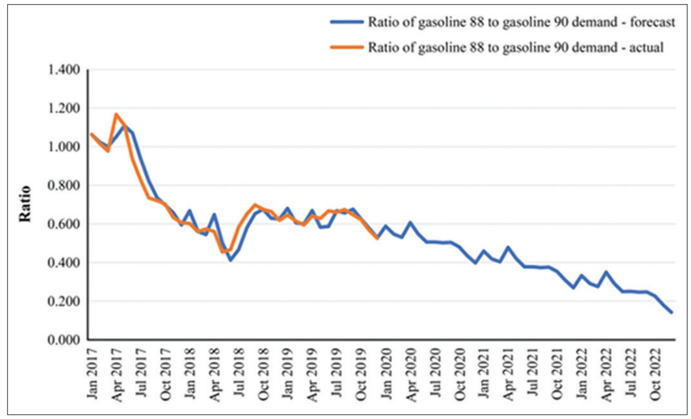


Table 10: Gasoline 92 forecast assumption

Period	Price difference of gasoline 92 and gasoline 90 assumption	% gasoline 92 demand to total gasoline demand
January 2020	2150	12.66
February 2020-December 2022	1550	18.24

Step 2.

At this stage the demand for gasoline 88 and gasoline 90 demand is calculated using the predicted demand ratio.

Gasoline 90 demand = 1/(1 + consumption ratio) × (demand for gasoline 88 + gasoline 90)

Gasoline 88 demand = Demand ratio × gasoline 90 demand.

8. RESULT AND DISCUSSION

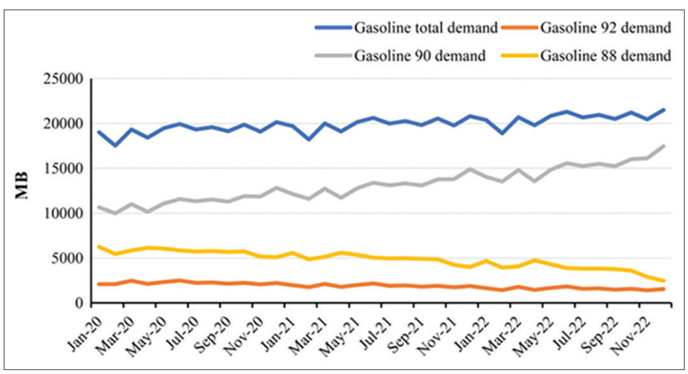
The Holt-Winters additive and the ARIMA models were analyzed to determine a suitable forecasting model. The results indicated that the Holt-Winters additive model is more accurate than the ARIMA model because it has lower MAPE and RMSE. We identified the appropriate correlation model between the price difference and the ratio of gasoline 92 to total demand and compared the linear regression model and the NN model. The results showed that the NN model has better accuracy than the linear model. These results further implied that the Holt-Winters additive is applied to forecast total demand and the ratio of gasoline 88 to gasoline 90. When forecasting gasoline 92 demand, the Holt-Winters additive model and the ratio of gasoline 92 to total gasoline demand are combined. Referring to Table 2, forecasting models of this study produce high accuracy that shows that the MAPE is <10%. The MAPE for total gasoline demand is 1.472, and is 3.45 for gasoline 92, and the ratio of gasoline 88 to gasoline 90 is 5.591. The results of the gasoline forecast and the components are presented in Figure 10 and are summarized in Table 11.

From 2017 to 2022, yearly total gasoline demand is predicted to increase by 13%, whereas gasoline 90 is predicted to increase by 88%. In contrast, gasoline 92 and gasoline 88 are predicted to decrease by 50% and 44%, respectively.

Table 11: Forecasting result of gasoline (in MB)

Gasoline	January-20	February-20	March-20	April-20	May-20	June-20
Total	18,747	17,256	19,055	18,156	19,194	19,667
Gasoline 92	2095	2085	2459	2126	2322	2503
Gasoline 90	10,492	9806	10,840	9981	10,906	11,397
Gasoline 88	6159	5364	5736	6048	5965	5766
Gasoline	July-20	August-20	September-20	October-20	November-20	December-20
Total	19,043	19,317	18,864	19,590	18,825	19,865
Gasoline 92	2242	2279	2151	2235	2071	2210
Gasoline 90	11,156	11,344	11,112	11,718	11,667	12,629
Gasoline 88	5645	5694	5601	5637	5087	5024
Gasoline	January-21	February-21	March-21	April-21	May-21	June-21
Total	19,234	17,743	19,542	18,643	19,681	20,154
Gasoline 92	1966	1747	2120	1788	1984	2165
Gasoline 90	11,827	11,273	12,409	11,404	12,462	13,054
Gasoline 88	5441	4723	5031	5451	5234	4934
Gasoline	July-21	August-21	September-21	October-21	November-21	December-21
Total	19,530	19,804	19,351	20,077	19,312	20,352
Gasoline 92	1904	1941	1813	1896	1733	1872
Gasoline 90	12,791	13,002	12,746	13,428	13,440	14,552
Gasoline 88	4835	4862	4792	4753	4139	3929
Gasoline	January-22	February-22	March-22	April-22	May-22	June-22
Total	19,721	18,230	20,029	19,130	20,168	20,641
Gasoline 92	1627	1408	1782	1450	1646	1827
Gasoline 90	13,584	13,030	14,300	13,096	14,336	15,052
Gasoline 88	4509	3791	3946	4584	4186	3763
Gasoline	July-22	August-22	September-22	October-22	November-22	December-22
Total	20,017	20,291	19,838	20,564	19,799	20,839
Gasoline 92	1565	1602	1474	1558	1394	1553
Gasoline 90	14,750	15,000	14,714	15,502	15,597	16,903
Gasoline 88	3702	3689	3649	3503	2807	2401

Figure 10: Gasoline demand forecast result



Demand for gasoline 88 has been declining over the years and is predicted to continue to decline. During 2016, gasoline 90 was launched as a substitute for gasoline 88. The expectation is that consumers will buy gasoline 90 instead of gasoline 88. However, because of a significant price difference between gasoline 90 and gasoline 92, many consumers who initially used gasoline 92 changed to gasoline 90.

9. CONCLUSION

As the population increased and oil production was depleted, Indonesia's domestic oil demand exceeded its production level. Therefore, Indonesia has been importing crude oil and refined oil product. Accurate supply planning predictions are required to balance supply and demand. This study is designed to facilitate the planning of Indonesian fuel oil to reduce the risk of domestic oil supply shortages.

This study concluded that the greater the price difference of two products with a closed quality, the lower the demand for products at a higher price. This study also revealed that forecasting by combining two models provides higher accuracy than by using one model. Moreover, 3 years of data generated a more accurate forecast than 5 years of data.

The time-series forecasting method generally uses the ARIMA model. This study applies the Holt-Winters additive method because it produces higher accuracy than ARIMA. A simple time-series method was found to generate more accurate forecasting results than a sophisticated method such as ARIMA. Empirical studies supported this finding (e.g., Fildes and Makridakis, 1995; Fildes et al., 1998; Li et al., 2010; Hussain et al., 2016), which concluded that the performance of simple forecasting methods is almost the same as that of sophisticated statistics. The reason is that simple methods can extrapolate the patterns of a time series better than sophisticated methods (Li et al., 2010). The NN model can accommodate the correlation between two variables that are not entirely linear and produces a model with higher accuracy than a linear regression. The conclusion reached is that the NN model is more appropriate than the regression model for nonlinear relationships

Because demand forecasting is part of logistic planning, further research is suggested to analyze the supply level. Forecasting results are not always accurate, and derivations from what was planned always exist in the oil supply chain. Therefore, supply analysis requires a simulation model to determine the impact of any deviation in the supply chain factors.

10. ACKNOWLEDGMENTS

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