Estimation Train Passengers Demand Using Artificial Neural Network

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Abstract: The number of passengers on the KRL Commuter Line, an electric train service in the Jabodetabek region, shows a significant upward trend. This trend poses challenges for the Indonesian Railway Company, including passenger congestion and customer inconvenience. The increase in the number of KRL Commuter Line users along the Jabodetabek route is quite significant in line with development in areas that are becoming agglomeration cities. Therefore, accurate number of train passenger demand estimation is very important for Indonesia Railway Company (PT. KAI) policy making. This study proposes a neural network model to efficiently, precisely and validly estimate number of train passenger demand in Jabodetabek. This model has five independent variables, such as GRDP (Gross Regional Domestic Product), Average length of schooling, life expectancy, population and regional Human Development Index. Data obtained from Central Bureau of Statistics of Indonesia and PT. KAI. The number of train passenger demand estimation is using a pessimistic, realistic and optimistic scenario that estimates of the number of passenger KRL Commuter Line in the next 10 years using artificial neural networks shows that the number of KRL Commuter Line passenger demand continues to have upward trend, both in pessimistic, realistic and optimistic scenarios which has been influenced by development conditions in the Jabodetabek area as an agglomeration city.

Keywords: Train Passengers Demand, Double Exponential Smoothing Holt, Artificial Neural Network.

1. INTRODUCTION

Jakarta is one of the metropolitan cities that since 1999, has been expanded into an agglomeration city which is then known as the Jabodetabek area. This area consists of Bogor Regency and City, Tangerang Regency and City, Depok Regency and City and Bekasi Regency and City. The expansion of the city of Jakarta is due to the problems in the city of Jakarta which are always related, especially to transportation problems. Transportation problems in the Jabodetabek area occur due to increased economic growth, thus triggering increased movement or mobility of activities. The high rate of movement will certainly also increase the need for transportation and the use of private vehicles, so that a series of urban transportation problems arise, one of which is congestion. Therefore, to overcome urban transportation problems, strategies and policies are needed to direct people's choices to use environmentally friendly mass transportation facilities. One of the environmentally friendly mass transportation in the Jakarta metropolitan area is the Commuter Line Electric Rail Train (KRL). The Jabodetabek Commuter Line is one of the mass transportation modes that is expected to be the backbone of future mobility that is always the mainstay of urban workers to travel during working days in the Jakarta metropolitan area (Rachmadina *et al.*, 2023). The large number of Jabodetabek Commuter Line passengers have upward trend except in 2021 and 2022 there was a very sharp decline due to the Covid-19 pandemic, which resulted in KRL Commuter Line passengers switching to other vehicles.

As can be seen in the table above, the economy growth of the Jabodetabek area studied has experienced an increase, marked by Gross Domestic Regional Product which continues to increase, as well as the number of passengers in Jabodetabek which continues to increase except in 2020, 2021 and 2022, it declines from the previous year due to the Covid-19 pandemic.

When everything is okay, the large number of Jabodetabek Commuter Line passengers have upward trend and this will cause problems that must be faced by PT KAI, such as the accumulation of passengers at several stations throughout the Jabodetabek area, passenger discomfort due to crowding etc. The increase in the number of KRL Commuter Line users along the Jabodetabek route is quite significant along with the development in areas that have become agglomeration cities. As is known, train passengers are one of the sources of cash flow besides advertising and other income that have an impact on the financial sustainability of railway companies (Hu *et al.*, 2022).

Therefore, predictions and analysis of the number of KRL Commuter Line passengers at each station in the Jabodetabek area are needed to help PT KAI anticipate passenger needs so that they remain comfortable, safe, and on time.

So, the identification and analysis of numbers trains passengers and the creation of train operational policy options are necessary. The forecasting of train passegers demand is a

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Table 1. GRDP and The number of passenger in KRL Commuter Line.

No	City/Regency	Gross Regional Domestic Product (million rupiah)									
		2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
1	South Jakarta	310,185,285.60	329,155,038.27	349,251,707.95	371,253,513.45	394,429,957.63	421,300,849.02	419,257,189.07	429,259,254.89	451,772,636.51	475,806,324.07
2	East Jakarta	236,464,307.74	249,476,978.00	264,810,038.51	281,363,139.62	298,530,651.22	313,540,959.02	299,515,155.43	313,808,696.85	329,572,830.23	346,552,326.44
3	Central Jakarta	332,896,524.18	355,092,532.22	377,781,737.53	400,474,897.03	424,204,369.37	452,521,528.81	449,518,143.92	459,971,274.03	481,954,448.23	506,554,143.75
4	West Jakarta	235,186,461.82	249,328,636.84	264,434,925.84	281,570,445.13	299,452,401.52	318,927,928.71	316,172,607.15	327,599,160.15	345,619,547.84	363,931,254.11
5	North Jakarta	256,807,476.27	271,155,619.99	283,654,318.62	301,779,314.69	320,658,347.86	332,807,591.51	312,100,575.62	330,890,182.47	350,233,718.35	364,818,970.18
6	Bogor Regency	117,339,503.44	124,486,977.40	131,760,367.20	139,561,453.80	148,203,354.22	156,876,009.09	154,113,604.44	159,589,545.13	167,966,182.41	176,683,583.63
7	Bekasi Regency	197,163,574.99	205,950,393.45	215,928,364.00	228,203,598.90	241,949,381.01	251,502,786.02	242,971,393.70	251,778,518.57	265,120,492.65	279,224,902.86
8	Bogor	23,835,310.77	25,298,604.31	27,002,251.51	28,654,970.95	30,413,574.60	32,295,729.41	32,162,742.35	33,372,476.44	35,258,870.02	37,055,362.79
9	Bekasi	52,534,090.06	55,456,074.56	58,831,077.37	62,202,006.16	65,845,093.42	69,406,530.40	67,619,238.66	69,796,935.84	73,260,650.00	77,241,786.49
10	Depok	35,192,761.81	37,529,475.37	40,263,233.18	42,981,282.50	45,978,885.33	49,076,576.47	48,135,927.56	49,947,235.26	52,564,975.78	55,221,820.93
11	Lebak	15,756,246.97	16,733,237.57	17,665,397.46	18,683,739.22	19,735,870.92	20,810,486.83	20,622,043.72	21,278,484.95	22,087,738.08	22,706,798.37
12	Tangerang regency	73,828,384.71	77,962,945.83	82,183,596.15	86,964,026.88	92,011,405.21	97,129,166.45	93,480,392.05	97,869,379.61	103,221,020.69	108,570,429.08
13	Serang Regency	42,300,934.77	44,454,582.21	46,715,184.52	49,154,636.22	51,754,319.98	54,347,487.78	52,866,430.97	54,844,646.90	57,607,109.12	60,370,564.40
14	Tangerang	86,183,522.76	90,807,569.45	95,654,618.05	101,274,679.40	106,283,617.41	110,556,398.12	102,415,675.10	106,413,710.65	112,780,033.83	119,060,332.19
15	Cilegon	57,261,922.79	59,982,731.73	62,981,047.41	66,444,529.41	70,502,082.41	74,228,640.69	73,319,124.76	77,163,935.90	80,647,729.97	84,537,543.85
16	Serang	16,745,083.89	17,808,478.25	18,935,486.29	20,153,022.86	21,482,093.45	22,813,096.37	22,518,660.21	23,392,750.37	24,495,316.78	25,655,605.62
17	South Tangerang	42,411,467.14	45,485,613.63	48,552,983.88	52,098,555.88	55,999,106.77	60,137,014.46	59,531,079.34	62,393,119.54	66,021,910.49	69,562,289.19

No	Station	The number of KRL Commuter Line Passenger Demand (people)									
		2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
1	All Station in Jabodetabek	206,809,273	257,527,772	280,586,407	315,849,947	336,348,316	336,048,369	153,579,957	124,773,451	213,537,376	290,890,677

key policy tool used by Indonesia Railway company policy making. Overestimating train passengers demand can lead to resource redundancy, whereas underestimating train passengers demand can lead to the increase number of passengers not being anticipated properly so it can make passenger unconvenient and discomfort.

So, an important factor for PT. KAI passenger service policy is an accurate assessment of future passengers needs. The purpose of this research is to present a realistic and accurate model in estimating the number of KRL Commuter Line passenger demand by using soft computing techniques, be called artificial intelligence. The artificial intelligence methodis the best method today to make estimates and predict the future ahead because it provides several advantages, such as nonlinear mapping capabilities, more accurate forecasting capabilities, and the ability to handle noise data (Satrio et al, 2022). Using the ANN model, it produces accurate precision and very small errors when compared to other forecasting methods (Gallo *et al.*, 2019; Lin *et al.*, 2020; Vasconcelos *et al.*, 2021; Satrio *et al.*, 2022).

Artificial Intelligent methods that are often used and are among the best in forecasting are Artificial Neural Networks. Research on forecasting the number of train passenger demand using artificial neural networks based on economic regional development has never been carried out in Indonesia.

This research focuses on forecasting the number of train passenger demand, based on demographic and socio-economic indicators. The model is created using GRDP (Gross Regional Domestic Product), Average Length of Schooling, Life Expectancy (AHH), Population and Regional Human Development Index. Three different scenarios are used to estimate the value of future KRL Commuter Line Passenger demand.

In this model use the term ceteris paribus to signify that all the relevant variables, except those being studied at that moment, are held constant (Mankiw, 2008).

2. LITERATURE REVIEW

Several studies on predicting the number of train passengers have been widely conducted using computational intelligence-based algorithm models, namely Artificial Neural Network (ANN). Ma *et al.* (2019) predicted the number of metro train passengers based on ANN with a Convolutional Neural Network (CNN) model using Long Short Term Memory Network (LSTM) to extract spatial and temporal features. Gallo *et al.* (2019) proposed the use of ANN to predict metro passenger flow as a function of the number of passengers whose access is controlled by station turnstiles. Zhang *et al.* (2020) studied the application of ANN with the Back Propagation (BP) model in predicting train passenger flow. Liu *et al.* (2019) proposed ANN with the Recurrent Neural Networks (RNN) model using LSTM and end-to-end Neural Network to estimate metro passenger in/outflow and optimize schedules. Huang *et al.* (2020) predicted passenger flow using ANN Recurrent Neural Networks (RNN) method using LSTM, Gated Recurrent Unit (GRU) and Wavelet Transform to solve urban railway operation problems. Jing & Yin (2020) predicted the number of passengers entering a train station at different time intervals using ANN to provide station security guarantees, resource allocation and personnel placement. Zhang *et al.* (2020) predicted passenger flow of train stations based on ANN using LSTM Network and Multi-Source-Data to control the passenger transportation situation. Yang *et al.* (2020) predicted passenger flow in and out of metro stations based on ANN using end-to-end Neural Network Deep Passenger Flow to describe the characteristics of metro stations with all available information at each station. Lin *et al.* (2020) predicted metro passenger flow based on the relationship between land use and metro stations with ANN using LSTM. Amalia & Putri (2020) predicted the number of train passengers in Indonesia based on ANN with Back Propagation (BP) and using SARIMA models. Vasconcelos *et al.* (2021) predicted the demand for train passengers for the economic and financial feasibility study of a passenger train project based on ANN. Pontoh *et al.* (2021) predicted the number of train passengers with high accuracy for improving railway management based on ANN with a Machine Learning model for feed-forward systems and using the Facebook Prophet Model. El Maazouzi *et al.* (2022) predicted the flow of train passengers based on ANN with a Recurrent Neural Networks (RNN) model using (LSTM) and ARIMA Models. Nar & Arslankaya (2022) estimated the flow of train passengers to determine the train arrival headway to minimize passenger waiting time at the station based on ANN with a Machine Learning (ML) model. Wu *et al.* (2023) increased the number of passengers using the MRT based on ANN with a Recurrent Neural Networks (RNN) model using multiple-attention deep neural networks. Meanwhile, many researchers use time series forecasting modeling with the Double Exponential Smoothing Holt method. Shukor *et al.* (2021) compared the Double Exponential Smoothing, Holt's Linear Trend and Random Walk methods to obtain the best forecast of gold, silver, crude oil and platinum stock market prices. Aminudin & Putra (2019) predicted the Poverty Line, to help the government obtain accurate and fast information using the Double Exponential Smoothing Holt method.

3. METHOD, DATA AND ANALYSIS

3.1. Types and Sources of Data

This study uses secondary data sourced from the Indonesian Central Statistics Agency (BPS) and PT. KAI, including socioeconomic indicators relevant to forecasting KRL Commuter Line demand. An Artificial Neural Network (ANN) model, specifically the Multi-Layer Perceptron (MLP), was chosen for its ability to handle complex, nonlinear data patterns. The data used are KRL Commuter Line passenger demand Data, Indonesian Regional Economic Development Data (GRDP (Gross Regional Domestic Product), Average Length of Schooling, Life Expectancy, and Regional Human Development Index), Indonesian Demographic Data (Regional Population) in the last 10 years (from 2014 to 2023).

In macroeconomics, emphasis was on the idea that economic activity could be explained by a set of relationship between economic variables (Spencer, 1993), as well as train passengers demand forecasting which can be calculated with several variables that influence it.

3.2. Train Passengers Demand Prediction Method

In this study to predict the train passenger demand in Indonesia, the model used is the Artificial Neural Network Model. Train Passenger demand is predicted for the next 10 years. That is until 2033. Prediction of the train passenger demand in this study is carried out based on the value of forecasting six categories (GRDP (Gross Regional Domestic Product), Average Length of Schooling, Life Expectancy, and Regional Human Development Index), Regional Population and The Number of Train Passenger).

GRDP (Gross Regional Domestic Product), Average Length of Schooling, Life Expectancy, and Regional Human Development Index), Regional Population were collected from Indonesian Central Statistics Agency (BPS) and the number passenger of KRL Commuter Line were collected from Indonesian Railway Company (KAI), Five independent variables (GDRP(Gross Regional Domestic Product), Average Length of Schooling, Life Expectancy, and Regional Human Development Index) and dependent variable (Train Passenger Demand) are reffering to precedent researches from (Satrio *et al.*, 2022). Before predicting Train Passenger Demand, it is necessary to predict the independent variables in advance.

The forecasting method that will be used to predict the independent variable (x variable) in this study is the Double Exponential Smoothing Holt. The Double Exponential Smoothing Holt method is a forecasting approach used for data with trend patterns. The Double Exponential Smoothing Holt method is part of the data that is based on time series analysis (Aminudin & Putra, 2019).

Forecasting in this method is obtained using two parameters, namely the alpha value (α) as a parameter in smoothing the level or average of the data, while the second parameter, the beta value (β) is a parameter for smoothing trends (Aminudin & Putra, 2019; Shukor et al ., 2021). These alpha and beta values are to determine the best parameter values. The alpha and beta values are obtained from trial and error until the optimum alpha and beta values are obtained ($0 \leq \alpha, \beta \leq 1$). This model was developed by Charles Holt and Peter Winter's (1958) with the following forecasting model:

Smoothing level with $0 \leq \alpha \leq 1$

$$S_t = \propto X_t + (1 - \propto)(S_{t-1} + b_{t-1})$$

Smoothing trend with $0 \leq \beta \leq 1$

$$b_t = \beta(S_t - S_{t-1})(1 + \beta)b_{t-1}$$

Forecasting mean value:

$$F_{t-m} = S_t + b_t\, m$$

Description: Ft+m = Forecast period m St = Smoothing value α = Smoothing weight (constant) for original data (0<α<1) m = Future period (many forecasts after t) Xt = Actual value of period t bt = Smoothing value β = Smoothing constant for trend data (0<β<1) The Double Exponential Smoothing Holt method is carried out with three forecasting scenarios, namely pessimistic (Forecasting Lower), Optimistic (Forecasting High), and middle value forecasting. The forecasting value of the pessimistic scenario is always smaller than the forecasting result of the middle value. While the forecasting value of the optimistic scenario is always greater than the forecasting result of the middle value.

$$Forcasting\ \ Lower = F - Z\frac{s}{\sqrt{n}}$$

$$Forcasting\ \ Lower = F + Z\frac{s}{\sqrt{n}}$$

$$S = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{F})^2}{\sqrt{n-1}}}$$

Description,

F = Forecasting Result,

Z = Z value

S = Standard deviation

To ensure the reliability of forecasting from the Double Exponential Smoothing Holt method, one of the forecasting accuracy methods is used, namely Mean Square Error (MSE). MSE is one of the residual or error-based methods that can be used to select the best model (Omotola, Olafioye *et al.*, 2023; Yuniati & Sugandha, 2021). Model feasibility via MSE uses the formula :

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2$$

Description:

At = actual value

Ft = estimated value

n = number of observations

t = observation period

The forecasting method used to predict the dependent variable (y variable) in this study is the ANN (Artificial Neural Network) method. After GRDP (Gross Regional Domestic Product), Average Length of Schooling, Life Expectancy, and Regional Human Development Index), Regional Population have been predicted for the next 10 years respectively. so that this data can be used as predictor data to predict KRL Commuter Line Demand. The KRL Commuter Line passenger demand data used is KRL Commuter Line passenger data with an annual period from 2014 to 2023.

3.3. Artificial Neural Network

The model used in this study to predict the total The KRL Commuter Line passenger demand in Indonesia is the Artificial Neural Network Model. The ANN method is a form of artificial intelligence and represents an imitation of the neural network in the human brain that has the ability to learn from existing data to solve complex problems (Graupe, 2007). These artificial nerves are connected in a model similar to the brain nerve network (Rahma, 2019). The ANN model is inspired by the ability of the human brain, which has extraordinary capacities and capabilities in analyzing incomplete, unclear or obscure information, and can make decisions or judgments about it (Satrio et al, 2022). An ANN model generally consists of three layers, that is the input layer, hidden layer and output layer (Kukreja *et al.*, 2016). This multi-layer model is called the Multi Layer Perceptron (MLP). The ANN model used in this study is the Multi Layer Perceptron (MLP) and the training process used is supervised training.

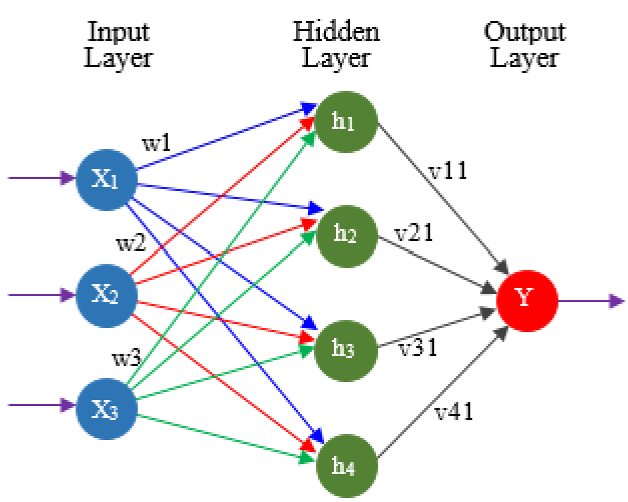

Fig. (1). ANN Multilayer Structure.

3.4. Research Location

The KRL Commuter Line is a rail-based mass transportation mode within the city that serves trips to the Jabodetabek area which is divided into five lines and one local route, with more than 82 stations connecting the Jakarta area and its surroundings. The routes and routes include: KRL crossing Bogor, KRL crossing Cikarang, KRL crossing Rangkasbitung, KRL crossing Tangerang, KRL crossing Tanjung Priok, and the local KRL route to Merak. The Jabodetabek track and route map is presented in the following image.

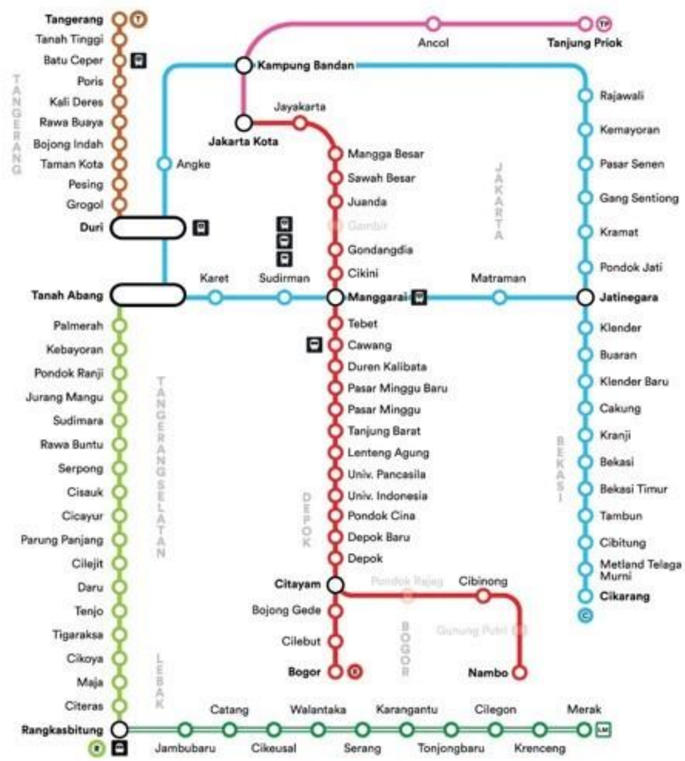

Fig. (2). Jabodetabek Track and Route Map for KRL Commuter Line.

4. RESULT AND DISCUSSION

4.1. Forecasting of Independent Variable

To create an estimation model for number of KRL Commuterline in Indonesia, The Double Exponential Smoothing Holt method works to smooth trends in data from economic growth parameters in the Jabodetabek area, that is GRDP, Average Years of Schooling, Life Expectancy, Population and Human Development Index. The initial step in predicting using this method is to plot the data to produce a Time Series Plot graph for the period 2010-2023, as input data for forecasting. After going through the steps of the forecasting flow using the Double Exponential Smoothing Holt method, the alpha value parameter (α) is obtained as a parameter in the smoothing level, the beta value (β) as a parameter for smoothing trends, and the Forecasting value of the middle value. In addition to the forecasting of the middle value, this method also obtains three scenarios, that is pessimistic forecasting (Forecasting Lower), realistic forecasting and optimistic forecasting (Forecasting High) for the period 2024-2033. Based on the simulation results of this method, from the scenario graph against the economic growth parameters of the Jabodetabek region, the data pattern on average shows an increasing trend. Therefore, the results of the forecast if predicted in the next 10 years also tend to increase. The results of the forecasting simulation using this model are shown in the forecast graph for the Central Jakarta which represents all areas studied.

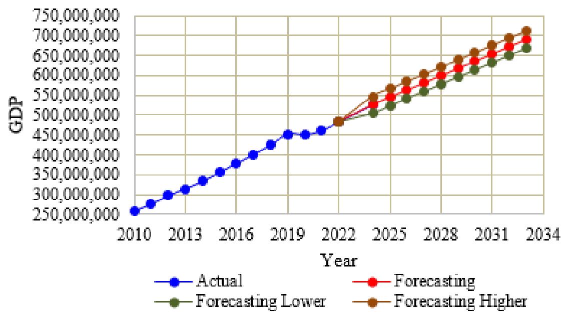

Fig. (3). Forecasting GRDP.

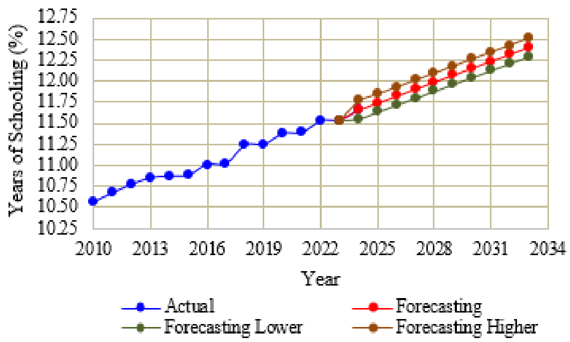

Fig. (4). Forecasting Average Years of Schooling.

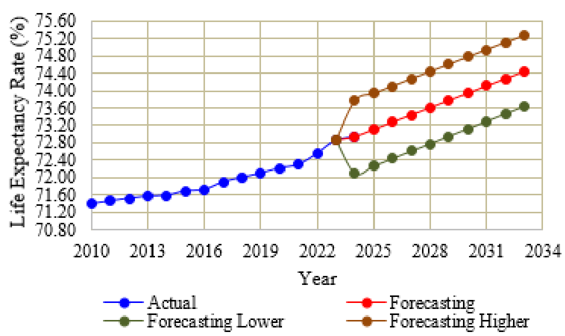

Fig. (5). Forecasting Life Expentancy.

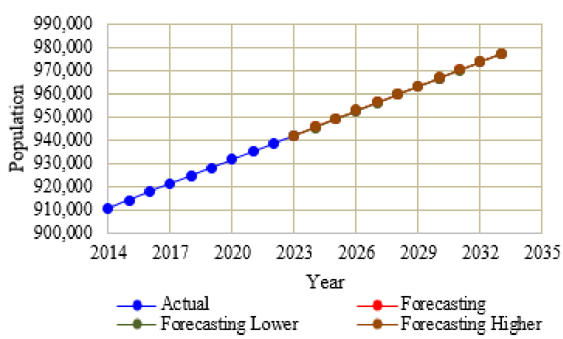

Fig. (6). Forecasting Population.

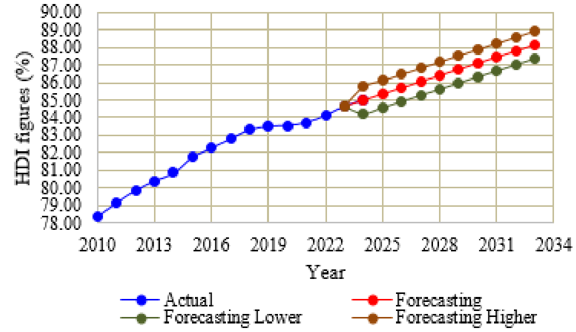

Fig. (7). Forecasting Human Development Index.

Based on the simulation results of this method, from the scenario graph of the economic growth parameters of the Jabodetabek area, the data pattern on average shows an increasing trend. Therefore, if the results of the experience are predicted in the next 10 years, they will also tend to increase.

4.2. Forecasting Y variable using Artificial Neural Network (ANN) Model

The ANN model used in this study is Multi Layer Perceptron (MLP) and the training process used is supervised training. Using the MLP model, because the Input Layer includes five (5) nodes, namely: Life Expectancy (X1), Population (X2), PDRB (X3), Average Length of Schooling (X4), and Human Development Index (X5). While the Output Layer (Y Variable) is the total number of passengers predicted for the next 10 years, that is from 2024 to 2033. in this article there are a station whose train passengers are predicted for the next 10 years from 2024 - 2033, this station are a representation of the 82 stations, 17 regions and 5 Province studied in this article.

4.2.1. Bekasi Station (representing stations in West Java Province)

In the Bekasi Station Forecasting there are RSquare = 98,68 % and the ANN model with 5 Hidden Nodes has very small error that is 0.0043734. In addition, the number of nodes 5 in the hidden layer has a very high R-SQUARE of 0.9868 or 98.68%. In other words, the ANN model is able to explain the diversity of the Number of Passengers by 98.68 %. So the ANN model that will be used for forecasting the Number of Passengers is a model with a hidden layer with 5 nodes. The ANN model with 5 hidden nodes can be seen in the following Figures.

From the graph at Bekasi Station, it can be seen that the number of train passengers is The graph is wavy even though the trend is increasing, this is due to the actual graph is also wavy due to the Covid-19 pandemic, but the trend is increasing due to the increase in regional development variables which have also increased from year to year in Central Jakarta. In 2019-2021 the Commuter Line experienced a decrease in the number of passengers due to the Covid-19 pandemic, after that the number of passengers increased significantly which caused the forecast for the number of passengers at Bekasi Station trend also increase. This also happened in Bogor, Depok, Tangerang, Gondangdia stations, which represent all stations in Jabodetabek and the three provinces studied.

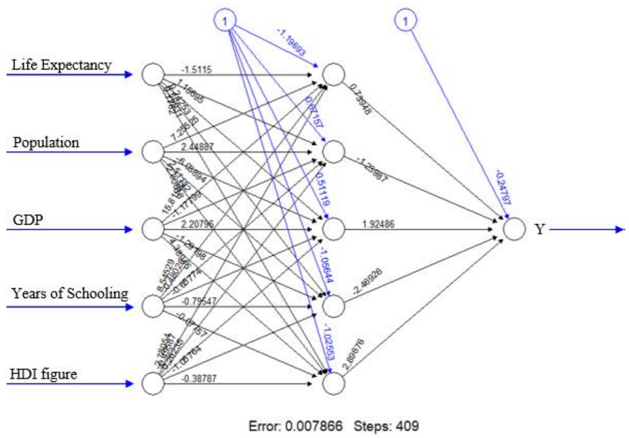

Fig. (8). ANN forecasting of the number of passengers on the Bekasi Station Commuter Line.

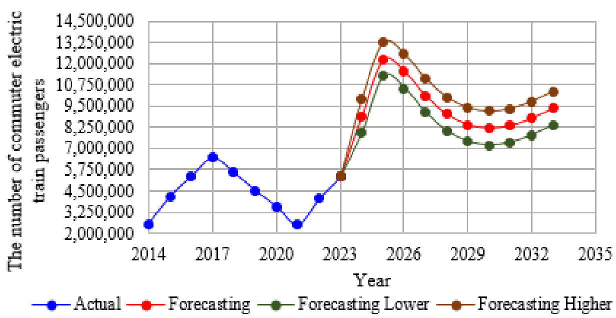

Fig. (9). Forecasting Graph of Bekasi Station with ANN.

CONCLUSION

Based on the results discussed in this paper, the forecast of the number of passengers at each station in Jabodetabek for the next 10 years has increasing trend each year (the forecast of the number of passengers at each station in Jabodetabek is attached) due to regional development represented by regional development parameters (PDRB, AHH, IPM, Length of Schooling and Population) which also increased in the forecast for the next 10 years. To address this, PT KAI should consider expanding train capacities, optimizing schedules, and exploring new route options. Implementation of these recommendations could improve passenger convenience and operational efficiency**.**

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