A Novel Approach for Passenger Demand Forecasting of a New Railway Services

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Abstract

Forecasting for passenger demand in a new railway service is a challenging activity. There are many variables that could affect the number of passengers that will use railway services and many of those variables may be unique to each specific situation. In this study, we present a study that attempts to forecast railway passengers for a newly constructed railway line of Makassar – Parepare in South Sulawesi, Indonesia. We propose a combination of the System Dynamics and Artificial Neural Networks (ANN). The system dynamics is a simulation method that is used to generate a set of training data for the ANN. The initial data were collected through a survey of willingness to use and willingness to pay among the selected potential passengers. Different price scenarios are also investigated in the model. Our study shows that with an optimistic scenario, there are potentially around 8000 – 9000 train tickets sold weekly. However, as the study is conducted prior to the railway operations, the results need to be reviewed and adjusted once it is operated and sufficient initial data is available.

Keywords
Passenger Demand Forecasting, Railway Passengers, System Dynamics, Artificial Neural Network, Indonesia

1. Introduction
Forecasting has been an important prerequisite for any planning. Demand forecasting is used in production planning in a manufacturing as well as service systems. It is also an important input for infrastructure development. A good forecast can reduce the risk of overcapacity as well as shortage of capacity in any system.With a good forecast, infrastructure development can be measured, and demand and revenue risks can be controlled (Bent Flyvbjerg, 2020).According to Nilabhra Banerjee et al. (2019), forecasting is divided into four types: Quantitative Model, Qualitative Model, Mix Model, and Ancillary Tools. If historical data is available, quantitative model may be used. Otherwise, we may have to reply on qualitative models (such as expert judgment). In some situation we may also use a combination of qualitative and quantitative approaches.

In the transportation sector, there have been many studies on demand forecasts. In this sector, forecasting is mainly to predict the passenger or freight volume. In case it is used for the development of a new transport infrastructure, the existing demand does not exist and thus a pure quantitative approach could be used. Changfeng Sui (2005) uses a system dynamics approach to forecasts train passengers. Profillidis (2006) uses market surveys to forecast passenger demand. Xiayou Zi (2008) uses system dynamics to perform short-term forecasts by modelling the characteristics of train passengers. Other than the above approaches, many researchers also used neural network model to predict passenger demand. Tsung-Hsien Tsai et al. (2009) discussed short-term railway passenger demand forecasting using Artificial Neural Networks to facilitate decision-making on revenue management. Rongfang Liu et al. (2012) explained forecasting high-speed rail (HSR) with the logit method to forecast inter-city trips.

In this study we concern with the prediction of passenger demand for a new railway that has been developed in South Sulawesi, Indonesia. The new link will connect Makassar and Parepare, two major cities in South Sulawesi. The railway will have a length of about 140 kilometers. As this is a new infrastructure, we use a two stage approach. First is to generate initial data by using system dynamics. Second is to predict the demand by using Artificial Neural Network

2. Literature on Railways Passenger Demand Forecasting
Demand forecasting for railway passengers corresponds to a set of approaches needed to estimate the number of passengers that will potentially use rail.This will be used to plan for the rail capacity in the medium as well as long term. There are various approaches that has been used to forecast demand for rail passengers. For example the application of the adaptive forecast method to forecast flow passenger and freight in railway(Ji-bing & Zhi-ping, 1985), a hybrid approach of combining mode decomposition and gray support vector machine to forecast short-term high-speed rail demand(Jiang, et al., 2014), deterministic and probabilistic forecasting capacities based on the residual component disposing for forecast high-speed rail passenger demand (Cao, et al., 2021). system dynamics modeling for forecasting railway demand, trains, and employees to create safety, security improvement and support rational policymaking for future railway management(Wijayanto, et al., 2022), and one possible approach to use for forecasting is artificial intelligence techniques using Artificial Neural Network (ANN) (Wu and Kumar 200).

Many types of ANN can be used in forecasting, namely Multi-Layer Perceptron. MPL is artificial feedforward neural network. This model consists of the input layer, output layer, and one or more hidden layers. However, each layer has several neurons connected to another neuron in another layer. In recent years, Multi-Layer Perceptron (MLP) neural network frameworks have become popular to make a forecast. It can be used in long-term demand forecasting (Kourentzes, 2004)and short-term forecasting (Chena et al. 2021).

On the other hand, Wei and Cheng (2012) used hybrid neural networks. Furthermore, MLP can be used to forecast railway passengers. Tsung-Hsien Tsai (2009) made a short-term forecast for railway passenger demand with a neural network. Shadi Sharif Azadeh et al. (2013) make a forecast for railway passengers that use reservation and cancellation to predict the actual demand for revenue management. Zhucui Jing et al. (2020) make a Neural Network-Based Prediction Model for Passenger Flow in a Large Passenger Station.

3. Problem Description

The Government of Indonesia has been developing a new railway in South Sulawesi, connecting Makassar and Parepare. This railway is partially completed and in some path, it is still under construction. As this is the first railway in Sulawesi Island, the Government needs to carefully predict the number of passengers that will be using this new railways in the future. This study deals with the demand forecasting for passengers for this new rail link.

This new railwaysis planned to have an initial length of 140 kms, divided into 6 segments and 17 stations spread across different districts: Makassar, Barru, Maros, Pangkep, and Pare-Pare areas. Train stations are also categorized into several classifications, ranging from large, medium, to small stations. Passenger trains will have a very positive impact on the mobility of the people of South Sulawesi. Figure 1 is an illustration of the train track from Makassar to Parepare.

Figure 1: Railway Track Map

4. Methods

To forecast passenger demands, we use the following three steps. Figure 2 illustrates these three steps.

1. Collect some input data, including macroeconomic data from secondary sources and potential customer direct survey. The survey is to obtain general perception of the public about the potential use of rail in their future transportation need as well as to assess their willingness to pay.
2. Use system dynamic to model interconnection among various variables to obtain initial prediction data based the inputs obtained in step 1. The system dynamic is a simulation method that can dynamically evaluate the change in variables' values. This initial prediction will be used to do a more thorough forecasting process, which is done using artificial neural network in step 3 below.
3. Use artificial neural network to forecast the railways passenger demand more thoroughly. The artificial neural network used the initial predication from system dynamics in step 2 as training data. The use of ANN also

enables us to predict the demand for any given ticket price beyond the discrete price scenario that we obtain from passenger survey.

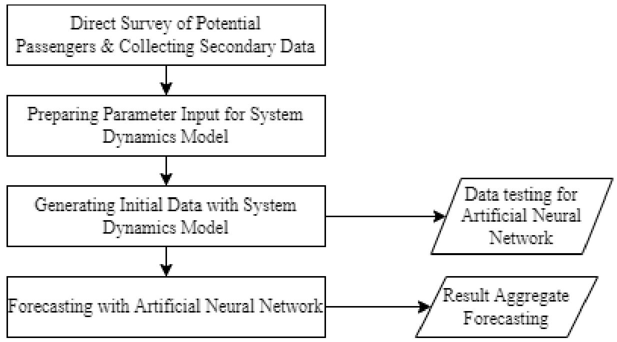

Figure 2. Proposed Methodology for Passenger Demand Forecasting

5. Data Collection

The data collection stage is divided into two main classifications, namely primary data and secondary data. Primary data is the direct collection of data (field observations, direct surveys, interviews) needed in this research, in contrast to secondary data, which is data that has been processed in advance and can be obtained from the results of previous research journals, books, publications, government, and other supporting sources. The direct survey that has been carried out covering all community in South Sulawesi focuses on 5 districts/cities, namely Makassar, Barru, Maros, Pangkep, and Pare-Pare, all of which are crossed by the railways. We interviewed 100 local residents and the number is proportional to the weighted population size of each district / city. The weight is determined by the population size and distance from the railway. The distance is classified into 3 categories, which is exhibited by different color in Figure 3. In addition, we also classify respondents into their occupations which is presented in Table 1.Each respondent can answer the commuting and non-commuting part of the questionnaire simultaneously considering that respondents have different transportation needs.

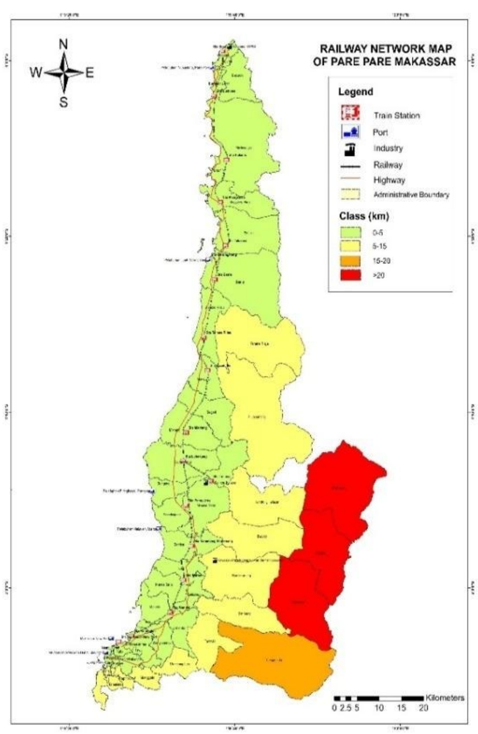

Figure 3. Map that shows weighting of potential passengers in different geographic area

Table 1. Proportional Respondent based on Type of Work

No	Type of Work	Respondent Percentage
1	Student/College	20%
2	Entrepreneur/Business	20%
3	Government Employees	20%
4	Housewife	20%
5	Others	20%

6. Developing and Running the Models

6.1 System Dynamics Modelling for Passenger Demand

We model the passenger demand as a function of various variables, including total population, birth rate, and death rate.The system dynamic approach can accommodate the interrelation among variables in a dynamic way. To model the system, we observe if the relationship is positive or negative and two or more variables can have a closed-loop relationship. We divide the system into two sub-systems, one is for commuting trip and the other one is for non-commuting trip. Then this is further divided into working age and non-working age. To run the model, the relationships need to be defined in quantitative terms and the inputs must be fed into the model. The inputs are obtained from the survey data, secondary data, and some index that can be obtained from other, but similar cases. For example, the percentage of population that use train as a mode of transportation can only be obtained from other regions, like in Java Island, as there in this island, train exists since a long time ago. The survey data provides various input parameters including the willingness to use, willingness to pay, and frequency of travel. The snapshot of the system dynamic model is presented in Figure 4.

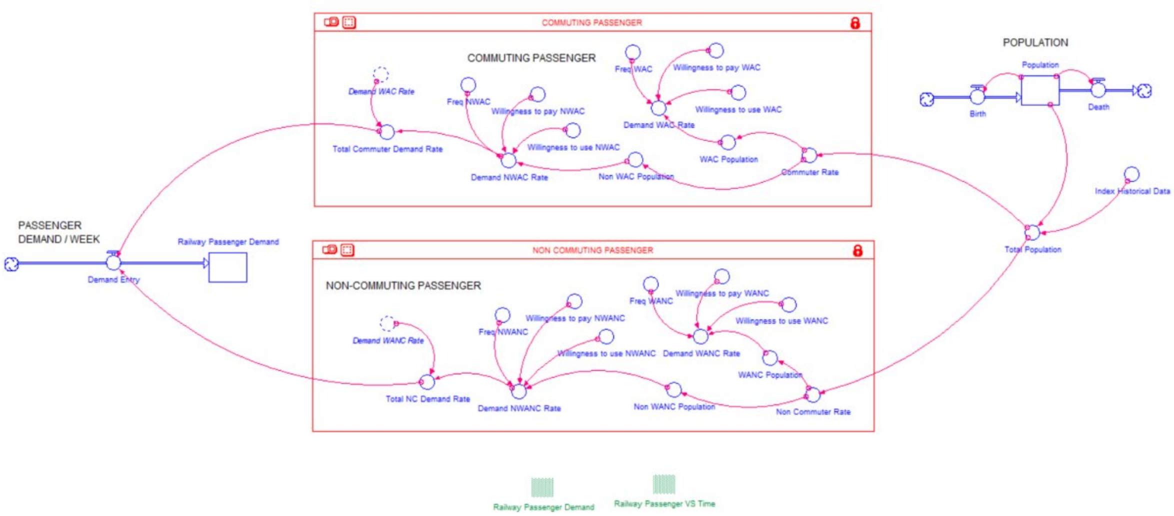

Figure 4. System Dynamics Model for Passenger

The result of the dynamics system will be the number of customers with price variations according to the questionnaire. The results will be used as input for the artificial neural network in the form of training data and testing data. The author will do further forecasting using an artificial neural network to forecast demand with more price variations.

7.2. Artificial Neural Network for Passenger Demand

The neural network used in this model is created by referring to the results of system dynamics. In this study, Multi-Layer Perceptron (MLP) is applied to forecastrail passenger demand. MLP is a fully forward-connected network with three layers: input, hidden, and output. The number of input layers depends on the feature that is used. The hidden layer can be a feature extractor. It mixes information from all input layers and processes in a hidden layer for learning. The output layer is the layer that generates forecasts and propagates errors for parameter estimation.

According to the type of potential passengers in Railway Makassar Pare-Pare, there are four types of potential passengers, namely people who are Working-Age commuters (WAC), Working-Age Non-Commuter (WANC), Non-Working-Age Commuter (NWAC), and Non-Working-Age Commuter (NWAC). Accordingly, we need four set of neural network in order to be able to predict each type of customer. In the end, all these results will be aggregatedas the total forecast of train passengers. The MLP needs training data. The monthly forecast for 10 years by using system dynamic was used as training data. These data are entered as the input layer and the output layer as learning from the neural network. Then, the new input data will be provided by changing several parameters in order to obtain smoother forecast.

For the passenger, several parameters are used as neurons in the input layer, namely total population, number of commuter / non-commuter, number of working-age / non-working-age, willingness to use, price, willingness to pay, and frequency. Please note that the system built consists of 4 neural networks. The image below only shows a general picture of the neural network used. For example, suppose we want to predict the working-age commuter customer type. In that case, the inputs needed are the total population, the total commuter population, the total working-age population, willingness to use for working-age commuters, price, willingness to pay for working-age commuters and frequency for working-age commuters.

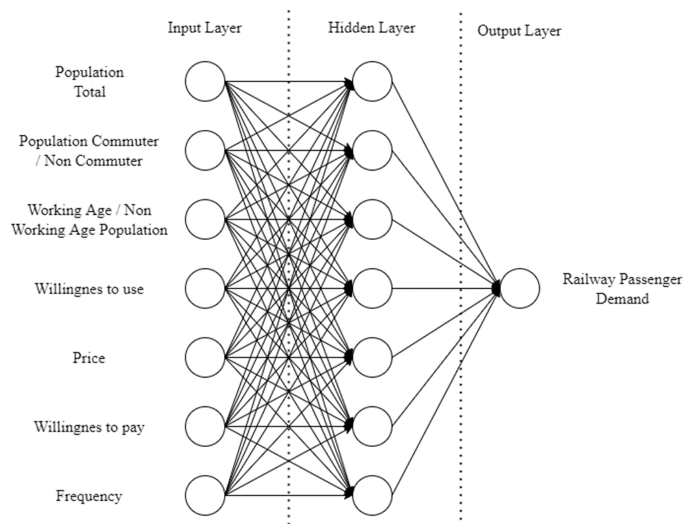

Figure 5: Artificial Neural Network Graphic

The results of the demand prediction will be used as the output layer. We use Mean Absolute Error (MAE) to calculate the error obtained in each training. The data will be divided into 20% testing and 80% training then forecasting will be carried out with new data input. The number of epochs that the author used is 1000. After training and testing, the weuse new data for input layer to predict the demand. As an example, in the results of the system dynamics model, the displayed price can only be divided into 4, namely IDR 12,500, IDR 10,000, IDR 7,500 and less than IDR 7,500 because the survey results are only limited to these four discrete prices. However, passenger forecasts become smoother with this neural network because the price data entered can be any value, from IDR 500 to IDR 13,500. This forecasting can produce a smoother demand with more parameter benchmarks. Many combinations of scenarios or other factors can be added to the neural network, and the result is not a single-point estimate.The result of the Neural Network is divided into 4 types of customer types that have been described

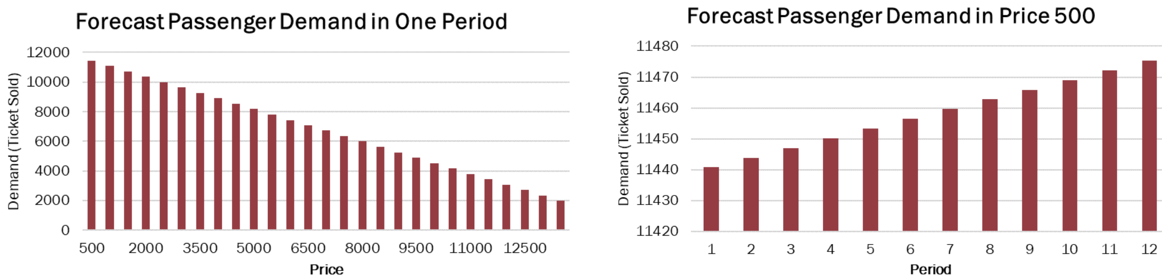

Figure 6. Forecast Passenger Demand in One Period and One Price

If we look at the computation in one week of departure, it is known that the tendency of customers is between 11,400 at a price of IDR 500 to 2000 customers at a price of IDR 13.500 every 20 kilometers. The increase is partially influenced by the population growth rate in South Sulawesi and the improvement of supporting rail services that will attract public interest to use rail services and especially influenced by fare rate in 20 kilometers. This trend draws a conclusion that tickets per day that are sold if only consist of 5 working days are effectively around 2280 - 4000 per day, along Makassar – Pare-Pare link, assuming that the number of passengers is spread evenly among different days

8. Conclusion

This paper proposes a new approach for forecasting passenger demand by combining the system dynamics and artificial neural network. The system dynamics is used to generate initial data and this initial data can be used for training and testing purposes in the artificial neural network.The proposed approach is used to forecast passenger demand of a newly constructed railway that connects Makassar and Parepare in South Sulawesi, Indonesia. In order to run the model, we collect both secondary and primary data. We predict the passenger demand under different price scenario. We have used the survey results that predict the willingness to use and willingness to pay as input to the model. As a snapshot, the estimated passenger demand is in the range of 2000 to 11400 tickets sold in a week, depending on the ticket price.

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