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Spare Part Demand Forecasting in Automotive Industry Using Artificial Neural Network

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Abstract: ***The development of business in Indonesia today has developed rapidly, resulting the competition in the business become very competitive. One of the business line that currently developing rapidly is automotive industry. Each of automotive company trying to be able to win the hearts of customer with all the best offers and services, so they remain loyal to the product of company. A good management system needs to respond for local, regional, and national markets demand quickly. If business cannot fulfill the market demand quickly, the customer may change their willingness for purchase the products or services that sold by the company. In this paper, an Artificial Neural Network (ANN) was designed to help automotive distributor company predict Spare Part demand in each of Province in Indonesia. ANN was chosen since the method can model the situations, where highly nonlinear relationships among the variables can be captured.***

Keywords: Automotive Industry, Spare Part Demand Forecasting, Artificial Neural Network (ANN), Nonlinear Relationships

1. Introduction

Demand forecasting in automotive industry is very complex. Indeed, a wide range of car unit and spare part item references exists, and their historic sale data are often perturbed by numerous factors, which are neither strictly controlled nor identified. These factors can depend on the macro economy (USD/IDR rate, inflation rate, GDP growth), commodity (coal, crude oil, CPO, rubber), total working days, number of distributor in the area or Province, and promotion – all the mention before impacting both for car unit and spare part sales, and then the factor that may impact for the sales of spare part such as, number of stores that sell spare part, number of end customer that already purchase the cars in the area, distance between dealer and customer's home, and spare part stock availability. These factors have different impacts on sales and not always available. For the automotive industry, uncertainty comes from many sources, such as, inability to forecast customer demand, primary and secondary tier manufacturer reliability/quality, logistical system reliability, complexity in the manufacturing supply process, inaccuracies in point of sale data or bar codes.

Demand Forecasting refers to computing the probability of the future value. The underlying assumption in most forecasting methods is that the past patterns or behavior will continue in the future [4]. Forecasting the expected demand for a certain period of time with one or more products is one of the most relevant targets in an enterprise. Despite the need for accurate forecasting to enhance the commercial competitive advantage, there is no standard approach [3].

2. Artificial Neural Network

ANNs learn from experience/training to predict future values while being fed with relevant input information [1]. The advantages of these networks include but are not limited to self-organization, adaptive learning, fault tolerance, ease of integration with existing network/technology, and real-time operation. The abilities to generalize and to capture non-linearity in complex environments make ANNs very attractive in problems of load forecasting.

Neural networks are built from a large number of very simple processing elements that individually deal with pieces of a big problem. In short, artificial neural networks are highly distributed interconnections of adaptive nonlinear processing elements (PEs). A processing element simply multiplies inputs by a set of weights, and nonlinearly transforms the result into an output value. The principles of computation at the PE level are deceptively simple. The power of neural computation comes from the massive interconnection among the PEs, which share the load of the overall processing task, and from the adaptive nature of the parameters (weights) that interconnect the PEs [2].

Normally, a neural network will have several layers of PEs. Figure 1 illustrates a simple multi layered perceptron (MLP), which is the most commonly used neural network architecture for pattern recognition, prediction and classification problems. The circles are the PEs arranged in layers. The left column is the input layer, the middle two columns are the hidden layers, and the right most column is the output layer. The lines represent weighted connections (i.e., a scaling factor) between PEs [2].

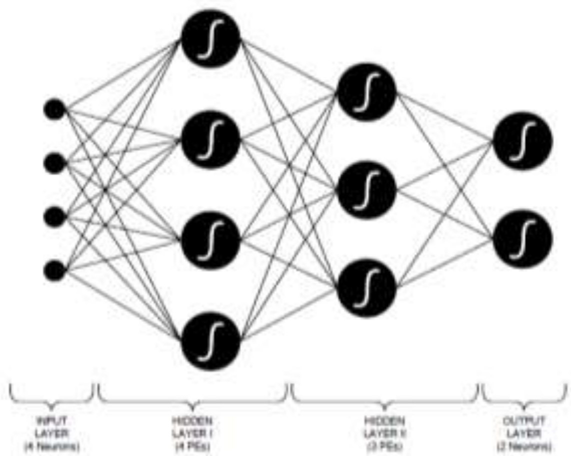

Figure 1: A Simple Multilayer Perceptron

By adapting its weights, the neural network works towards an optimal solution based on a measurement of its performance. For supervised learning, the performance is explicitly measured in terms of a desired signal and an error criterion. For the unsupervised case, the performance is implicitly measured in terms of a learning law and topology constraints [2].

The process of modifying network parameters to improve performance is normally called learning. Learning requires several ingredients. First, as the network parameters change, the performance should improve. Therefore, the definition of a measure of performance is required. Second, the rules for changing the parameters should be specified. Third, this procedure (of training the network) should be done with known (historical) data [2].

The mathematical representation of a neuron depicted above can be described as:

$$Y = f\left(\left(\sum_{i=1}^{n} x_i . w_i\right) + b\right) \quad (1)$$

where k x , x ,....x 1 2 represent an input vector, and k w , w ,....w 1 2 represent the weights (or strengths) of the incoming synapses (or interconnections). The bias (b) performs an affine transformation of the linearly combined input signals, and the activation function (f) applies to produce the final output (Y) from the neuron. There are many types of activation functions that are popularly used in the neuron, of which the most popular ones are Sigmoid Function, Softplus Function [5], and Rectified Linear Units (ReLu) Function [5].

3. Methodology

3.1 Research Stages

In General, the process of research methodology conducted by researchers can be seen in Figure 2. This research is divided into four stages. Stage one is Data Preparation, stage two is Artificial Neural Network (ANN) Architecture Preparation, step three are Training and Validation, and step four are Visualization and Accuracy Analysis. The implementation and experiment in this research is using SQL Server for step one, study literature for step two, python programming language for step three, and for the step four, will be using Microsoft Excel.

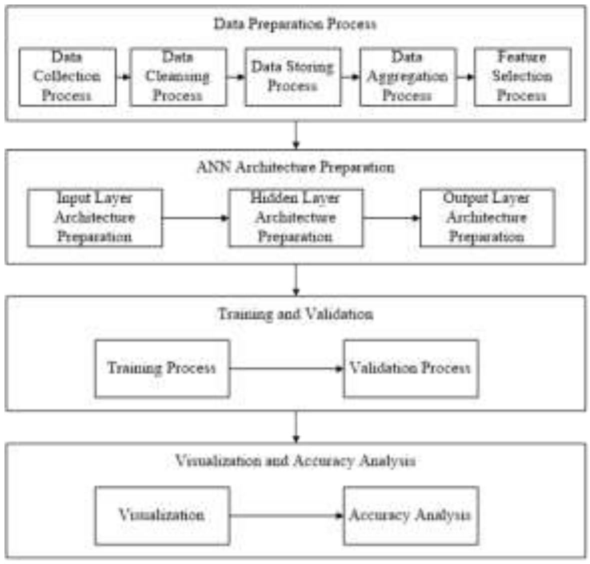

Figure 2: Research Stages

3.2 Data Preparation Process

The data that needed for spare part demand forecasting mostly using company transactional data that stored in multiple separated database. In addition, several data from outside the company also need to be collected and stored into a single repository. Company data combined with the outside data, will be in a huge volume, thus we need software that can help us handling the data. We will be using SQL Server for it.

The first step in handling the data is data collection process. Data from inside and outside will be pulled using SQL Server. During data collection process, data cleansing will be also run to make sure the data is ready to use. After data cleansing process finished, all data will be stored into a single repository, which is also using SQL Server. Then we will combine the data in the repository into a dataset, which contains features that will be using for spare part demand forecasting. After the dataset is ready, we conduct features selection using statistical method: feature importance. All input and output variable were presented in Table 1:

Table 1: Input and Output Variable

Type	*Name*
Input	Year
Input	Month
Input	Province
Input	Spare part material code
Input	Sales Qty of spare part in the month-1 to month-12
Input	Sales Qty of car type 1 in the month-1 to month-12
Input	Sales Qty of car type 2 in the month-1 to month-12
Input	Sales Qty of car type 3 in the month-1 to month-12
Input	Sales Qty of car type 4 in the month-1 to month-12
Input	Sales Qty of car type 5 in the month-1 to month-12
Output	Sales Qty of spare part in the current month

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3.3 ANN Architecture Preparation

In input layer architecture preparation, as researchers already assumed that there are 108 features that may affect the spare part demand forecasting, the number of neuron will be also 108 to accommodate each of the features. It may change after the feature selection conducted. For example, if the result of features selection only 8 features that significantly affect spare part demand forecasting, the neuron also will be updated to 8 neurons. Activation function for Input layer will be using Softplus Function.

For deciding the number of hidden layer, researchers refer to some experiments that already conducted by Chawla et al, 2019 that using single hidden layers to forecasting Walmart's Sales in the future. For the number of neuron in hidden layers, there is no best practice and exact theory about it. So, researchers decide to have number of neuron in input layer multiply by two, to accommodate the combination among the features. Activation function for Hidden layer will be using Softplus Function.

In output layer architecture preparation, as the objective of this research is to forecast the demand of spare parts, there will be one neuron in this layer. Activation function for Hidden layer will be using ReLu Function.

3.4 Training and Validation

For ANN model training, validation, and testing, researchers will split the dataset with proportion 70:15:15. 70% of the dataset will be used for training. Then 15% of dataset will be used for validation, then the last 15% of dataset for testing. During the training and validation process, researchers will be using R programming language since the library already support for conduct ANN forecasting

3.5 Visualization and Accuracy Analysis

The visualization will be presented after training and validation process finished. It is for helping the researchers have an image of the accuracy of prediction model for spare part demand forecasting. Since it is a simple visualization, researchers decide to use Microsoft Excel. For the accuracy analysis, researchers will be using MSE and MAPE method

4. Conclusions

An artificial Neural Network model for predicating spare part demand in each Province was presented. The model used feed forward backpropagation algorithm for training. The data collection process is necessary for elaborate all factors that may affects the forecast into one single source database. The input variable for the model were obtained from expert in the field. Number of neuron in input, hidden, and output layer was presented with some business assumption. The activation function also chosen for smoothing the training process, and make the output never negative (ReLu function will make it 0 or above 0). This study showed the potential of the artificial neural network for predicating spare part demand in each province or area depend on the needs.

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