Prediction of Warranty Cost and Warranty Period using Neuro-Fuzzy Approach: Case Study of Automobile Warranty Data

Nur Izzati Jamahir, Hairudin Abd Majid, Azurah A.Samah

Abstract— Nowadays, warranty has its own priority in business strategy for a manufacturer to protect their benefit as well as the intense competition between the manufacturers. In fact, warranty is a contract between manufacturer and buyer in which the manufacturer gives the buyer certain assurances as the condition of the property being sold. In industry, an accurate prediction of optimal warranty period and warranty costs is often counted by the manufacturer. A warranty period may be unprofitable for the manufacturers if the choice of duration given is either too short or too long. Same thing goes to warranty cost which is an underestimation or overestimation of the warranty cost may have a high influence to the manufacturers. This paper presents a methodology to adapt historical maintenance warranty data with neuro-fuzzy approach. The main motivations for conducting this paper are simplicity and less computational mass of the neuro-fuzzy based on previous studies on this method compared to single method such neural network and fuzzy logic.

Index Terms— neuro-fuzzy, two-dimensional warranty, warranty cost, warranty period.

I. INTRODUCTION

The great market competition makes that the companies look for high quality of products. Basically, there are six types of warranty that can be offered either by manufacturer or dealers of a product or services which are basic warranty, extended warranty, warranty for used, repair limit warranty, service warranty and lifetime warranty. The different types of warranty policy were established in order to fulfill the demand of manufacturers and the requirement of buyers so that a win-win situation could be acquired. For this study, we apply basic warranty which mean that it will covers all factory-installed parts against any type of defects in their manufacturing and workmanship.

This paper is interested to discuss about the problems on warranty with using soft computing specifically by using neuro-fuzzy approach. Majid *et. al* (2012) mention that there are several studies in warranty problem specifically by using soft computing method. In general, neuro-fuzzy is an integrated combination between artificial neural network and fuzzy inference system (FIS). Neuro-fuzzy was originally proposed by J.S.R. Jang in 1993. It seems like a new study but there are many studies using this method because of its ability. Neuro-Fuzzy also is well known as ANFIS which stand for adaptive neuro-fuzzy inference system.

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Nur Izzati Binti Jamahir, Department of Modeling and Industrial Computing, Universiti Teknologi Malaysia, Johor Bahru, Malaysia.
Hairudin Abdul Majid, Department of Modeling and Industrial Computing, Universiti Teknologi Malaysia, Johor Bahru, Malaysia.
Azurah A. Samah, Department of Modeling and Industrial Computing, Universiti Teknologi Malaysia, Johor Bahru, Malaysia.

There are two outputs that we need to predict which are warranty cost and warranty period. Previously, there are some researches on warranty cost. For example begins with modelling the failures and the costs of rectification actions over the warranty period as stated by Murthy and Djamaludin (2002). The time to first failure is modeled by a probability distribution function. Kim and Rao (2000) try to find expected warranty cost of two-attribute free replacement warranties based on a bivariate exponential distribution.

To find the warranty period, it can be said that it is not as easy to use the data solely by using the age of the vehicle. With that, we decide to find reliability of period for our data and from the analysis of it we can find the warranty period for our problem. In fact, warranty cost also depends on the reliability of a product. Reliability which represents quality performance is defined as the probability that the product or a system performs the intended function adequately for a specified period of time, under specific operating condition and environment. Studies on reliability and warranty have been carried out by researcher such as Murthy (2006), Yang and Zaghati (2002) and Yadav *et.al* (2003).

Since we are going to find two outputs, we have to deal with some obstacles. It is because neuro-fuzzy originally used to solve a problem with one output. However there are two way to get multiple output which is by using multiple ANFIS (MANFIS) and another one is coactive neuro-fuzzy inference system (CANFIS).

II. FRAMEWORK OF STUDY

In this section had presented framework of study in this paper. This is an important element to ensure every activity in this research will go smoothly.

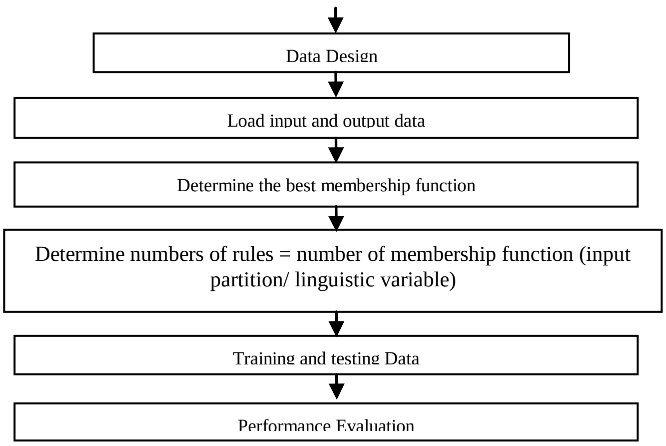

Fig. 1: Framework of Study

Firstly, we have to design the collected data. Then we divide the data into input and target output. To select the input, the selected elements must correspond to parameters, which mean it will directly or indirectly affect the prediction result. The input that we are chosen is age and mileage. Then, we load input and output data. To make the result more effective, we determine the best membership functions and the number of rules needed to produce lower MSE. Lastly we trained the result and find the accuracy of the result which shows the performance of neuro-fuzzy system.

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

In this subtopic, we will give a review on basic theory of ANFIS model. ANFIS is one of the hybrid methods that are often used by researchers due to its ability. ANFIS is created from the combination of neural network architecture and fuzzy logic system. ANFIS consist of *if-then* rules and couple of input output.

To make the explanation more simple and easy to understand, the fuzzy inference system under consideration is assumed to have two inputs which we define as x_1 (mileage) and x_2 (age) and also one output *z* (cost of inspection). For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is as the following:

Rule 1: If x_1 is A_1 and x_2 is B_1, then $f_1 = p_1x_1 + q_1x_2 + r_1$,

Rule 2: If x_1 is A_2 and x_2 is B_2, then $f_2 = p_2x_1 + q_2x_2 + r_2$.

where p, r and q are linear output parameter.

Fig. 2 illustrates the ANFIS architecture, where nodes of the same layer have similar functions, as described next. The following explanations are the process inside each layer and we denote the output of the *i*th node in layer *l* as $O_{l,i}$.

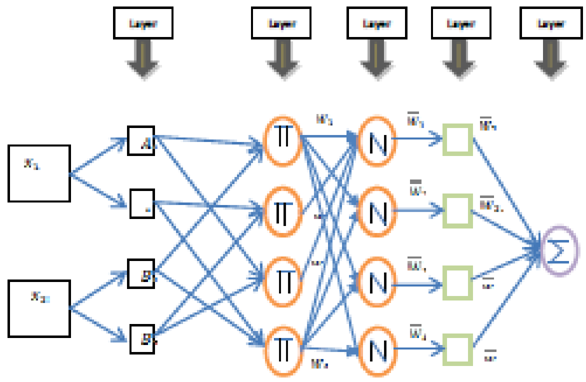

Fig. 2: First order ANFIS model

Layer 1: This layer we call as membership function layer. Every node *i*in this layer is a square node with a node function

$$O_{1,i} = \mu_{A_i}(x_1), \text{ for } i = 1,2, \text{ or}$$
$$O_{1,i} = \mu_{B_{i-2}}(x_2), \text{ for } i = 3,4$$

where x_1(or x_2) is the input to node i, and A_i(or B_{i-2}) is a linguistic label, such as (small, large, etc.) associated with this node. In other words, is the membership grade of a fuzzy set $A = (= A_1, A_2, B_1 or B_2)$ and it specifies the degree to which the given or satisfies the quantifier A. Here the membership function for A can be any appropriate parameterized membership function such as the generalized bell function:

$$\mu A_i(x_1) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b}}$$

or

$$\mu A_i(x_1) = \exp\{-\left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}\},$$

Where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell shaped functions vary accordingly, thus exhibiting various forms of membership functions for fuzzy set A. In fact, any continuous and piecewise differentiable functions, such as commonly used trapezoidal or triangular-shaped membership functions, are also qualified candidates for node functions in this layer. Parameters in this layer are referred as premise (nonlinear) parameters.

Layer 2: This layer we named it as rule layer. Every node in this layer is a circle node labeled п, which multiplies the incoming, signals and sends the product out. For instance,

$$O_{2,i} = \omega_i = \mu_{A_i}(x_1)\mu_{B_i}(x_2) \quad , \quad i = 1,2.$$

Each node output represents the firing strength of a rule. A rule node receives inputs from the respective fuzzification nodes and calculates the firing strength of the rule it represents. (In fact, other T-norm operator that performs generalized AND can be used as the node function in this layer). Basically, number of rule can be calculated by using this formula:

Number of Rule layer: (Number of input partition (linguistic variable)) ^ (number of input variable)

Layer 3: This is the normalization layer. Every node in this layer is a fixed node labeled N. The *i*th node calculates the ratio of the *i*-th rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \varpi_i = \frac{\omega_i}{\omega_1 + \omega_2} \quad i = 1,2.$$

For convenience, outputs of this layer will be called normalized firing strengths.

Layer 4: Every node *i*in this layer is a square node with a node function

$$O_i^{\,4} = \varpi_i f_i = \varpi_i(a_0^{\,1} + a_1^{\,1}x_1 + a_2^{\,1}x_2),$$

where ϖ_i ,is the output of layer 3, and$(a_{0i} + a_{1i}^{\,1} + a_{2i})$ is the parameter set. Parameters in this layer will be referred to as consequent parameters.

Layer 5: The single node in this layer is a circle summation node labeled $\sum$, that computes the overall output of defuzzification nodes and produces ANFIS output as the summation of all incoming signals, i.e.,

$$O_{5,1} = overalloutput\ j = \sum \varpi_i f_i = \frac{\sum \omega_i f_{ji}}{\sum \omega_i} \quad where\ j = 1.2.3$$

Thus we have constructed an adaptive network, which is functionally equivalent to a Sugeno fuzzy model.

The structure of NN layer for MIMO (multiple input multiple output) Simulink Model of Fuzzy Neural Network is introduced. We add layer 1 for distribution.

We use layer 1 to distribute inputs; one input per one membership function. Also, we add sub layer in the consequent parameter for layer 5 to compute multiple outputs. Layer 6 is the overall outputs.

However, in ANFIS, there is constraint which is ANFIS can only be used for single output whereas in our case we want to solve two output. One way to get multiple outputs is to place as many ANFIS models side by side as there are required outputs. In this multiple ANFIS (MANFIS), no modifiable parameters set of fuzzy a rule which is each ANFIS has an independent set of fuzzy rules, which makes it difficult to realize possible certain correlation between outputs. An additional concern resides in the number of adjustable parameters, which drastically increases as output increases. That method is illustrated in Fig. 3.

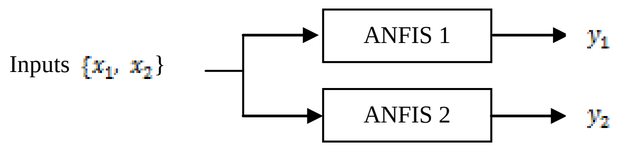

Fig. 3: MANFIS Structure Decoupling ANFIS Structure

IV. DATA DESIGN AND EXPERIMENTS

In this research, the historical maintenance data is drawn from automobile Malaysia company. The data that we concerns is single product which is MTB 150dx. There are 100samples of vehicles adopted in all algorithms. The vehicles information and status are recorded once a maintenance service is made. There are about 739 historical data recorded from the 100 samples vehicle beginning from the first inspection to the end inspection for each vehicle. Some element that can be found in this historical data are the date of sales, the date when the claims made, vehicle mileage, number of failure and defect and cost of every inspections.

When we do input data design, we have to filter the data because there are some missing data and also sometimes there are data that do not meet with the model we want to use. After that, the data are sort randomly from the historical data. It is because when we want to train the data, we want to refer from the historical data and not only from one vehicle in sequence. This is the reason for why we do not sort the data according to vehicle. Then, the data are divided into two parts which is for training and testing the models. Out of 739 historical data recorded from the 100 samples (vehicle), only 535 data are used as they are valid with their target output. We consider using data mileage, age, number of defect and number of failure as input data. Since the age and mileage increase accordingly, the data of failure and defect also we sort cumulatively. We decided to use 80 percent data for training and 20 percent for testing to verify the accuracy of the models.

For the first output data, we use the inspection cost per vehicle and for the second output data, we used formula for reliability. This formula for reliability is used when we just rely on the data set and the following Table I are sample of data to produce reliability data set. Based period we set to zero because the day of a year started from the first day.

$$Reliability\ (period) = \frac{10\ x\ Average\ Inspection\ period}{yearly\ Period - Based\ period}$$

Table I: Sample of data to produces reliability.

	Mileage (km)	Age (day)	Average Inspection	Yearly Period	Reliability
Vehicle 1	5096	62	163.25	305	5.352459
	13149	104	163.25	305	5.352459
	19304	182	163.25	305	5.352459
	28920	305	163.25	305	5.352459
Vehicle 2	1000	17	60	103	5.825243
	7891	103	60	103	5.825243

V. EXPERIMENTAL RESULTS

The neuro-fuzzy system in this problem is simulated using MATLAB (R2012a). ANFIS with various input membership functions were trained. Fig. 4 shows actual and predicted values (FIS output) of modelling system for generalized bell (gbell) input membership functions.

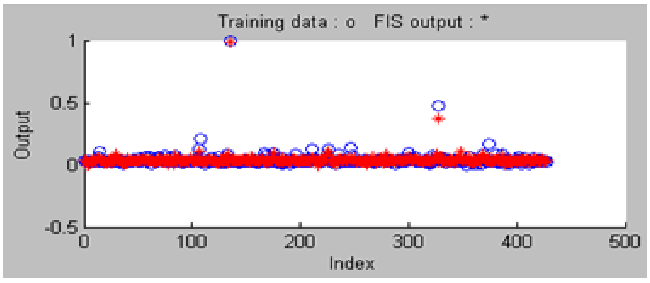

Fig. 4: The comparison of actual and predicted values for gbell membership functions

Besides, ANFIS topologies with various input membership functions were trained. The result on means square error (MSE) are as in Table II for the first target output which is inspection cost, and Table III for the second output which is reliability to determine the period of warranty. We test four membership functions which are generalized bell (gbellmf), triangular (trimf), trapezoidal (tramf), and Gaussian (gaussmf).

Table II: MSE values for output 1 based on the used membership function

Membership Function	MSE
Generalized bell (gbellmf)	0.020179
Triangular (trimf)	0.03894
Trapezoidal (tramf)	0.026956
Gaussian (gaussmf)	0.021547

Table III: MSE values for output 2 based on the used membership function

Membership Function	MSE
Generalized bell (gbellmf)	0.14837
Triangular (trimf)	0.17709
Trapezoidal (tramf)	0.18064
Gaussian (gaussmf)	0.16488

From the result, we know that generalized bell membership function will produced smaller MSE for both output. Therefore we test generalized bell membership function with different number of input partition to test which is the best input partition to choose.

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Table IV: MSE values for each number of input partition for generalized bell membership function (gbellmf)

	Number of input partition for gbellmf	MSE
OUTPUT 1	2	0.026996
	3	0.020179
	4	0.017638
	5	0.017638
OUTPUT 2	2	0.16726
	3	0.14837
	4	0.14548
	5	0.12978

From the result, it is shown that when we increased the number of input partition will improves the training accuracy, as indicated by the smaller MSE values. Basically, the number of input partition are depends on the data that we used. Sometimes, when reduces the number of input membership functions will results in lower MSE values [2]. Beyond the certain point the training process will take more time when we increased the number of input membership function. It is because when we increase the number of input membership function will result the increase of rule layer and consequently the time taken to complete the process will increase. But, when we increase the number of input membership function, it will decrease the iteration of process to converge.

VI. DISCUSSIONS AND CONCLUSIONS

The successful of implementing neuro-fuzzy is heavily depends on prior knowledge of the system and the training data. The strength of neuro-fuzzy systems involves two contradictory requirements in fuzzy modeling which is interpretability versus accuracy. In this paper, a neuro-fuzzy method is proposed to predict warranty cost and warranty period. The accuracy for warranty cost inspection (output 1) is 99.97 percent and accuracy for reliability (output 2) is 85.2 percent. These values are very satisfying and shown that soft computing techniques have been successfully applied to solve warranty problem. Neuro-fuzzy or ANFIS is definitely superior to fuzzy logic algorithm as it inherits adaptability and learning. As the result, it can be said that ANFIS is an appropriate technique for the prediction of warranty problem.

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AUTHORS PROFILE

Nur Izzati Jamahir has received Bachelor of Science (major in mathematics) from Universiti Teknologi Malaysia in 2011. Currently, she is doing her M. Sc. in Computer Science from Universiti Teknologi Malaysia and has two paper publications.

Hairudin Abdul Majid has received Diploma and Bachelor of Science in Computer Science-majoring Industrial Computing from Universiti Teknologi Malaysia in 1993 and 1995 respectively. In 1998, he obtained his M.Sc. in Operational Research and Applied Statistic from University of Salford, UK. Currently, he is a lecturer in Faculty of Computer Science and Information System, Universiti Teknologi Malaysia. His research interests focused on Image Processing, Operations Management and Warranty and Maintenance. Mr. Hairudin received Excellent Service Award by Universiti Teknologi Malaysia in 2004 and Excellent Staff Award by ISS Service in Manchester UK in 2006. Mr. Hairudin is the author of about 19 papers, 1 book chapter entitled 'Recent Operations Research Modelling and Applications (Warranty Modelling)' (UTM, 2009) and 1 text book entitled 'Permodelan Simulasi' (UTM, 2000). He has been a member of UK Operational Research Society and an active member of Operations and Business Intelligence (OBI) Research Group.

Azurah A. Samah has received the Diploma and Bachelor from Universiti Teknologi Malaysia in 1991and 1993 respectively. In 1996, she obtained her M.Sc. from the University of Southampton, UK and recently in 2010, she received her Ph.D from Salford university, UK. Currently, she is a lecturer in Faculty of Computer Science and Information System, Universiti Teknologi Malaysia. Her research interests encompass Image Processing, Soft Computing Techniques and Operational and Simulation Modeling.