Super Warranty Measurement Model Based on Lifetime Knowledge

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***Abstract*— As the price of traditional fuels soar, the alternatives are becoming more viable. And manufacturers are promoting the growing viability of electric and biofuel-powered vehicles through longer warranties. Now, these longer emissions warranties, sometimes called extended warranties or "super warranties," have been adapted. This paper is to present a FuNN (Fuzzy Neural) approach used in such super warranty. In green IT's point of view, it is to assess the environmental warranty claims of current vehicle systems. It also aims to provide a repository of environmental lifetime knowledge based on lessons learned from previous vehicle programs in a form that enables the knowledge to be easily retrieved and applied in greenery vehicle programs as a decision making tool. Further, it can be used in the construction of the knowledge base for a greenery warranty system.**

Keywords- Exhaust system; FuNN; Lifetime knowledge; Super warranty

I. INTRODUCTION

In virtually every industry from air conditioning to aerospace, there are efforts under way to create products that use less energy and create less waste. Warranty is frequently a factor. With new technologies, long warranties are a sign of the manufacturer's commitment. With old technologies, warranty is part of the mechanism now being used to create alternatives to landfill. Automakers are now adjusting their product lines and promotional efforts to deal with record high prices for gasoline and diesel. Smaller and more fuel-efficient vehicles are selling better, given the customer expectation that the cost of fuel per mile will continue to increase. The state of California was the early trendsetter in this area, setting both maximum emissions standards and minimum exhaust equipment warranty durations for vehicles registered in the state. These longer emissions warranties, sometimes called extended warranties or "super warranties," have also been adapted by the neighboring states of Oregon and Washington.

Many consumer durable goods - such as automobiles, appliances and personal computers - include a manufacturer's warranty to insure product quality and reliability. The resulting warranty claims contain field performance data, obtained under actual operating conditions, which manufacturers use to track product lifetimes. Automobile manufacturers provide customers with a basic two-dimensional warranty that quantifies vehicle lifetime with two metrics: time and usage (mileage). However, many manufacturers model field performance in the time domain due to the uncertainty associated with mileage accumulation. Two metrics have a close relationship, but not liner correlations in automotive vehicles. In particular, two-attribute warranty policy is more important in super warranty analysis.

This paper presents a greenery warranty system used in such super warranty problem, based on vehicle lifetime knowledge. A FuNN (Fuzzy Neural Network) system is used due to the uncertainty associated with usage accumulation. In a complex system, such as an automotive vehicle the analysis for generating knowledge is usually carried out from the complete vehicle cascading down to the component level. So, we discuss briefly the components of the super warranty system. It is important to identify all the failure modes of the automotive exhaust system under consideration. This is done through the analysis of the lifetime knowledge. The next step is the construction of FuNN module based on the lifetime knowledge in the performance characteristic of the component. Finally, partial validation of the suggested system in real conditions is illustrated by using the actual warranty data.

II. BACKGROUND

A. *Super Warranty System Architecture*

In a complex system, such as an automotive vehicle the analysis for generating knowledge of the greenery warranty amounts is usually carried out from the vehicle cascading down to the component level, figure 1. Due to the space constraint full expansion in Fig.1 has only been done for the exhaust system and for the refinement module of the emission system. These are the components of the system that will be used for the case study example later in the paper. Other components such as the engine component have similar expansion architecture as the exhaust system from the system level until the component level. As shown in Fig.1 the system has four main levels, which are the component level, the sub-system/module level, the system level and the greenery vehicle level. Starting from the component level and moving through the architecture towards the complete vehicle system it can be seen that each level connects with its superior level by a knowledge-base component.

For the connection of the component level with the sub-system/module level a knowledge-based FuNN system is used. The reason is that at the component level there is a lot of uncertainty and also there are many gaps in the data that can only be filled by qualitative assessments by environmental experts. This makes the use of fuzzy neurons. For the rest of the connections above the sub-system module level there is a fuzzy logic or a neural network module. The reason for that is that the main development of the initial warranty system has been done by using fuzzy logic but for the higher level connections in the warranty system there is only complete numerical data, which makes the use of neural networks a good possibility. At the moment the neural network version of the system is currently being tested for performance and effectiveness. Therefore for this work we only consider the connection knowledge-based modules to be using fuzzy neurons.

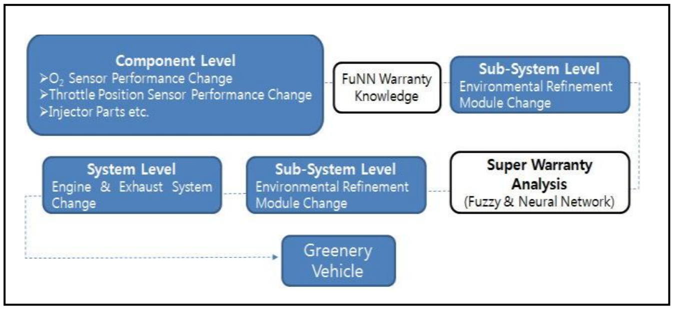

Figure 1. Super Warranty system organizational architecture

B. *Lifetime warranty policy*

Much of the literature on warranty analysis considers failure models which are indexed by a single metric, such as time or age. The age is measured by calendar time such as one year, two years, and so on. But, there are situations where different attributes are used together as criteria for identifying the warranty eligibility of a failed product. For instance, usage is measured by real operating time in terms of mileage, number of copies, etc. The usage is also included in lifetime knowledge. Usually, the usage warranties are restricted to 80,000km regardless of its time in case of environmental parts. Thus, the usage knowledge is more important than the general time one in the super warranty problem. Most studies on warranty policy consider some statistical models based on the lifetime. The age-specific analysis of product failure data has engendered considerable interest in the literature [3]. Kim and Rao discussed two-attribute warranties for non-reparable items and deal with the expected warranty cost analysis based on a bivariate exponential distribution [2]. In particular, Majeske considered a general mixture model framework for automotive vehicle warranty data [8].

In the real world, however, vague phenomenon is quite common in the production models. In order to process the vagueness, a production model that can be more closely related to the real vagueness and can take account of the vague factors that contribute to production costs, is required. Especially, in warranty policy, there is a lot of uncertainty and also there are many gaps in the data that can only be filled by qualitative assessments by warranty experts. The model can be extended or altered to fit in with the fuzzy situation. In this context, Lolas, et al. discussed an approach used in the construction of the fuzzy logic knowledge base for a new reliability improvement expert system, whose main objectives are to be able to improve the reliability of new vehicle systems [7]. In regard to two-attribute warranty policy, Rai and Singh discussed a method to estimate hazard rate from incomplete and unclear warranty data [5]. Recently, Lee and Moon presented a new sets-as-points geometric view of fuzzy warranty sets under two-dimensional warranty policy [4].

III. WARRANTY FUNCTION APPROXIMATION

In the greenery warranty system, FuNN modules have as input, information coming from lower levels, i.e. the component level, which they link through the use of network layers to their output, i.e. refinement module of the sub-system/module level (see Fig.1 and Fig.2, which depicts the fuzzy neural system in more detail). In this section, we suggest a knowledge acquisition phase and FuNN module construction process.

A. *Knowledge Acquisition*

This phase is the most important phase in the whole FuNN construction process. The information generated during this phase usually determines the capability of the FuNN system to perform efficiently (see Fig. 2). In the field of automotive engineering, there are a large number of available information sources where knowledge engineers can extract information from. Some of them include environmental failure mode and effect analysis, and environmental warranty expertise.

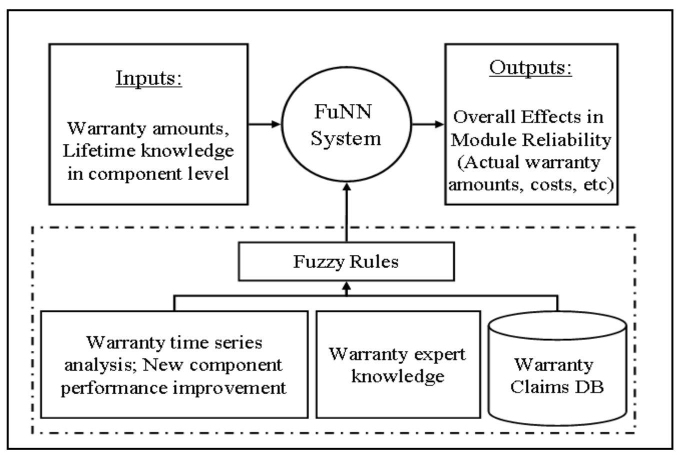

Figure 2. FuNN module layout

The first task is to identify all the environmental warranty claims of the automotive system under consideration. This is done through the analysis of warranty data and attributes cascade. Then the causes of the warranty claims and the performance parameters of the environmental components that contributed to the failure modes need to be defined and linked to the specific actions taken that led to the improvement or deterioration of the component's performance. The next step is the calculation of the effect on the overall reliability of the module or system due to this change in the performance characteristic of the component. This calculation considers data from the actual warranty amounts excluding invalid claims reported by the customer

B. Fuzzy Neural Network (FuNN) Structure

The fuzzy neural network is an architecture that combines standard MLP network with fuzzy logic in one system. The FuNN consists of 5 layers of neurons with partial feed-forward connection as shown in figure 3. The input layer of neurons represents the warranty variables (X_1=age, X_2=mileage) as crisp values. These values are fed to the condition layer which performs fuzzification by gauss membership functions with centers represented as the weights into this layer. The outputs from the condition layer are propagated to the rule layer. The rule layer is identical in its structure and operation to a hidden layer of a standard MLP network. The difference is that in FuNN each neuron in the rule layer represents one fuzzy rule. The semantic meaning of the activation of a rule layer node is that it represents the degree to which input data matches the antecedent component of an associated rule.

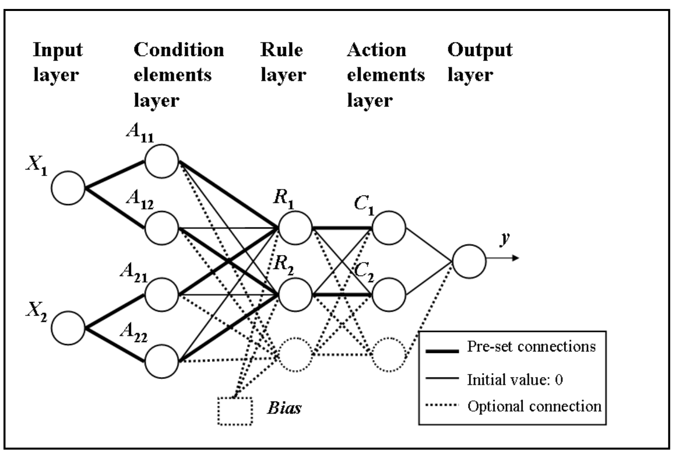

Figure 3. Fuzzy Neural Network

Outputs from the rule layer are fed to the action element layer. As for the rule layer, the operation and the structure of the activation layer is identical to the standard hidden layers of MLP networks. In this layer each node represents a fuzzy label from the fuzzy quantization space of an output variable, for example 'little', 'some' or 'moderate'. The activation of the node represents the degree to which this membership function is supported by the current data. The rule layer can be also seen as an antecedent layer and the activation layer as a consequence layer as they represent the antecedent and consequence part of IF-THEN fuzzy rules. The output layer performs a modified center of gravity defuzzification. Singletons, representing centers of triangular membership functions are attached to the connections from the action to the output layer. This layer uses a linear activation function

IV. LEARNING ALGORITHM

A 2-input-1-output fuzzy neural network has *m* fuzzy IF-THEN rules which are described by IF x_1 is A_1^k and x_2 is A_2^k THEN y is B^k, where x and y are input and output fuzzy variables, respectively. Fuzzy sets A_1^k, A_2^k and B^k are defined by gauss membership functions as follows,

$$\mu_{A_i^k}(x_i) = \exp[-(\frac{x_i - a_i^k}{\sigma_i^k})^2] \quad \mu_{B^k}(y) = \exp[-(\frac{y - b^k}{\eta^k})^2] \tag{1}$$

The 2-input-1-output fuzzy neural network with simple fuzzy reasoning is defined below:

$$f(x_1, x_2) = \frac{\sum_{k=1}^{m} b^k [\prod_{i=1}^{n} \mu_{A_i^k}(x_i)]}{\sum_{k=1}^{m} [\prod_{i=1}^{n} \mu_{A_i^k}(x_i)]} \tag{2}$$

Given 2-dimensional warranty vectors x^P (*i.e.*, $x^P = (x_1^P, x_2^P)$) and one output vector y^p for p=1, 2, ... , N, (i.e., N training data sets). The energy function for p is defined by

$$E^p = [f(x_1^p, x_2^p) - y^p]^2 / 2 \tag{3}$$

For simplicity, let E and f^p denote E^p and $f(x_1^P, x_2^P)$, respectively. After training the centers of output membership functions ($\partial E^P/\partial b^k$), the widths of output membership functions ($\partial E^P/\partial \delta^k$), the centers of input membership functions ($\partial E^P/\partial a^k$) and the centers of input membership functions($\partial E^P/\partial \sigma a^k$), then we obtain the training algorithm as the following.

$$b^k(t+1) = b^k(t) - \theta \frac{\partial E^P}{\partial b^k}\bigg|_t \tag{4}$$

$$\sigma^k(t+1) = \sigma^k(t) - \theta \frac{\partial E^P}{\partial \sigma^k}\bigg|_t \tag{5}$$

$$a^k(t+1) = a^k(t) - \theta \frac{\partial E^P}{\partial a^k}\bigg|_t \tag{6}$$

$$\eta^k(t+1) = \eta^k(t) - \theta \frac{\partial E^P}{\partial \eta^k}\bigg|_t \tag{7}$$

Here, η is the learning rate and t=0, 1, 2, …

The main steps using the learning algorithm as follows:

- Present a warranty data sample, compute the corresponding output.
- Compute the error between the output(s) and the actual target(s).
- The connection weights and membership functions are adjusted.

- At a fixed number of epochs, delete useless rule and membership function nodes, and add in new ones.
- If Error > Tolerance then go to Step 1) else stop.

When the error level drops below the user-specified tolerance, the final interconnection weights reflect the changes in the initial fuzzy rules and membership functions. If the resulting weight of a rule is close to zero, the rule can be safely removed from the rule base, since it is insignificant compared to others. Also, the shape and position of the membership functions in the fuzzification and defuzzification layers can be fine tuned by adjusting the parameters of the neurons in these layers, during the training process.

V. Results

Most often automotive warranty is specified in terms of {*Tmax*, *Mmax*} with *Tmax* being a specified maximum time period and *Mmax* a specified maximum mileage.

Table 1 provides a summary table for the warranty amounts analyzed in exhaust system. This table is based on actual warranty claims reported about particular type cars during recent years in automotive company, South Korea.

The exhaust system is composed of automobile parts in connection with emission controls, yet most motorists do not even know they have one or more of these devices on their vehicle – let alone what it does. For instance, the only time most people even become aware of exhaust an oxygen sensor's existence is if they get a check engine light and there is a code that indicates an O_2 sensor problem their vehicle fails an emissions test because of a sluggish or dead O_2 sensors.

TABLE I. Two-way automotive warranty counts.

Mileage(1,000km)	Time (months)				
	0~24	24~48	48~72	72~96	Total
0~5	1	0	0	0	1
5~20	7	1	0	0	8
20~60	13	46	26	1	86
60~100	1	31	37	17	86
100~120	1	7	12	9	29
Total	23	85	75	27	210

Table 2 denotes a table based on one assumption that all activations of an input fuzzy set are regarded to be a piece of fuzzy concerns supporting the warranty knowledge an expert formulated via rules and fuzzy sets. This assumption can be implemented in the warranty accumulation and normalization. Figure 4 illustrates a result by applying a 2-input-1-output fuzzy neural network which has 20 fuzzy IF-THEN rules, and fuzzy sets defined by equation (1) are calculated from Table 2.

TABLE II. Accumulation and normalization table.

Mileage	Time			
	0.125	0.375	0.625	0.875
0.02	0.02	0	0	0
0.10	0.14	0.02	0	0
0.33	0.27	1.00	0.57	0.02
0.67	0.02	0.68	0.80	0.37
0.92	0.02	0.15	0.26	0.18

After the network trains to a sum squared error (SSE) goal of 0.5%, the outputs compared to the target vectors.

Figure 5 represents SSE result of the trained data to the actual data. The error plot stopped at 100 epochs when the SSE error dropped to 0.000189, which is less than the error goal of 0.001.

When we look only at the peak points in figure 4, we conclude that super warranty problem is needed to give attention to the neighborhood of 4 years and 60,000km.

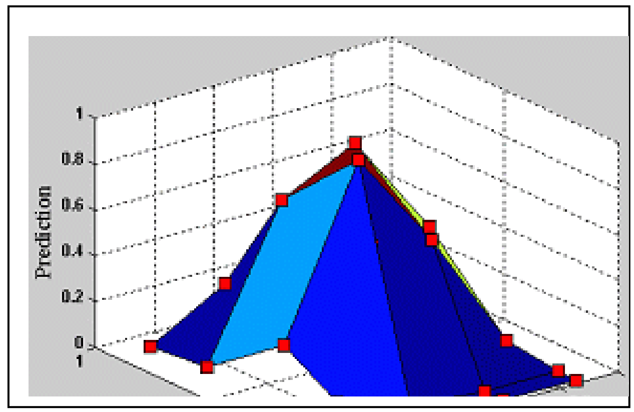

Figure 4. Mapping surface of actual warranty proportions.

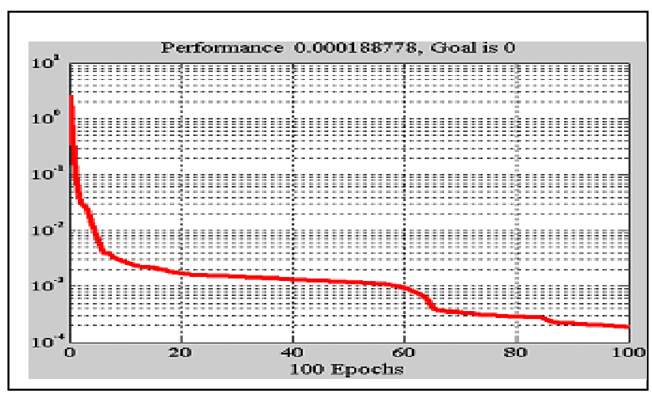

Figure 5. Network error

In particular, the surface is similar to the graph of a Gaussian that is a characteristic symmetric "bell curve" shape that quickly falls off towards plus/minus infinity.

In view of super warranty, this gives us useful warranty information like we get from nonlinear function optimization for continuous data. In two-dimensional warranty problem, one can vary a warranty surface in more parameters: not only may one vary a single width, but one may vary two separate widths, and rotate: one thus obtains various warranty models according to the warranty level sets.

VI. CONCLUSIONS AND FUTURE WORKS

What we would like to have for super warranty problem is techniques that give us useful greenery information like we get from correlation and regression analysis for continuous data. Recall that the regression equation, in particular the slope from the regression equation, and the correlation value give us information we want to know. Both neural networks and fuzzy systems have some things in common. They can be used for solving a warranty problem in which there does not exist any mathematical model of the given warranty data. They solely do have certain disadvantages and advantages which almost completely disappear by combining both concepts. In particular, a fuzzy neural network or neuro-fuzzy system is a learning machine that finds the parameters of a fuzzy system by exploiting approximation techniques from neural networks. This paper has investigated the possibility of the application of fuzzy neural networks to super warranty problem in green IT's point of view. The obtained result show that this approach works very well, is robust noise, and captures small scale details of two-attribute warranty policy. Despite the encouraging initial results from the trials of the suggested system there are a number of areas in the methodology and the structure that need to be improved by further research.

Automatic processing of new information, automatic learning capability and a user friendly interface are still features that can be added to the system to enhance its performance and usability.

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