

AHP-Based Determination of Warning Grade in a Warranty Claims

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AHP-기반으로 보증클레임의 위험등급 결정

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Abstract Two perspectives on developing better decision capabilities for a warranty system can be identified: one involving the inclusion of a ‘learning’ module and the other the inclusion of a ‘prioritization’ capability. This paper demonstrates how a warning process can be included in a warranty system by coupling with a neural network’s learning capabilities. In addition to the neural network, a method is employed for assigning priorities to warning criteria by using the analytic hierarchy process (AHP). Thus, it is possible to construct an integrated system with three components: the warranty system, the AHP module, and the neural network system. A case study is provided to enhance the accuracy of warning/detection judgment in a warranty system for automobile companies, having many factors related to the warranty system.

요약 보증 시스템의 ‘학습’ 모듈과 ‘우선순위’ 등을 포함한 두 가지 기능을 이용하여 의사결정시스템을 개발을 할 수 있다. 본 논문은 품질보증 시스템과 신경망 학습기능을 이용한 위험분석 방법을 보여준다. 분석 방법은 신경 네트워크뿐만 아니라, 계층 분석방법을 사용하여 경고 기준에 우선순위를 할당을 위해 적용되었다. 따라서 보증 시스템, AHP 모듈 및 신경 네트워크 시스템의 세 가지 구성 요소와 함께 통합 시스템 구축을 가능하게 한다. 사례 연구에 제공되는 자동차 회사에서 사용되는 보증 시스템 내에 많은 요인을 이용해 정확한 판단의 “경고 / 검출”을 향상시키고자 한다.

Key Words : Warranty claims; Neural network; AHP; Quality information report

1. Introduction

This Modern industrialized societies are characterized by (i) new products (consumer durable, industrial, and commercial products) appearing at an ever-increasing rate on the market, (ii) products with more complexity (due to technology advances), (iii) more demanding customers, and (iv) more stringent government regulations regarding product liability(Murthy, Solem and Roren, 2004)[8].

A warranty is a contractual agreement between a manufacturer (seller) and a consumer (buyer) that requires the manufacturer to rectify all the failures occurring

within the warranty period (Jack and Schouten, 2000)[11]. In addition, a warranty is a guarantee given to the customer by the manufacturer stating that the product will perform its intended function (i.e. it will be reliable) under normal conditions of use for at least the warranty period. The purpose of a warranty is to establish the liability of the manufacturer in the event that an item fails or is unable to perform its intended function when properly used (Karim and Suzuki, 2005)[14]. When a warranted product fails within the warranty period and the consumer makes a legitimate claim to the manufacturer for repair or replacement of the product, the claim is

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known as a warranty claim. A warranty claim means a complaint from a client when a product does not satisfy the client's request concerning its function, quality, or delivery date.

Warranty claims for manufactured products record claims experience and information about concomitant factors. If properly constructed and maintained, warranty claims data bases may be used for a variety of purposes, including the prediction of future claims. The systematic and efficient usage of a warranty claims database can lead to better decision making in connection with the causes, the cost, and so on of customer complaints (Quayle, 1999; Canel et al., 2000; So and sculli, 2002)[18,5,20]. Specifically, this leads to business automation and the reduction of warranty claims through an information system (kalbfleisch et al., 1991)[13].

Manufacturers analyze field reliability data to enhance the quality and reliability of their products and to improve customer satisfaction. There are many sources for collecting reliability-related data. In many cases, it would be too costly or unfeasible to continue an experiment until a reasonable number of items had failed. Warranty claim data is a prime source of field reliability data, which is economically and efficiently collected through service networks.

Suzuki et al. (2001) mentioned that the main purposes and uses of warranty claim data are[21]:

- (i) early warning/detection of a bad design, poor production processes, defective parts, poor materials, etc.;
- (ii) observing the targets of new product development, i.e. whether targets are achieved or not;
- (iii) grasping the relationships among the test data at the development stage, the inspection results of the production stage, and the field-performance;
- (iv) determining whether a recall, halt in production, or modification is necessary;
- (v) comparing the reliability of similar or competing products;
- (vi) constructing a database of failure modes/mechanisms and their relation to both environmental conditions and how the product is used; and
- (vii) predicting future warranty claims and costs.

Warranty claims are the information obtained by analyzing field data. This field data provides important

information used to evaluate reliability, to assess a new design and manufacturing changes, to identify causes of failure, and to compare designs, vendors, materials, or manufacturing methods.

If an automobile under warranty fails, for instance, it is repaired by the original manufacturer, and the manufacturer obtains information, such as the failure times, the causes of the failures, the manufacturing characteristics of the items (e.g., the model, the place or time of manufacture, etc.), and the environmental characteristics during the use (e.g., personal characteristics of the users, climatic conditions, etc.) (Junga and Bai, 2007)[12].

Many manufacturers remove pre-delivery claims from the population to allow the data to fit with traditional methods, rather than developing techniques to accommodate this unconventional data, which regularly occurs in automobile warranty claims. Majeske (2003)[16] proposed a general mixture model framework for automobile warranty data that includes parameters for product field performance, the manufacturing and assembling process, and the dealer's preparation process.

Identifying the warning lists in a warranty claims system is a sort of warranty planning system that needs reliability information, such as the tolerance error in the nonconforming fraction, the degree of error variation, and the deviance of control limit. It also needs artificial intelligence in the assessment of system risk. There are many studies in connection with this problem: data mining modeling in the automotive industry (Hotz et al., 1999)[11]; warranty claims process modeling of the automobile (Hipp and Lindner, 1999)[10]; a software cost model for quantifying the gain and loss associated with warranty claims (Teng and Pham, 2004)[23]; software-based reliability modeling (Jeske and Zhang, 2005)[24], and so on. These studies are mainly related to the forecasts of the warranty claims. Sometimes warranty claims may depend on information about the manufacturing conditions or the environment in which the product is used, such as the production and/or the operating periods. In regard to this problem, a way to detect the change points using the adjacent distribution of warranty data in terms of identifying sub-units of the product serviceable during the warranty period is a reasonable and useful method (Karim and Suzuki,

2005)[14]. In warranty claims analysis using these covariates, inventory knowledge can be extended in the usual way to allow covariate analysis. Inventory knowledge for countable data, such as claims, is required in forecasting the warranty claims.

Chukova and Hayakawa (2005)[6] provided a brief introduction to warranty analysis and a classification of general repairs, and introduced the notion of accelerated probability distribution and used it to model warranty repairs. In the warranty repairs problem, however, there are many qualitative factors in practical implications. Buczkowski et al. (2005)[4] considered the problems with outsourcing the warranty repairs to outside vendors, such as variations between regional services, when items had priorities in service. This is the same as considering the qualitative factor, and fuzzy logic needs to be applied to it. According to the study of Pizzi and Pedrycz(2003)[17] on software quality evaluation, it is desirable that, in the construction of a warranty system, the fuzzy relation concept needs to be used for the expansion and maintenance of the warranty system as a quartile for the sake of processing various qualitative factors. However, the problem is that multilayer perception learning is overfitting, since there is no feedback from quality experts on the basis of predestinating quality class, and the same with how to set the approximate figures for hidden neurons.

Ali and Chen (2005)[1] suggested the neural network model, which can map a process-measured value in light of product quality for which, with a problem in product quality, different approaches are needed according to its goals. This suggested model emphasized that issues occurring in the processing of product properties and quality control can be processed. The problem is that the constraint of a neural network's structure is strenuous, especially the limitation that the input neurons are constricted to three. Grzegorzewski and Hryniewicz (2002)[9] attempted to take a fuzzy theory-like approach that can model ambiguous data in that, in relation to product reliability, colloquially expressed malfunction information and partially described defects frequently appear in the real world. However, the interpretation of the approximate inference result is an issue because the decision-making for warranty degree is free to gauge sensational and multidimensional qualitative information.

Montis et al (2000)[7] presented the application standard of NAIDE, MAUT and MOP/GP, and the merits and demerits of their methods in relation to a case study on four MCDA (Multi-Criteria Decision Aid) methods.

Since the current warranty systems do not provide decision-making modules that reason well on decisions, and are primarily based on manual techniques and human judgment for problem solving, individuals should have the decision rules in place before a warranty system can be utilized. Other limitations incurred in the current warranty system approaches include a failure to provide methods to consider individual preferences and a failure to evaluate the trade-offs among the decision criteria essential to multi-criteria problems, such as site selection. Two perspectives on developing better decision capabilities for warranty system can be identified - one involving the inclusion of a 'warning/detection learning' module and the other the inclusion of a 'warning/detection prioritization' capability. This paper demonstrates how a warning/detection process can be included in a warranty system by coupling them with a neural network's learning capabilities. In addition to the neural network system, this study employed a method for assigning variations to warning/detection criteria called the analytic hierarchy process (AHP) (Saaty, 1980)[19]. Zhu et al (2005)[22] conducted a representative study related to warranty systems and the AHP technique, including systems with various structural designs dealing with diverse warranty properties. The internal correlation among the quality properties is enormous. At the same time, the setup of critical tradeoffs and sensitive times by ranking is very important, since everything must be considered. To achieve rapid product development, Kengpol and O'Brien (2001)[15] presented a decision tool for the selection of advanced technology.

This paper is intended to minimize the warning/detection errors of warranty claims using AHP analysis, which can naturally quantify the qualitative information. Thus, we propose a neural network model that uses the results of the AHP analysis as its inputs and has feedback from expert evidence. This reduces the warning/detection errors arising from the warranty system. Eventually, this study illustrates a method for constructing an integrated system of three warning/detection support tools - the warranty claims information system, the AHP module, and the

neural network system. Finally, we apply the resultant system to an industrial decision problem that searches for a respective warning grade in the warranty claims database.

2. INTEGRATION OF THE WARRANTY SYSTEM WITH THE AHP

In this section, we introduce the warranty claims information system and the AHP module as the warning/detection support tools, and we present the system architecture for the integration of the warranty system and the AHP.

2.1 Warranty claims information system and Reliability

The warranty claims information system is generally composed of a warranty claims master(attributes: # of warranty claims, unit identification code, division of unit by use, unit model code, operation code, cause/reason code, production/sale period, service code, use period, warranty repair cost, repair vendor etc.), a product sales master(attributes: # of unit identification code, division of unit by use, unit model code, model index, production/sale period, etc.), and the product operation master(attributes: # of unit group, division of unit catalog, unit name, cause name, name of catalog division, etc.) files. From this warranty system, it is possible to develop several modules that distinguish between commonality and uniqueness in constituting the warranty claims data. They use an operation code as a key variable, and determine the warranty type of a given product. The operation code related to the product type and the model indexes of the product are simultaneously taken into consideration in developing the warning/detection modules for the warranty claims data. These modules are related to data mining methodology for extracting reliability knowledge. The reliability knowledge is composed of the applied product, the aggregation of the warranty claims master, the warranty claims counts per operation code, the group reliability statistics, etc. In particular, the warranty reliability analysis can be divided into the detection of the warranty claims time series as a quantitative aspect and

the AHP analysis of the influences on the warranty claims data as a qualitative one.

It can be used in two methods with respect to identifying the warranty claims data. First, it is used to calculate the warranty claims using the point of production as a reference. It can also do so by using the repair period as a point of reference. The former is favorable for monitoring quality in light of production control because the warranty claims index is calculated by the point of production, whereas the difficulty with this is that it is too complex to judge quality abnormalities and the detection time comes relatively late in comparison with calculating by occurrence period. The time series identification is used to complement the monitoring of the fraction of nonconforming warranty claims data by means of a repair period. The fraction of nonconforming claims per product is important reliability knowledge, and is obtained as follows:

- (i) Obtained from the applied product through the files by the product related to the warranty claims model index, which summarizes the warranty claims master.
- (ii) Obtained from aggregation per warranty claims operation, the fraction of nonconforming claims per operation and one per product in the product sale master.

2.2 Integration of AHP analysis

AHP is a multiple criteria decision-making tool that has been used in almost all applications related to decision-making. It also provides a methodology to calibrate the numeric scale for the measurement of the quantitative as well as the qualitative performances. A warning/detection of the warranty claims is the same as an integrated selection process, where both the quantitative and the qualitative aspects are considered. The AHP module can be divided into two main parts, starting with the warranty claims master. First is the AHP data file obtained from the customer information file and the local service file, such as a regional warranty repair service. The other is the AHP file obtained from the master summary of the product. The qualitative reliability knowledge, such as the product significance, can be made up of the respective files, including the product division, the product number code, the malfunction type, the customer's complaint code, the warranty-related service information, the significance rate, and so on.

AHP analysis can be used to minimize the warning errors resulting from difficulties in quantifying the qualitative information in the warranty claims system. For example, there are variations based on the seasonality of a product, or among operational lines, which are due to the workers' skill and locality errors in the case of bringing about a specific region's caution warranty claims. The integration of the AHP is essential for quantifying the warranty claims-related qualitative information, such as variations in customer satisfaction, variations in local networks under warranty service, and variation arising from the product type and the model differences for a product. Further, a certain decision-making model structure must be obtained, in which the quality experts are satisfiable to multilaterally assessing the influence on the alternatives and the product significance, as an example.

The AHP of variation between the products is represented as the relationship property between the product type and the product model. Here, it is important to distinguish between the commonality and the uniqueness of a product in constituting the warranty claims. The correlation pattern of each case is asserted, and the corresponding interpretation and the risk are described. The AHP of the variation between the models defines the correlations among the models based on the model index. The correlation can be obtained in the same way as the correlation coefficient calculation of the product types. The AHP of the variation between the regional attributes can be represented by using statistical calculations. For example, the Goodness of Fit test can be applied to the detection of regional errors. It uses a Chi-Square probability distribution to detect whether there is a difference between the practically observed degree and the theoretical expectation degree. The internal relationship between the repair costs and the warranty claims is necessary for the AHP of the product significance. The quantification of the repair cost is usually determined through the opinion of the expert(s).

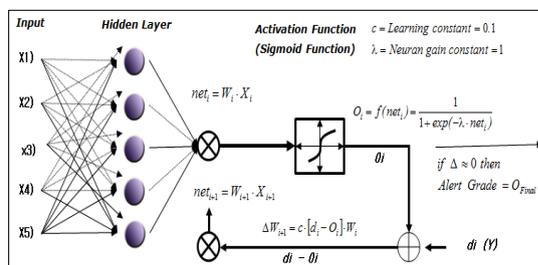
3. Warning/Darning based on multilayer perceptron

A neural network system is proposed as one of the

warning/detection support tools. By creating external inputs, such as the variations between product types, the variations between product models, those among service regions and seasonality through the AHP, we can carry on the warning/detection of the warranty claims, which is linked to neural network learning.

3.1 The AHP Input Layer

Multilayer perceptrons (MLPs) are feedforward neural networks trained with a standard backpropagation algorithm. They are supervised networks, so they require a desired response to be trained. They learn how to transform input data into a desired response, so they are widely used for pattern classification. With one or two hidden layers, they can virtually approximate any input-output map. Figure 1 represents a multilayer perceptron using 5 input(x_1 =time series detection, x_2 =variation between products, x_3 =variation between models, x_4 =Regional difference, x_5 =Seasonal factors) neurons, which are extracted by the AHP.



[Fig. 1] Multilayer perceptron with AHP input

The sigmoid function can be used as a transfer function, and the final grade judgement is adjusted as the output neuron value by using the product significance.

The product significance groups are categorized into three basic kinds: (1) the product serious degree (the nonconforming type, the product type), (2) the customer information, and (3) the warranty repair information. The product serious degree type is further divided into two types, that is, the nonconforming type and the product type. First, the quantification of the nonconforming type can be done by categorizing the phenomenon codes into three code types, that is, codes representing a platform problem, a function quality, and a sensation quality. A platform problem is linked to the function, whereas the

function quality is related to the product's operation. The sensation quality is a user subjectivity problem. Suppose that is the quantification value of the phenomenon codes, is the warranty claims coefficient of the k-order phenomenon code, and is the warranty claims rating related to the k-order phenomenon code. The equation can be expressed as follows in (1).

$$N_m = \sum_k \sum_i C_i^k \times G^k / \sum_k \sum_i C_i^k \quad (1)$$

The quantification of the product types makes 5 possible degrees of quantification for the security/safety product, the environment product, the past recall product, the general product, and the consumptive product. This section needs the person in charge of the products to thoroughly define even the part number code level of the product groups. It is worth special mention that the security/safety products, being ones that cause significant defects in the products owing to product nonconformities, do harm to customers by technical loss or harm associated with the regulations by region. The quantification of customer information represents the time series of the item number in question by classifying the complaints accepted at a customer center into the product type and into similar parts groups. The scope of the customer information is usually 1 year, and the product type involves all the similar things. In the quantification of the warranty service information, the cost of the warranty service is ordinarily the total sum of the product cost, the labor cost, and the transportation cost. In order to quantify the repair cost, the concept of quartile, octile or 16 quantile is applied. It is applied to divide various classes after standardizing the mean repair cost and the standard deviation of the part number code per product.

3.1 Multilayer perceptron learning

The learning steps of a multilayer perceptron are as follows:

Step 1. Determine the initial values (learning rate $c=0.05$; gain $\beta=0.0001$; the initial weight is the value of a random number generator multiplied by 0.5 and the initial threshold is also the random number multiplied by 0.5).

Step 2. Calculate the network output, o (multiply the

initial weigh matrix and the input vector, and add the threshold value).

Step 3. Calculate the transfer function f and its differentiation.

$$f(n) = (1/[1 + \exp(-n)])(1 - [f(n)]^2) \quad (2)$$

Step 4. Calculate the difference between target (d) and the neuron output.

$$\delta = (d - f(n) \times f'(n)) \quad (3)$$

Step 5. Update the weight and threshold by δ .

$$W^{new} = W^{old} + c \times \delta \times X_i, \theta^{new} = \theta^{old} + \beta \times \delta \quad (4)$$

Step 6. Repeat the learning and determine the final weight.

The final quantification process is usually determined by the final significance grade by applying the integral results to the Box-Cox transformation, in which the respective weight is given according to the attributes of each group. In order to calculate the probability distribution of the nonconforming fraction, the Box-Cox transformation is performed, and the ideal method for performing this transformation is by calculating the β multiplier of the data for the optimal normal distribution. The problem is how to find the multiplier for the data; this multiplier is determined by means of repeatedly finding the maximal value in the highest level of significance in the normal test. The experiment results revealed that the optimal normality is required in a case where the multiplier is typically 0.2.

The neuron output transforms the Quality Information Report (QIR) acquired in the service support and the quality improvement system into binary numbers. The reason is that it is not a good method to give a special weight considering the QIR degree. In most cases, the judgement of the QIR query is not by means of the warranty claims information acquired (use period, part number, and so on), but it, rather, applies the circumstances, like the relationship between the products

[Table 1] The AHP results for the variation between the products

Division	correlation Pattern	Interpretation	Risk
Common	High correlation between the car type and the models	Independent of the relationship properties among the car type and the model, the warranty claims occur	Most high
	High in the case of the car types and low among the models	In case the relationship properties among the car types are great or temporary phenomena	Nomal
	Low in the case of the car types and high among the models	In case the relationship properties among the models are great or temporary phenomena	Nomal
	Low correlation between the car types and the models	Temporary phenomena	Low
Unique	High correlation between the car type and the models	Temporary phenomena or data error	Low
	High in the case of the car types and low among the models	Temporary phenomena	Nomal
	Low in the case of the car types and high among the models	Temporary phenomena	Nomal
	Low correlation between the car types and the models	Causes specific products	Most high

and the seasonality, presented in the already determined products. In a case where the neuron output is binary, it is necessary that the coefficients of 0 and 1 are suited as equally as possible for the optimal modeling. This is because if either of the two is greater, there is a possibility of over learning with a view to reducing the least square error. Therefore, matrix reduction becomes necessary in the way of summing up the rows of the data matrix.

4. CASE STUDY

4.1 Applying to an Automobile Company

In this paper the vehicle information regarding the particular model year, vehicle, sub-system name, and failure mode is not disclosed to protect the proprietary nature of the information.

In order to apply the AHP analysis related to the warranty system presented in this study, the warranty claims about the N car type has been used. The access file for product significance includes the PNC (Part Number Code) and the significance record, and is connected to the car catalogs. The catalog master involves the records of the PNC, the part numbers, and so on. If the product code is not the security and the environment products or the release date is less than 9 months or there

is an improvement effect, then preprocessing is required. The data set composition for the AHP is the task to transform the product numbers into the PNC, which is obtained from the catalog master file.

In the 45-day correlation coefficient with the same car model from this data collection, in the same period of the correlation coefficient with the same car type in which the most warranty claims occurred for the same product for 6 months from the occurrence time between the same car types, and in the ratio of the sales region divided into 15 areas for 6 months from the occurrence time, the appropriateness was measured through 45-day propriety verification, and the data collection for the neural network application was constituted. Especially, the time series verification value was calculated in the probability product of the OP code's critical value, and the slant and the seasonality was revealed in the order of the car flame intensity in accordance with the season, i.e., 1 for the fall, 2 for the spring, 3 for the winter, and 4 for the summer.

Table 1 is the AHP results of the variations between the products revealed according to the relationship properties between the car types and the models.

The AHP analysis of the variation between the models defines the correlations among the models based on the model index divided into an engine and body type.

$$\gamma = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sigma_x \cdot \sigma_y}, \sigma_x = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n-1}}, \sigma_y = \sqrt{\frac{\sum (y_i - \bar{y})^2}{n-1}}$$

, $x_i = i$ hour day time accumulation claim ratio
 , $y_i = i$ hour day time accumulation claim ratio (5)

[Table 2] Goodness of Fit test for the repair regions

Region	Warranty Claims Number	Estimation Number	Goodness of Fit
Seoul	13	15	0.27
Incheon	4	3	0.33
Chungnam	2	2	0.00
Chungbuk	3	2	0.50
Daegu	1	2	0.50
Gyeongbuk	3	2	0.50
Jeonnam	3	1	4.00
Jeonbuk	1	2	0.50
Gyeonggi	3	11	5.82
Gangwon	4	2	2.00
Daejeon	1	1	0.00
Busan	4	4	0.00
Ulsan	2	2	0.50
Gyeongnam	5	3	1.33
Gwangju	4	2	2.00
Jeju	2	0	0.00

[Table 3] Repair cost rating of the N car model

Range of the Warranty Service Cost	Rating	Mark
0 - 27,138	H	0.7
27,138 - 57,672	G	0.8
57,672 - 88,207	F	0.9
88,207 - 118,742	E	1.0
118,742 - 149,276	D	1.2
149,276 - 179,811	C	1.6
179,811 - 210,345	B	1.8
210,345 - or more	A	2

The AHP of regional fitness is reflected in the ratings by detecting the regional errors. Table 2 shows the results of the Goodness of Fit test on the 16 servicing regions, including Seoul. The repair number in the Gyeonggi servicing region was revealed to be relatively high, but it can be known that the significance level is 0.2882 because it is greater than the critical value of 0.01. This means that there is no trouble with the distribution of the maintenance and repair regions. The internal relationship between the repair cost and the warranty claims is

necessary for the AHP of the parts significance. The quantification of the repair cost is determined through the opinion of the company's parts expert as in Table III. This value, which divides the warranty claims numbers (C) in the case of n = 3 months in the short term and n = 12 months in the long term by the sales number (S) is applied for the quantification of the warranty claims ratios. Table 4 is the severity results for the part significance. The tabulated results of the final rating considering the neural network learning using MATLAB version 7.1.

[Table 4] Part significance

Category	Gonelation Coefficient	Releva-n ce	Reference
Engine	0.82	High	
Seat	0.81	High	
Transmission	0.90	High	[Category in High Relevance]
Thermostat	0.64	Middle	:Engine>Seat>Tra nsmission
Exterior	0.63	Middle	[Category in Low Relevance]
Traveling/Steering/BrakeSystem	0.34	Low	:Thermostat, Exterior [Category in No Relevance]
Convenience Device	0.28	Low	:Convenience, Interior, Traveling/Steering /Brake System, Sound System
Interior	0.29	Low	
Sound System	-	None	

The final rating results reveal that the S, A, and B grades are mapped to the S grade while the grades from C through A, under, are mapped to A as their respective best grades. In reality, a grade settlement for early strict parts is often followed by frequently unnecessary improvement activities for parts not belonging to the grade in question, but the application result of the proposed technique brought about results very close to the quality experts inside the company. Ultimately, the result of a remarkably reducing factor for improvement cost is given birth by considerably reducing the error warning about the parts that substantially do not need an

improvement in this improvement activity.

4.2 Analysis of the Expectation Effects

We conducted an expectation effects analysis with the data collected at a domestic automobile company during the year 2004 and divided the expectation effects analysis into two major viewpoints - the qualitative and the quantitative.

Through the qualitative expectation effects analysis, we could maximize the customer satisfaction by preventing quality problems from enlarging using an early warning, and we could improve the quality by real time information sharing and cooperative activities to enhance the quality. We could also gain the following advantages by the qualitative expectation effects analysis: 1) the improvement of the validity ratio about the issued claim, 2) the curtailment of the quality improvement period, and 3) the cost reduction for the claim guaranty.

The period curtailment by the quality improvement activities and the emergent meeting for the countermeasures against the main quality problems, such as maintenance, quality guaranty, and so on.

5. Conclusions

It is very important to make appropriate warning/detection judgments in a warranty claims information system. The difficulty of the problem arises from the qualitative parts, such as the interrelations among the products and models, the service or repair attributes, the customer satisfaction, the product significance, and so on. Until now, the determination of strict warning/detection grades by crisp logic has been unacceptable from the viewpoint of quality experts. This is in accordance with the exclusion of qualitative factors, which it was unable to quantify in product quality improvement activities. We have suggested a method of applying the AHP that is able to involve these factors in the warning/detection judgment and we have, additionally, introduced a neural network that can reflect the knowledge of the quality experts. Subsequently, as a result of applying the proposed model aimed at a famous national car company, the warranty claims were

reasonably reduced and showed alignment with the opinion of the car product quality experts in comparison with a case not applying AHP analysis data. The good results led to minimizing the economic losses arising from warranty services in the concerned company.

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