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보증 클레임 시계열 데이터를 위한 퍼지 PID 제어

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Fuzzy PID Control of Warranty Claims Time Series

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■ Abstract ■

Objectifying claims filed during the warranty period, analyzing the current circumstances and improving on the problem in question is an activity worth doing that could reduce the likelihood of claims to occur, cut down on the costs, and enhance the corporate image of the manufacturer.

Existing analyses of claims are confronted with two problems. First, you can't precisely assess the risks of claims involved by means of the value of claims per 100 products alone. Second, even in a normal state, the existing approach fails to capture the probabilistic conflicts that escape the upper control limit of claims, thus leading to wrong control activities.

To solve the first problem, this paper proposed that a time series detection concept where the claim rate is monitored based on the date when problems are processed and a hazard function for expression of the claim rate be utilized. For the second problem, this paper designed a model whereby to define a normal state by making use of PID (Proportion, Integral, Differential) and infer by way of a fuzzy concept. This paper confirmed the validity and applicability of the proposed approach by applying methods suggested in the actual past data of warranty claims of a large-scaled automotive firm, unlike hypothetical simulation data, in order to apply them directly in industrial job sites, as well as making theoretical suggestions for analysis of claims.

Keyword : Fuzzy PID Control, Warranty Claims Data, Reliability, Time Series

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1. Introduction

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 have failed. Warranty claim data is a prime source of field reliability data, which is collected economically and efficiently through service networks. Suzuki et al.[10] mentioned that the main purposes and uses of warranty claims data are early warning/detection, grasping the relationship among the warranty claims data, determining the warranty degree, comparing the reliability of products, constructing the warranty claims database and predicting future warranty claims and costs. The important aspects of warranty are also discussed in Murthy and blishcke[7] and Murthy and Djamaludin[8]. Chukova and Hayakawa[3] presented a brief introduction to concepts and problems in warranty analysis.

Since randomness is not merely an aspect of uncertainty in many fields of application, the fuzziness of the environment cannot be neglected in modeling an observed process. It is difficult to capture warranty claims data on reliability in polluted and imprecise situations, especially for new and durable products, non-mass products, and short product development times. Usually, there is no comparative reliability information available, the warranty claims data trend to be based on subjective evaluation or rough estimate[5]. To deal with the problems above, the modeling of reliability distribution has to be based on the fuzziness of warranty claims data. Many studies also demonstrate that the fuzzy theory is suitable for modeling the reliability property of a product[1, 2, 4, 6, 9]. Existing analyses of claims are confronted with two problems. First, you can't precisely assess the risks of claims involved by means of the value of claims per 100 products alone. Second, even in a normal state, the existing approach fails to capture the probabilistic conflicts that escape the upper control limit of claims, thus leading to wrong control activities.

It is desirable to apply the fuzzy theory to analyzing the warranty claims data for the warranty model. In this paper, we suggest the use of time series detection and hazard function and fuzzy PID control model. The remainder of this paper is presented as follows. Section 2 proposes the time series detection of warranty claims data with hazard correction and calculation of average failure rate. Section 3 suggests a fuzzy reasoning based on feedback control theory. Then, in section 4, confirms the validity and applicability of the suggested method with actual past data of a large-scaled atutomotive firm. The closing section presents conclusions and suggestions for future studies.

2. Time Series detection of Warranty Claims

In general, it can be used two standard ways in calculating the fraction nonconforming of warranty claims. One is to use a production point, and the other is to use a repair point. For example, C per 100 products (claims per one hundred products) denotes the calculation of the production point in most automobile companies. The production point has the advantage of monitoring the quality with respect to production management, but it is hard to identify the quality, and is relatively not to quickly detect the occurrence of assignable causes or process shifts. It is because the use point is fixed in calculating the fraction nonconforming in terms of the production point, so that the loss of information occurs. Time series detection can be used to complement this problem and to monitor the fraction nonconforming based on the repair point.

2.1 Hazard Correction

Hazard or failure rate is a scalar quantity that includes the restriction on time, and the fraction nonconforming refers only to the case without the restriction on time. The failure rate is defined as a probability of failure occurrence in the constant time. The Weibull distribution has been used extensively in reliability engineering as a model of time to failure in electrical and mechanical components and systems. Several functions are used and are equally suitable for describing the failure distribution, namely, the failure function f(t) when it exists, the cumulative function F(t), the reliability function, R(t) and the failure rate $\lambda(t)$. The fraction nonconforming of warranty claims can be obtained by the failure rate $\lambda(t)$. For example, a failure rate correction of three use period is as follows.

$$\frac{N_w}{N_s \times \frac{\lambda(0)+\lambda(1)+\lambda(2)+\lambda(3)}{\lambda(0)+\lambda(1)}} \tag{1}$$

Here N_w is the number of warranty claims, and N_s is the number of production and sales. Also,

$$\lambda(0)+\lambda(1)+\lambda(2)+\lambda(3)= \tag{2}$$

$$\int_0^3 \frac{f_{(t)}}{1-F_{(t)}}dt = [-\log_e R(t)]_0^3 \tag{3}$$

In particular, $H(t) = -\log_e R(t)$ is called as cumulative hazard function.

A standardization of failure rate can be obtained by using H(t). We define the standardization of failure rate as certain failure impact which is presented as time series through the correction of time (failure rate) and space (number of unit sales). H(t) can be obtained in terms of the Weibull parameters m and η, which are average estimates of each electrical and mechanical component and system data during the most stable period. The standardization of failure rate is defined as follows.

Fraction nonconforming of warranty claims (%)

$$= \frac{N_w}{N_s \times [\frac{H(t)-H(t-t_u)}{H(t_u)}} \times 100 \tag{4}$$

where N_s is the cumulative count of sales from each production period, and t_u is the use period. Dividing H(t) by H(t_u) is to standardize as the use period observed in the present time.

2.2 Calculation of Average Failure Rate

A data table can be used for the standardization of failure rate. It is composed of repair time, warranty claims frequency, division of warranty claims (for instance, based on production period) and cumulated count of sales. Since warranty claims ratio is a function of failure rate due to use period, it needs a correction of time in case of fraction nonconforming calculation. Let C_j, S and R(t) be warranty claims count, production/sale count and reliability function, respectively. Then, the warranty claims ratio by failure rate correction is computed as following.

$$H_{correction} = \sum_{j=1}^{n} \frac{C_j}{S \times \frac{\in(R(t))}{\in(r(1))}} \tag{5}$$

To develop an average value of the standardized fraction nonconforming, say $\overline{P}$, the following assumptions are needed.

Fraction nonconforming occurred in current point of time will be the same as one in previous time. Average of cumulative hazard function is t time.

Since the standardized warranty claims are calculated by daily unit in time series detection module, a control limit is derived through transforming the average by daily average fraction nonconforming(P_D), and thus a daily upper control limit (UCL_D) is defined as summing P_D and UCL_D (determination coefficient by the parts significance) multiplied by the standard deviation (σP_D).

$$UCL_D = P_D + \alpha \times \sigma P_D \tag{6}$$

$$= \sum_{i=s}^{c} \sqrt{\frac{\overline{P_{mt}} \cdot (1-\overline{P_{mt}})}{Sale_t}} \times \frac{1}{30} + 3.09\sigma P_D \tag{7}$$

where s is start, c is current, t is total and e is end.

$$\sigma \overline{P_D} = \sum_{i=s}^{c} \sqrt{\frac{\overline{P_{mt}} \cdot (1-\overline{P_{mt}})}{Sale_t}} \times \frac{1}{30} \tag{8}$$

where mt is monthly total.

3. PID Tuning and Fuzzy Reasoning

In this section, we suggest a fuzzy reasoning based on feedback control theory to ensure more robust warranty system modeling.

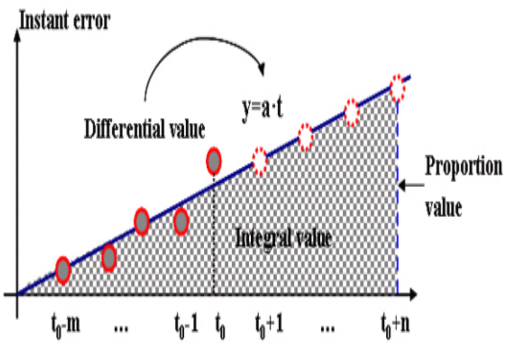
3.1 Instant Error Function

The instant error with respect to the warranty claims data can be obtained by weighted moving average which is defined as some differences between the standard nonconforming fraction and the types of the upper control limit. Specifically, the weighted moving average of span s at time t is defined as

$$\frac{\sum_{t=0}^{t_0 - s + 1} w_t D_t}{s} \tag{9}$$

Here, t_0 is the current time, w_t is the warranty time series, $D_t = (C_t^* - UCL_t^a) + (C_t^* - UCL_t^c)$, C_t^* is the standard nonconforming fraction, UCL_t^a is the upper control limit of the analysis control chart, and UCL_t^c is the upper control limit of the managed control chart. If the managed control chart is not used, then D_t is replaced by $2 \times (C_t^* - UCL_t^c)$. The instant errors can be approximated as a linear equation until t_0 from past time.

The PID(Proportion, Integral, Differential) controller can be obtained by supplement the predicted values, which are computed from the above linear approximation of the instant errors with $b=0$ (see [Figure 1]).



[Figure 1] The PID value estimation

The Proportion value is the same as the prediction error in time t_0+n, the Differential value is the slope of the linear equation, and the Integral value is corresponding to the area from t_0-m to t_0+n.

The PID tuning is to obtain some parameters K_p, K_i and K_d, which determine the reaction thresholds corresponding to the Proportion, the Integral and the Derivative values, respectively. First, a step response method can be used as the basic PID tuning principle. Draw a tangent line to the rising curve, and find L, T and K, which is corresponding to 63 percent of steady-state value. An instant error function of the PID tuning can be approximated to 3rd polynomial equation from t_0-m to t_0. Each coefficient of this polynomial can be calculated by Gauss-Jordan method. Thus, a reaction threshold is obtained by using the coefficients which represent the parameters K_p, K_i and K_d, respectively. Each parameter value of the response is managed according to some parts significances, system manager updates overshooting and no response appropriately through the feedback control. If an error occurs at CE to let the error to minimize is then passed through the same process. Now think about how a fuzzy phase-locked loop (PLL) might work. A PLL estimates the phase of a time-varying sinusoidal signal which is corrupted by noise. In addition to the signal being corrupted by noise, the PLL's phase measurement is noisy. The PLL's task is to find the best estimate of the true phase in spite of the noise.

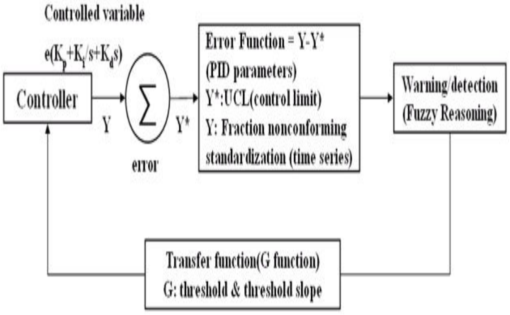
As the PLL estimates the phase, it also predicts what the next phase measurement is going to be (based on its past estimates). We will call the difference between the actual phase measurement and the PLL's prediction of the measurement the error. The change in error is the change in this quantity from one time period to the next. So we can see that if the error is positive (i.e., the measured phase is larger than we expected it to be based on past estimates), then we probably need to increase our phase estimate or we may lose lock on the phase. If both the error and the change in error is positive, then we probably need to increase our estimate by a large amount because there may not be much time before we lose lock.

3.2 Fuzzy reasoning for warranty time series

The slope of threshold plays an important role about the increase of the warranty claims. It is computed as the slope of the linear function from the current time t_0 to the end time t_0+n. In particular, the overshooting can be derived as the slope calculation after sorting the warranty claims in the ascending order. There is sometimes the explosive increase of temporary over-shooting and the warranty claim rates, with no regard for the quality problems as the below. So, the increase of the threshold can be occurred.

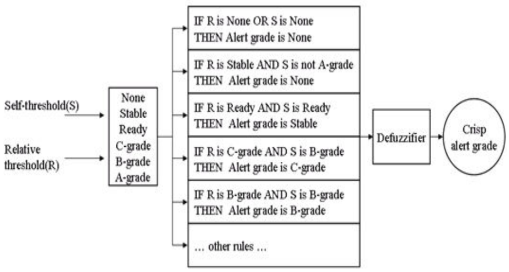
- When the products with less sales in the early of certain time are repaired.
- When a product that is manufactured and sales in the same time period is repaired several times.
- When a product manufactured during strike is stored at the first time of manufacturing and sales.

In order to prevent these cases, skewness should be considered in calculating a gradient of the threshold. Once the reaction threshold and the slope of it are estimated, we can produce the warning degrees of the warranty time series by using a fuzzy reasoning method (see [Figure 2]).



[Figure 2] Fuzzy feedback control of warranty claim time series

This fuzzy reasoning can be interpreted as an application of the fuzzy logic matrix about the probability composing the self-threshold and the relative threshold. Now, consider the design of a fuzzy controller for the threshold terms. The block diagram of this control system appears as [Figure 3]. There are two input variables, self-threshold and relative threshold, and a single output variable, the fuzzy warning degree.



[Figure 3] Block diagram of fuzzy control system

The truth values of the input variables are obtained from the probability through the normalization of self-threshold and relative threshold. The descriptive statistics of the threshold terms are required to obtain the normal probability distribution. These statistics can be computed by P-bar control chart. The truth values of the input variables are as the following.

- Derive a quantitative matrix by multiplying each grade of several divisions.
- Compute the probability value of each cell under the assumption of the exponential distribution.

The fuzzy warning degrees can be defined as None, Stable, Ready, C-grade, B-grade, and A-grade. Then, the rule set is considered as the following.

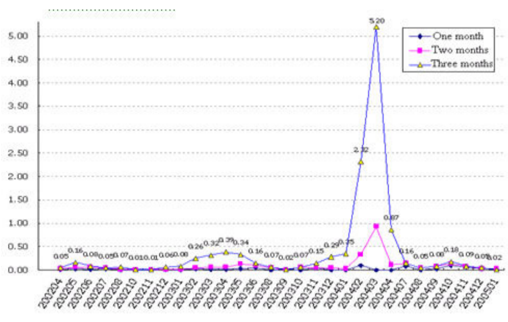
〈Table 1〉 Fuzzy warning degrees

RS	S1	S2	S3	S4	S5
R0	None	None	None	None	None
R1	None	None	None	None	C등급
R2	None	None	Ready	C등급	C등급
R3	None	Stable	C등급	C등급	B등급
R4	None	Ready	C등급	B등급	A등급
R5	None	C등급	B등급	A등급	A등급

4. Application of Automobile Warranty Claims

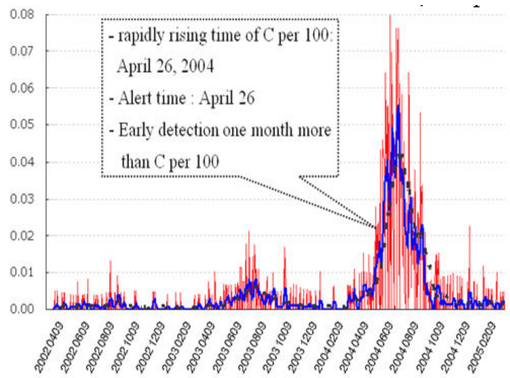
This section introduces the practical cases of applying the proposed fuzzy feedback control of the warranty claims data in the automobile industry. We used actual data of warranty claims of a large-scaled automotive firm instead of hypothetical simulation data. Because recent warranty claims of an enterprise are hypersensitive to its fame and collecting time series data should have started a long time ago, this study used claims data from the past.

[Figure 4] denotes the result of C per 100 analysis of warranty claims data related to X-Car pulse generator of car company in korea; dating from April 2002 to January 2005. The collected warranty claims are within the bounds of use three months and that month sale per that month production.



[Figure 4] C per 100 of X-Car Pulse Generator

[Figure 5] denotes the warranty time series analysis, and the ratio of the warranty claims is calculated as the percentage of the warranty claim counts divided by the production-sale counts (multiplied by the cumulative hazard function). In this analysis, it can be seen that C per 100 is rising rapidly around April 26, 2004. Thus, a warning time is about April 26, and early warning/detection of the warranty claims can be attained more than one month, compared to C per 100.



[Figure 5] Warranty time series analysis of X-Car Pulse Generator

[Figure 6] illustrates how the monthly average fraction nonconforming is calculated in the case of March. The daily average fraction nonconforming can be obtained by means of multiplying the monthly average fraction nonconforming by 1/30 (days). The warning/detection sensitivity is represented by means of controlling the standard deviation coefficient for the part number code of occurred claims according to the parts significance.

Produced car in Jan. (10)	warranty claim in Jan. (1)	warranty claim in Feb. (1)	warranty claim in Mar. (1)	$\overline{P}_{Jan} = \frac{3}{10 \times 3^{1.0}} \times \frac{10}{30} = \frac{1}{30}$
	Produced car in Feb. (10)	warranty claim in Feb. (1)	warranty claim in Mar. (1)	$\overline{P}_{Feb} = \frac{2}{10 \times 2^{1.0}} \times \frac{10}{30} = \frac{1}{30}$
		Produced car in Mar. (10)	warranty claim in Mar. (1)	$\overline{P}_{Mar} = \frac{1}{10 \times 1^{1.0}} \times \frac{10}{30} = \frac{1}{30}$

$$\overline{P}_{Total} = \overline{P}_{Jan} + \overline{P}_{Feb} + \overline{P}_{Mar} = 0.1$$

[Figure 6] Monthly average fraction nonconforming (m = 1.0)

[Figure 7] illustrates how the average fraction nonconforming is calculated in the case of m = 1.0 and 4 parts grade.

Repair date	Cumulated warranty claims	Decomposition of warranty claims (production month basis)						Cumulated sales count per Production month (∑ S)						UCL	Stand. fraction nonconforming
		2005 01	2005 02	2005 03	2005 04	2005 05	2005 06	2005 01	2005 02	2005 03	2005 04	2005 05	2005 06		
2005-01-01	0	0	0	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮												
2005-06-27	4	1	1	2	0	0	0	1,000	1,000	1,000	1,000	1,000	850		0.000173
2005-06-28	3	0	0	0	2	1	0	1,000	1,000	1,000	1,000	1,000	900		0.000233
2005-06-29	2	0	0	0	0	1	1	1,000	1,000	1,000	1,000	1,000	950		0.000300
2005-06-30	2	1	1	0	0	0	0	1,000	1,000	1,000	1,000	1,000	1,000	0.0001251	0.000073
Summary		∑ Claim						∑ Sale							
	32	12	10	8	6	4	2	1,000	1,000	1,000	1,000	1,000	1,000		

$$\overline{P}_{month} = \frac{\sum C_i}{t_i^m \times S_{total}} \times \frac{1}{30} = 0.0024 \qquad \overline{P}_{daily} = \overline{P}_{month} \times \frac{1}{30} = 0.00008$$

$$\sigma_{daily} = \sqrt{\frac{\overline{P}_{month}(1-\overline{P}_{month})}{S_{total}}} \times \frac{1}{30} = 0.000002307$$

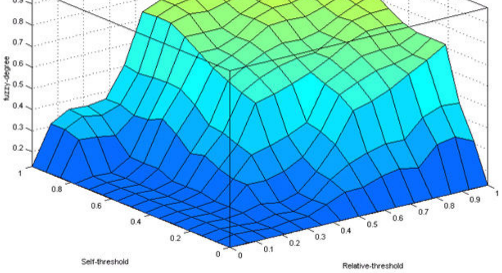
$$UCL = \overline{P} + \alpha \cdot \sigma = 0.00008 + 1.96 \cdot 0.000002301 = 0.0001251$$

$$\overline{P} = \frac{C_i}{t_i^m \times S_{total}} = \frac{1}{6^1 \cdot 5000} + \frac{1}{5^1 \cdot 5000} = 0.000073$$

[Figure 7] Upper control limit and Standard fraction nonconforming

The instant error can be approximated as a linear function by curve fitting (from seven days ago to the current time). It is possible to derive the PID parameters with this function see [Figure 3]). The PID values can be estimated by supplementing five days data in current time. In the case of N-Car (Sun visor assembly), for example, the PID parameters are tuned by $K_p = 92$, $K_i = 29$, and $K_d = 190$, respectively. Now consider the fuzzy rules where R and S are associated with fuzzy values None, Stable, Ready, C-grade, B-grade and A-grade with triangular membership functions. The “Bisector” method is fast and generally produces good results but is inaccurate for asymmetrical shapes. In addition, this method requires two calculation sequences. The first determines the total area of the figure and the second determines the point corresponding to the half area. Unlike this, a simple method for computing a “Centroid Approximation” by fitting the fuzzy output area into a “Triangular” shape presents considerable advantages when the output is highly asymmetrical and especially for highly asymmetrical base lengths. More, the output calculation can be done in one single sequence.

For a given input x1 and x2, the non-fuzzy output u is computed using the centroid method. The input surface generated by the self-threshold and the relative threshold is shown in [Figure 8].



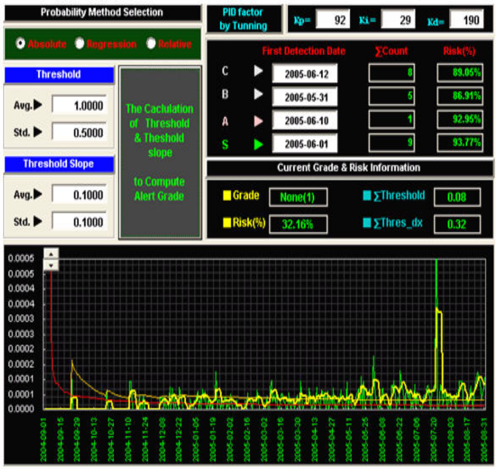
[Figure 8] Surface based on 36 rules

Crisp alert grades based on finer partitions of the output u (such as 12 grades) can be considered under the assumption of exponential distribution as the following.

If $u < 0.4$,
then warranty time series grade = None
Else if $u > 0.4$ and $u < 0.45$,
then warranty time series grade = Stable
Else if $u \geq 0.45$ and $u < 0.5$,
then warranty time series grade = Ready_C
Else if $u \geq 0.5$ and $u < 0.55$,
then warranty time series grade = Ready_B
Else if $u \geq 0.55$ and $u < 0.6$,
then warranty time series grade = Ready_A
Else if $u \geq 0.6$ and $u < 0.7$,
then warranty time series grade = C
Else if $u \geq 0.7$ and $u < 0.8$,
then warranty time series grade = CC
Else if $u \geq 0.8$ and $u < 0.85$,
then warranty time series grade = B
Else if $u \geq 0.85$ and $u < 0.9$,
then warranty time series grade = BB
Else if $u \geq 0.9$ and $u < 0.95$,
then warranty time series grade = A
Else if $u \geq 0.95$ and $u < 0.99$,
then warranty time series grade = AA
Else if $u < 0.99$,
then warranty time series grade = S

Threshold and alert grade module [Figure 9] can be used to obtain the history values of warranty time series detection. In “Probability Method Selection” menu, the selection of “Regression” is related to find a probability distribution through the mean and standard estimation by regression method. “$\sum Count$” and “First Detection Date” denote the detection count per alert degree and the first detection date in connection with each alert degree.

"Current Grade and Risk Information" denotes some current analysis values of time series detection. Alert degree is none until now, and risk is 32.16 %. Also, self-threshold is 0.08, and relative threshold is 0.32. In [Figure 9], yellow green graph denotes the standardized fraction nonconforming, yellow graph the Bollinger curve, red graph the control type chart, and pink graph the analyzing type chart.



[Figure 9] Threshold and Alert Grade Module

5. Conclusion

This study proposed a methodology to create a flexible formula for warning degrees determination in a fuzzy environment. Although the fuzzy control model adopted here is more complex than the classical model, the evidence shows that the classical model is inadequate for a fierce competitive environment. The reasons for this are as follows. It is inherent in reliability analysis to collect a relatively large amount of lifetime data because the classical reliability estimation is typically based on precise lifetime data. However, with new industrial technologies, demanding customers and shorter product development cycles, the lifetime of products has become contradictory. It is time-consuming, expensive, and sometime impossible to obtain enough exact observations to fit the lifetime distribution. With few available data points, it is difficult to estimate the lifetime distribution parameters using conventional reliability analysis methods. Hence, to enhance the success of marketing a new product, fuzzy theory or other theories should be implemented, by capturing the experience, subject judgment and available lifetime data to fit the reliability distribution in a faster way. However, in order to formulate a warranty model, the firm still needs to collect relevant data for all parameters of the model. The cost and time necessary to collect such data must be estimated before determining the warranty models. This study is useful for firms in deciding what the maintenance strategy and warranty period should be. It also allows for an extended warranty price to be derived, if the function of cost elasticity is available. However, several issues were neglected in this study. For example, parallel connection among the parts and the connection between sales and warranty price are not examined. Moreover, the fuzzy properties of cost and other relevant factors in the model are worthwhile topics to be examined in the future.

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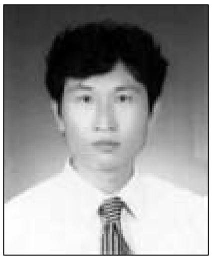

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현재 호남대학교와 목포대학교 컴퓨터공학과 시간강사 이며, 호남대학교 컴퓨터공학과에서 학사・석사를 졸업하고 전남대학교 전산학과에서 박사를 취득하였다. ICIC, ALPIT, LNCS 등의 국제학술지 및 한국 컴퓨터정호학회지, 한국정보처리학회지 등의 국내학술지에 논문을 게재한 바 있다. 주요 관심분야는 다차원 클레임 데이타 분석과 예측 모델, 인공지능 시스템, 품질 조기경보(Quality Early Warning System)시스템관련 지능형 임베디드 시스템 구축 등이다.

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현재 전남대학교 경영학과 부교수로 재직 중이다. 전남대학교 전산통계학과에서 학사, 석사, 박사를 취득하였고, 신경대학교와 서남대학교에서 교수로 재직하였다. Journal of Computer Information System, Lecture Notes in Computer Science 등 국제저널에 논문을 게재하였으며, 국내의 한국정보처리학회, 한국전자상거래학회, IT서비스 학회 등에 논문을 게재하였다. 주요 관심분야는 스마트 컴퓨팅, 서비스 사이언스, e-비즈니스, IT 거버넌스, 유비쿼터스 소프트웨어 등이다.

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현재 호남대학교 컴퓨터공학과 교수로 재직 중이며, 서울대학교 계산통계학과에서 학사·석사·박사를 졸업하였다. ICIC, ALPIT, LNCS 등의 국제학술지 및 한국 컴퓨터정호학회지, 한국정보처리학회지 등의 국내학술지에 논문을 게재한 바 있다. 주요 관심분야는 warranty 시스템 개발 관련 다차원 claim 분석과 예측 모델, warranty 관련 지능형 임베디드 시스템 구축 등이다.

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목포대학교 공과대학 컴퓨터학과 교수로 재직 중이며, 전남대학교 수학과를 졸업하고 조선대학교 전산통계학과에서 석사 및 박사를 취득하였다. 전산소장, 공과대학장, 평의회의장 등를 역임했으며 현재 공학교육혁신 센터 장으로 있다. 주요 관심분야는 정보화 전략 수립 및 추진, 공학교육혁신과 정보기술 활용, 확률 및 통계, 수치해석, 이산구조 등이다.