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A Study on Maintenance Reliability Allocation of Urban Transit Brake System Using Hybrid Neuro-Genetic Technique

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For reasonable establishing of maintenance strategies, safety security and cost limitation must be considered at the same time. In this paper, the concept of system reliability introduces and optimizes as the key of reasonable maintenance strategies. This study aims at optimizing component's reliability that satisfies the target reliability of brake system in the urban transit. First of all, constructed reliability evaluation system is used to predict and analyze reliability. This data is used for the optimization. To identify component reliability in a system, a method is presented in this paper which uses hybrid neuro-genetic technique. Feed-forward multi-layer neural networks trained by back propagation are used to find out the relationship between component reliability (input) and system reliability (output) of a structural system. The inverse problem can be formulated by using neural network. Genetic algorithm is used to find the minimum square error. Finally, this paper presents reasonable maintenance cycle of urban transit brake system by using optimal system reliability.

Key Words : Reliability, Urban Transit, Reliability Centered Maintenance, Maintenance System, Optimization, Inverse Problem, Neural Network, Genetic Algorithm

1. Introduction

The urban transit is an integrated system with a complicated, electronically and mechanically, structure ; it requires high qualities of maintenance for safety. According to Lee et al. (2003), it costs 60% of total operating expenses to maintain the urban transit. Therefore, it is really necessary to establish the reasonable maintenance standard to regulate the cost and the safety of the urban transit. This research introduces a concept of reliability to set up a reasonable standard for the

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urban transit maintenance. In general, reliability is defined as the 'probability that an item will perform a required function without failure under stated conditions for a stated period of time.' (Garcia Marquez et al., 2003) The concept can be altered to establish the maintenance cycle in order to support each vehicle device by applying it to the urban transit maintenance stage. This maintenance process using reliability concept is called RCM (Reliability Centered Maintenance).

Many studies have been on progress about RCM. Smith (1993) defined the RCM as a method to determine any reliable operations for physical equipments and presented a preventive maintenance by analyzing functional failures. Richard (1995) introduced the practical method applying RCM, which Smith et al. had presented, to industrial field. Jacobs (1998) studied the method that reduced maintenance tasks by using RCM. In the field of railway, the preventive diagnosis and the predictive maintenance for railway equipment was studied by Wada (1988). Recently, Mettas (2000) showed the optimization method to minimize the operating function and to satisfy the target system. However, it is still necessary to do researches on the maintenance data and the optimization performance with the maintenance. The reasons are as follows: 1) it is hard to find the real cases about the application of the Reliability Evaluation System (RES) for obtaining the reliability data in industrial construction; 2) it is not easy to gather historical data for the maintenance; and 3) it is difficult to calculate the cost function which can be applied to the specific structure so that there can be errors in case of the optimization using this function.

This research obtains the reliability information from RES of the VVVF (Variable Voltage variable Frequency) urban transit which is developed by web in previous research (Bae et al., 2005). In addition, the cost function problem will be solved out by applying the inverse analysis theory to the reliability optimization. To use the maintenance data in web system database effectively, the optimization has been done by using hybrid neuro-genetic algorithm. In other words, the optimization problem has been formulated by the neural network (Fahlman, 1990; Rumelhart et al., 1986) and performed by the genetic algorithm (Holland, 1975). The optimal maintenance reliability is calculated for each sub-component in the maintenance process by optimizing the brake system among the 14 systems in VVVF urban transit and the reasonable standard of the maintenance cycle is set up.

This paper is organized as follows: In section 2, a method is proposed which uses hybrid neuro-genetic technique to allocate the maintenance reliability; in section 3, the reliability based maintenance system for urban transit is developed to calculate the reliability index from maintenance data; in section 4, techniques proposed in this research are applied to the brake system of urban transit and the results of reliability allocation are drawn; and Section 5 provides conclusions.

2. Reliability Allocation Using Hybrid Neuro-Genetic Technique

This research allocates the maintenance reliability to each device by optimizing the reliability of sub-components for meeting a desired reliability of a subject system. If the allocated reliability is converted to a time domain, the operation time of each device can be derived from reliability index. Therefore, it is possible to estimate the standard of a reasonable maintenance cycle from historical data. To identify the optimal reliability with maintenance historical data, this research introduces hybrid neuro-genetic technique, one of soft computing techniques, aiming at escaping intensive computation. Back-propagation neural networks, one of neural networks, adopted to approximate the reliability relationship from the prepared learning data. Genetic algorithm, one of evolutionary algorithms, used to identify the optimal reliability minimizing the error which is the objective function.

2.1 Hybrid neuro-genetic technique for reliability allocation

Overall procedure of the present study is shown in Figure 1. There are a preparation phase and an application phase. In the preparation phase, first, the learning data of various sets of subcomponent reliability parameters and the corresponding response, which is the reliability of urban transit brake system, are prepared by RES database which are developed in section 3. The neural networks described in section 2.2 are adopted to approximate the response of the reliability relationship between subcomponent and urban transit brake system from the prepared learning data. In the application phase, the subcomponent reliability parameters are estimated by GA's described in section 2.3 using the trained networks obtained in the preparation phase. Using the trained networks, a maintenance reliability allocation problem can be constructed as an optimization with GA's. The optimization problem to be formulated is defined as follows :

$$\begin{aligned} \text{Min} \quad & \Psi = (R_S(X) - R_G)^2 \\ & X = (R_i)^T, \\ \text{s.t.} \quad & R_{i,\min} \le R_i \le R_{i,\max},\ i = 1, 2, \cdots, n \end{aligned} \tag{1}$$

where R_S, which is unknown variable, is the calculated reliability of a subject system, R_G, which is known reference variable, is the target reliability of a subject system, Ψ is the error function between R_S and R_G, and R_i is the reliability of each subcomponent composing a subject system. The general procedure is illustrated in Fig. 2.

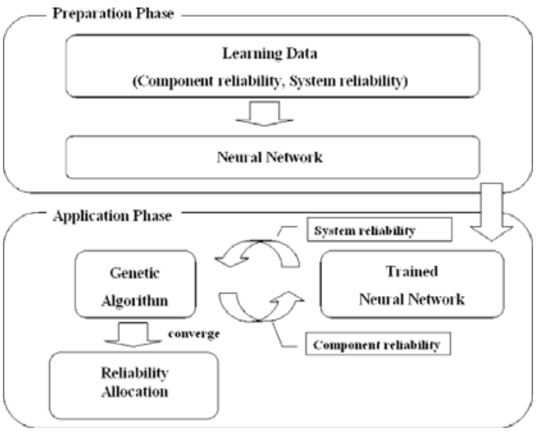


Fig. 1 Reliability allocation procedure based on hybrid neuro-genetic algorithm

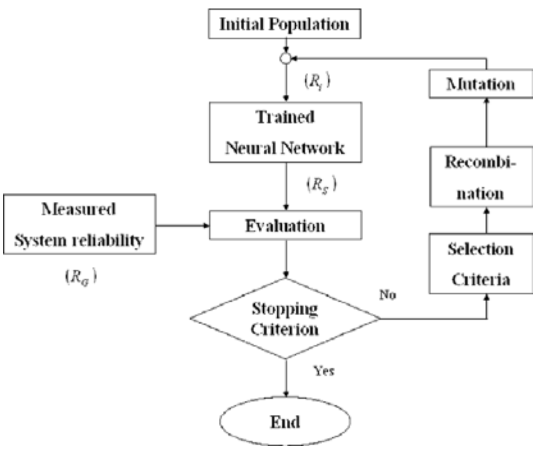


Fig. 2 Flowchart of the hybrid neuro-genetic technique

2.2 Neural network

Studies on neural networks have been motivated to imitate the way that the brain operates. A network is composed of the individual neurons, the network connectivity, the weights associated with various interconnections between neurons, and the activation function for each neuron (Fahlman, 1990 ; Rumelhart et al., 1986). The network maps an input vector from one space to another. The mapping is not specified, but is learned. The network is presented with a given set of inputs and their associated outputs. The learning process is used to determine proper interconnection weights and the network is trained to make proper associations between the inputs and their corresponding outputs. Once trained, the network provides rapid mapping of a given input into the desired output quantities. This, in turn, can be used to enhance the efficiency of the design process.

Consider a single neuron. This neuron receives a set of n inputs, x_i, $i=1, \cdots, n$ from its neighboring neurons and a bias whose value is equal to one. Each of the inputs has a weight (gain) w_{ji} connecting between the i-th and j-th units. The weighted sum of the inputs determines the activity of a neuron, and is given as (Fahlman, 1990)

$$net_j = \sum_{j=1}^{n} w_{ji} x_i \tag{2}$$

A simple function is now used to provide a mapping from the n-dimensional space of inputs into a 1-dimensional space which comprises of an output value a neuron sends to its neighbors. The output of a neuron is a function of its activity.

$$y=f(net) \tag{3}$$

Many types of neural networks have been proposed by changing the network topology, node characteristics, and the learning procedures. In this study, we use the back-propagation network, that is, a multi-layer feed-forward neural network topology with one hidden-layer as shown in Fig. 3. A back-propagation network consists of an input layer, hidden layers, an output layer and adaptive connections between successive layers. Back-propagation networks can learn when presented with input-target output pairs.

The back-propagation is used usually for its "supervised" learning. It is essentially a special purpose steepest descent algorithm to adjust the w_{ji} connection strengths, and other additional internal parameters that are sometimes added to increase flexibility, to reproduce the output of given input-output training sets within a required error tolerance. The training error is defined as follows: (Rumelhart et al., 1986)

$$E_{sum}=\sum_{p=1}^{n} E_p=\sum_{p=1}^{n}\sum_{k=1}^{m}(R_{T\_pk}-R_{O\_pk})^2 \tag{4}$$

where E_p is the square error for the p-th training pattern, R_{T_pk} is the teacher reliability signal to the k-th unit in the output layer for the p-th training pattern, R_{O_pk} is the output reliability signal from the k-th unit in the output layer for the p-th training pattern, and n is the number of output units and n is the number of patterns, respectively. In the training process, the connection wights w_{ji} is modified repeatedly based on the steepest descent method in order to minimize the above square error.

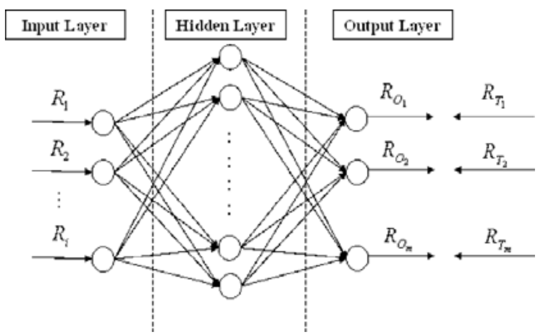


Fig. 3 Three-layer neural network

$$\begin{aligned}\Delta w_{ji}&=-\eta\frac{\partial E_{sum}}{\partial w_{ji}}\\ w_{ji}^{new}&=w_{ji}^{old}+\Delta w_{ji}\end{aligned} \tag{5}$$

where η is learning rate constant. The training is sensitive to the choices of the various net learning parameters. The first parameter is the "learning rate" which essentially governs the "step size", a concept familiar to the optimization community, and the learning rate constant should be updated according to the following rule.

$$\Delta\eta=\begin{cases}+a \text{ if } \Delta E_{sum}>0\text{consistently}\\ -b\eta \text{ if } \Delta E_{sum}<0\\ 0 \text{ otherwise}\end{cases} \tag{6}$$

This learning rate approach is an adaptive learning constant. The second parameter is the "momentum coefficient" which forces the search to continue in the same direction so as to aid numerical stability, and furthermore, to go over local minima encountered in the search. This scheme is implemented by giving a contribution from the previous step time to each weight change:

$$\Delta w(n)=-\eta\nabla E_{sum}(n)+\alpha_m\Delta w(n-1) \tag{7}$$

where $\alpha_m\in[0, 1]$ is a momentum parameter and a value as 0.9 is often used. The momentum term typically helps to speed up the convergence and to achieve an efficient and more reliable learning profile.

2.3 Evolutionary algorithms (EA's)

Evolutionary algorithms are probabilistic optimization algorithm based on the model of natural evolution and the algorithm has clearly demonstrated its capability to create good approximate solutions in complex optimization problems. The popularity of the algorithms is due to the following characteristics:

(1) Less possibility to converge to a local minimum as the search starts from a number of points;

(2) Compatibility with the parallel computer;

(3) Robustness since only objective function information is required; and

(4) Capability to find a solution in broad search space effectively through probabilistic operations.

Out of the algorithms such as genetic algorithms (GA's) (Holland, 1975), evolution strategies (ES's) (Rechenberg, 1973), evolutionary programming (EP) (Fogel et al., 1966), GA's are most popular by the fact that its reproductive processes use only a couple of deterministic rules (mostly randomized processes), causing them to be applicable to a variety of complex optimization problems. Genetic Algorithms developed, by Holland (1975), have traditionally used bit-strings of fixed length l, i.e. $u_i^k \in I = \{0,1\}^l$. The evaluation of the fitness can be conducted with a linear scaling, where the fitness of each individual is calculated as the worst individual of the population subtracted from its objective function value (Goldberg, 1989).

$$\Phi(x_i^k) = \max\{f(x^k) \mid k^k \in R^k\} - f(x^k), \quad \forall i \in \{i, \cdots, \lambda\} \tag{8}$$

$\Phi(x_i^k) \geq 0$ is thus satisfied by this equation. Selection in GA's emphasizes a probabilistic survival rule mixed with a fitness dependent chance to have different partners for producing more or less offspring. Holland identifies a necessity to use proportional selection in order to optimize the trade-off exploiting promising regions of the search space while at the same time also exploring other regions. For proportional selection, the reproduction probabilities of individuals u_i are given by their relative fitness:

$$p_s(x_i^k) = \frac{\Phi(x_i^k)}{\sum_{j=1}^{\lambda} \Phi(x_j^k)} \geq 0 \tag{9}$$

Recombination of the genetics is conducted by the crossover. An exogenous parameter p_c (crossover rate) indicates the probability per individual to undergo recombination. Typical values for p_c are in the range [0.6, 1.0]. In the case of one-point crossover, two randomly-selected individuals are renewed by two offspring individuals:

$$\begin{cases} u_\alpha^{k+1} = \{u_{\alpha 1}^k, \cdots u_{\alpha m}^k, u_{\beta(m+1)}^k, \cdots, u_{\beta l}^k\} \\ u_\beta^{k+1} = \{u_{\beta 1}^k, \cdots u_{\beta m}^k, u_{\alpha(m+1)}^k, \cdots, u_{\alpha l}^k\} \end{cases} \tag{10}$$

Mutation in GA's works on the bit string level and is traditionally referred to as a background operator. It works by occasionally inverting single bits of individuals, with the probability p_m of this event usually being very small.

$$u_{ij}^{k+1} = \begin{cases} u_{ij}^{k+1} & \vartheta_{ij} > p_m \\ 1 - u_{ij}^{k+1} & \vartheta_{ij} \leq p_m \end{cases} \tag{11}$$

where $\vartheta_{ij} \in [0,1]$ is a uniform random variable, sampled anew for each bit. These reproductive operations form one generation of the evolutionary process, which corresponds to one-iteration in the algorithm, and the iteration is repeated until a given terminal criterion is satisfied.

3. Development of Reliability Based Maintenance System

In this chapter, a reliability evaluation framework, which is a mathematical approach, is applied. This framework uses a reliability index for RCM (Reliability Centered Maintenance) of urban transit. The framework requires four factors: BOM (Bill of Materials) (Bae et al., 2004 and Lee et al., 2005), RBD (Reliability Block Diagram), FBD (Function Block Diagram), and standardization of failure code classification (Kim et al., 2004). Then, the MTBF (Mean Time between Failures) at the maintenance stage from the reliability evaluation framework can be computed. MTBF is similar to the life time of each component. The developed system defines the maintenance procedure for urban transit since successful maintenance system depends on an automated maintenance plan. This plan can be scheduled effectively by collecting and analyzing data from maintenance experience. For doing this, this chapter proposes the web-based maintenance system for collecting data and the computing of MTBF (Mean Time between Failures) for analyzing data. In previous research (Bae et al., 2005), we have developed the reliability evaluation system of VVVF urban transit. This chapter describes to develop the reliability based maintenance system by taking FBPC (Friction Brake & Pneumatic Control) system out of fourteen main system of urban transit as a sample model because the optimal maintenance reliability of FBPC system, which is a subject system in this research, should be allocated in chapter 4.

3.1 Sample model definition — friction brake & Pneumatic control

There are generally five kinds of braking in urban transit. Those are common braking, emergency braking, security braking, stoppage braking, and parking braking. For these five kinds of braking, urban transit brake system use two control methods. One is electric braking control method using electric propulsion system and inverter, and the other is friction braking control method using contact resistance between brake disc and brake pad. In case of normal condition, electric braking control method is mostly applied to urban transit braking. In case urban transit is below proper velocity or electric braking power is insufficient, friction braking control method is applied to urban transit braking. This friction braking control

Table 1 BOM of VVVF urban transit

1 Label	2 Label
Vehicle	◦ Vehicle Cabling ◦ Air Piping ◦ Bolt & Fastening
Carbody and Gangway	◦ Carbody Structure : Body-shell ◦ Exterior Appearance ◦ Gangway
Interior & Facility (for passenger & crew)	◦ Interior ◦ Windows Unit ◦ Exterior Equipment ◦ Cab's Equipment
Door & Door Control	◦ Passenger Door (Side Door) ◦ Cab's Door
Air Comport System (HVAC)	◦ Cooling Unit ◦ Line Flow Fan
Power Distribution & Auxiliary Equipment	◦ Static Inverter (SIV) ◦ Battery System ◦ AC & Low Voltage Equipment
Propulsion & Electric Braking system	◦ Power Supply (Pantograph) ◦ Mechanical Propulsion System ◦ Electric Propulsion System
Truck (Bogie)	◦ Bogie Frame ◦ Wheel set ◦ Primary Suspension ◦ Traction Link (Pivot) ◦ Secondary Suspension ◦ Bogie Additions
Friction brake & Pneumatic (System)	**◦ Brake Control ◦ Reservoir** **◦ Brakes ◦ Valves** **◦ Compressed Air Supply ◦ Pneumatic Horn**
Coupler and Draft Gear	◦ Coupler ◦ Draft Gear
Lighting (System)	◦ Interior Lighting ◦ Exterior Lighting
Train Control and Monitoring System (TCMS)	◦ Display ◦ Control
Information & Communication	◦ Train communication (Radio) ◦ Information & communication (PIS, PA)
Signal	◦ ATC/ATO

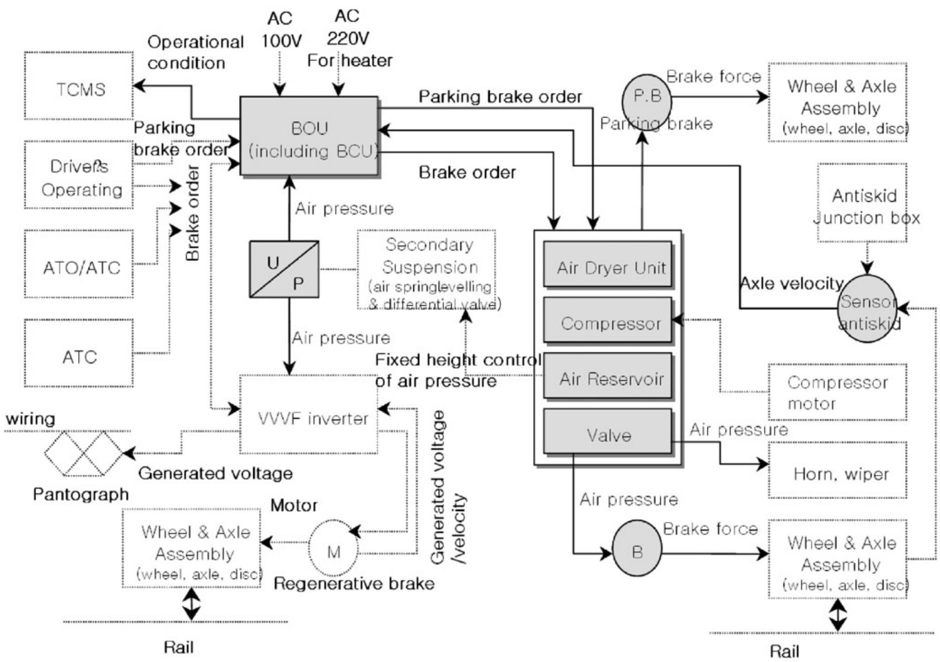
method uses FBPC (Friction Brake & Pneumatic Control) system. FBPC system is a kind of braking device, which makes urban transit stop or maintains the status by using air (Lee et al., 2001). As illustrated in Table 1, it has 6 parts : brake control, valves, air compressor, friction brake, reservoirs, and valves. FBD and RBD of FBPC system are shown respectively in Figure 4. Figure 4(b), RBD of FBPC system, shows a series structure of each subcomponent because each failure affects the braking performance of urban transit. Because parts of FBPC system have a relationship in a series of system, the failure rate of FBPC system is calculated by the following equation (12).

$$\lambda_{BRAKE}=\lambda_{BC}+\lambda_{AC}+\lambda_{FB}+\lambda_{RS}+\lambda_{VV}+\lambda_{PH} \quad (12)$$

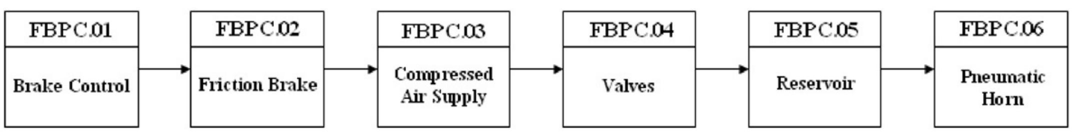
where,

λ_{BC} =failure rate of brake control
λ_{OP} =failure rate of air compressor
λ_{FB} =failure rate of friction brake
λ_{RS} =failure rate of reservoirs
λ_{VV} =failure rate of values
λ_{PH} =failure rate of pneumatic horn

(1) Brake control λ_{BC} : Brake control includes not only BOU (Brake Operating Unit) but also controllable parts, which secure the power of braking for urban transit. BOU is controlled by an electric signal. When braking in common or emergency is worked on/off, BOU controls whether reservoirs is filled up or emptied by air. BOU is composed of valves and electronic units, which control braking in common through, cross branding of vehicle. Electronic unit is control board which is composed of electric/electronic parts. This paper shall omit the modeling for prediction of its failure rate because of duplication of model for electric / electronic part in MIL-HDBK-217F.



(a) Function block diagram



(b) Reliability block diagram

Fig. 4 FBD and RBD of FBPC system

(2) Friction brake λ_{FB} : For decrease or stop of a vehicle, it is necessary to convert kinetic energy into heat energy. Friction brake is a device which absorbs or gives out this heat energy. Friction brake is composed of actuator, spring, friction materials, bearing, seal, and housing. The modeling for prediction of failure rate is illustrated in equation (13)

$$\lambda_{FB}=\lambda_{AC}+\lambda_{SP}+\lambda_{FR}+\lambda_{BE}+\lambda_{SE}+\lambda_{HO} \qquad (13)$$

where,

λ_{AC} =failure rate of actuator
λ_{SP} =failure rate of spring
λ_{FR} =failure rate of friction materials
λ_{BE} =failure rate of bearing
λ_{SE} =failure rate of seal
λ_{HO} =failure rate of housing

(3) Reservoir λ_{RS} : the failure rate of reservoir is calculated as the equation (14).

$$\lambda_{RS}=\lambda_{SE}+\lambda_{SP}+\lambda_{PC}\lambda_{VA}+\lambda_{CW} \qquad (14)$$

where

λ_{SE} =failure rate of seal
λ_{SP} =failure rate of spring
λ_{PC} =failure rate of cylinder interface
λ_{VA} =failure rate of valve
λ_{CW} =failure rate of cylinder wall

(4) Valve λ_{VV} : Generally, there are a poppet type and sliding-action type in a valve. A poppet type valve is utilized for controlling flow, pressure, direction of fluid. A sliding-action type valve is utilized for distributing uniform pressure of fluid.

The failure rate of poppet type valve can be written in equation (15).

$$\lambda_{VV\_PO}=\lambda_{PO\_B}\cdot C_P\cdot C_Q\cdot C_F\cdot C_v\cdot C_N\cdot C_S\cdot C_{DT}\cdot C_{SW}\cdot C_W \qquad (15)$$

where,

λ_{PO_B}=basic failure rate of poppet type valve
C_P =pressure factor of fluid
C_Q =factor of air leak
C_F =factor of surface disposal
C_v =factor of temperature/lubrication
C_N =factor of pollution level
C_S =factor of seat stress
C_{DT} =factor of seat diameter
C_{SW} =factor of seat land wide
C_W =factor of flow rate

The failure rate of sliding-action type is calculated in equation (16).

$$\lambda_{VV\_SV}=\lambda_{SV\_B}\cdot C_Q\cdot C_v\cdot C_N\cdot C_{DS}\cdot C_v\cdot C_\mu\cdot C_W \qquad (16)$$

where,

λ_{SV_B}=basic failure rate of sliding-action type valve
C_μ =factor of friction,
C_B =factor of spool clearance
C_{DS} =factor of spool diameter

3.2 Result of reliability evaluation and verification

Desired reliabilities are introduced based on standard that is managed at the maintenance stage. Then, actual reliabilities using the reliability evaluation method is predicted. Finally, this paper compares a desired reliability with a predicted reliability and estimates the result. In case a device typically follows random failure, the reliability index can be considered as MTBF (Mean Time between Failures), MDBF (Mean Distance between Failures), MTBSF (Mean Time between Service Failures), and MDBSF (Mean Distance between Service Failures). MTBF out of these indexes is considered as reliability standard of each device in developed reliability evaluation system. Desired MTBF (Lee et al., 2001) is derived from current maintenance standard. Under the current maintenance standard, the MTBF of a vehicle requires 115 hours. Table 2 shows the desired MTBF of fourteen subsystems.

By doing reliability analysis based on failure historical data of FBPC system, the results as shown in Table 3 are obtained. In Table 3, the MTBF of 2058 hours is the result per one unit of FBPC system. Because one unit of FBPC system is equipped in two vehicles, the MTBF of FBPC system becomes 1029 hours per vehicle. This result demonstrates that the MTBF of 1,029 (hour per vehicle) meets the desired MTBF of 898 (hour per vehicle) in Table 2. Besides, for verifying propriety, the MTBF of FBPC system was calculated by an application program, relex 7.0 (2002), with same input data and Table 3 shows the result. As shown in Table 3, the application program shows that the failure rate is 470.7×10^{-6} and the MTBF is 2,124 hours, and developed system shows that the failure rate is 485.9×10^{-6} and the MTBF is 2,058 hours. The total error is 3.23%. Therefore, it is reliable as much as the error is below five percent. By applying this reliability analysis repeatedly to fourteen subsystems of urban transit, this paper obtained MTBF and failure rate of each subsystem and illustrate in Table 2. The result shows that the MTBF of 208 hours meets the desired MTBF of 115 hours in terms of urban transit vehicle.

3.3 Development of web based maintenance system

For development of reliability based maintenance system using maintenance historical data, this paper assumes as follows: Each subcomponent composing urban transit vehicle is independent in terms of failure, All device are defined by two status, failure and available, Change and repair historical data of each device is regarded failure, and the failure follows an exponential function

Table 2 Desired and calculated reliabilities of urban transit

Subsystem	Desired		Calculated		
	MTBF (hours)	Ratio (%)	MTBF (hours)	Ratio (%)	Failure Rate ($\times10^{-4}$)
Vehicle Cabling/Piping	-	-	-	-	-
Carbody & gangway	46,000	0.25	-	-	-
Interior & facility	767	15.0	-	-	-
Door & door control	719	16.0	719	28.92	13.91
Air comport system (HAVC)	1,554	7.4	3,133	6.64	3.19
Power distribution & aux. equipments	1,173	9.8	3,212	6.47	3.12
Propulsion & electric braking system	1,513	7.6	4,231	4.91	2.37
Truck (bogie)	3,710	3.1	-	-	-
Friction brake & pneumatic control	**898**	**12.8**	**1,029**	**20.21**	**9.72**
Coupler & draft gear	14,375	0.8	16,667	1.25	0.6
Lighting (system)	-	-	-	-	-
Train Control & Monitoring system	3,485	3.3	4,472	4.65	2.24
Information & communition	685	16.8	973	21.4	10.28
Signal (ATC/ATO)	1,608	7.15	3,811	5.45	2.63
Total (unit)	**115**	**100**	**208**	**100**	**48.06**

Table 3 FBPC system reliability and verification

Subsystem	Developed system		Relex		Error (%)
	Failure rate ($\times10^{-6}$ hour)	MTBF (hour-Unit)	Failure rate ($\times10^{-6}$ hour)	MTBF (hour-Unit)	
Brake Control	202.2	4,946	195.9	5,104	3.21
Valves	106.9	9,355	104.4	9,578	2.39
(Friction) Brake	122.6	8,157	117.0	8,547	4.78
Air compressor	8.0	125,000	7.9	126,908	1.52
Reservoir	20.6	48,544	20.3	49,261	1.47
Pneumatic horn	25.6	39,063	25.2	39,682	1.58
Total (unit)	**485.9**	**2,058**	**470.7**	**2,124**	**3.23**

because failure of urban transit is accidental.

The architecture is shown in Fig. 5. The development environment is as below:

•Web-based Applications;

•Web Tier development environment: JSP＋Java;

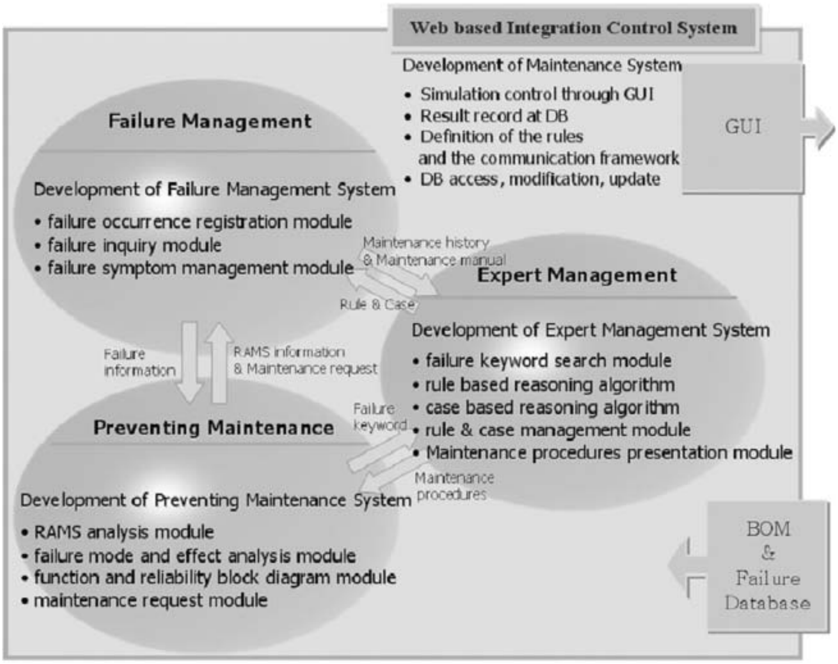


Fig. 5 Architecture of web based maintenance system

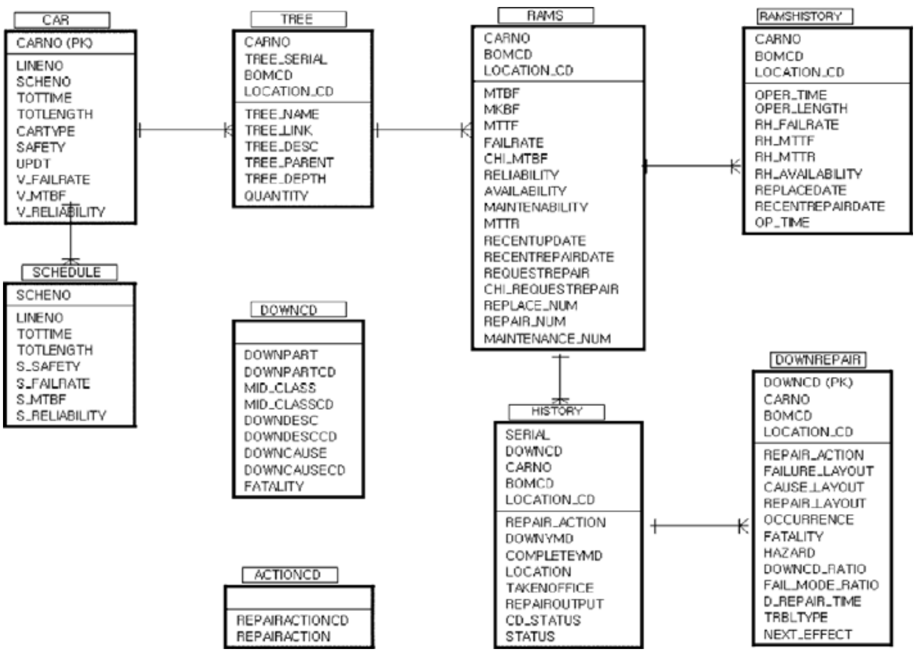


Fig. 6 Entity Relationship Diagram of database

- Development programming language: JDK 1.3.1_06, J2SDEE 1.3.1;
- Database: Oracle 9i; and
- WAS: WebSphere.

A database was constructed so that it can easily and quickly be accessed, updated and extended. Entity Relationship Diagram is illustrated in Figure 6. 'RAMS' table has results of reliability analysis. 'RAMSHISTORY' table contains historical data of reliability analysis and these data are used for graphing failure rate, MTBF, reliability indexes and MTTF (Mean Time to Failure). 'DOWNCD' table is for failure codes. 'CAR' table has basic information according to car number, vehicle number and line number of the urban transit. In the 'HISTORY' table, maintenance history is accumulated, and the 'TREE' table contains information to the hierarchical tree of BOM. To uniquely store, process and retrieve every possible data for the table, we set car number, BOM code and position number as Primary Keys.

The GUI shown in Fig. 7 displays failure rate, MTBF, and reliability of systems, sub-systems, equipments and parts by line number, vehicle number and car number of urban transit. Through graphs, changes of these indexes according to free operating time can be checked.

4. Application of Maintenance Reliability Allocation

4.1 orting main devices

Sorting main devices is accomplished in advance the reliability optimization of the brake friction and air pressure control system. It is because a number of devices which consists of the system can become a great burden to the calculation of formula approximation and optimization for the complicated system such as urban transit. So, this research, by sorting the main devices with respect to the degree of effect on the reliability of the brake system, reduces the calculation cost of

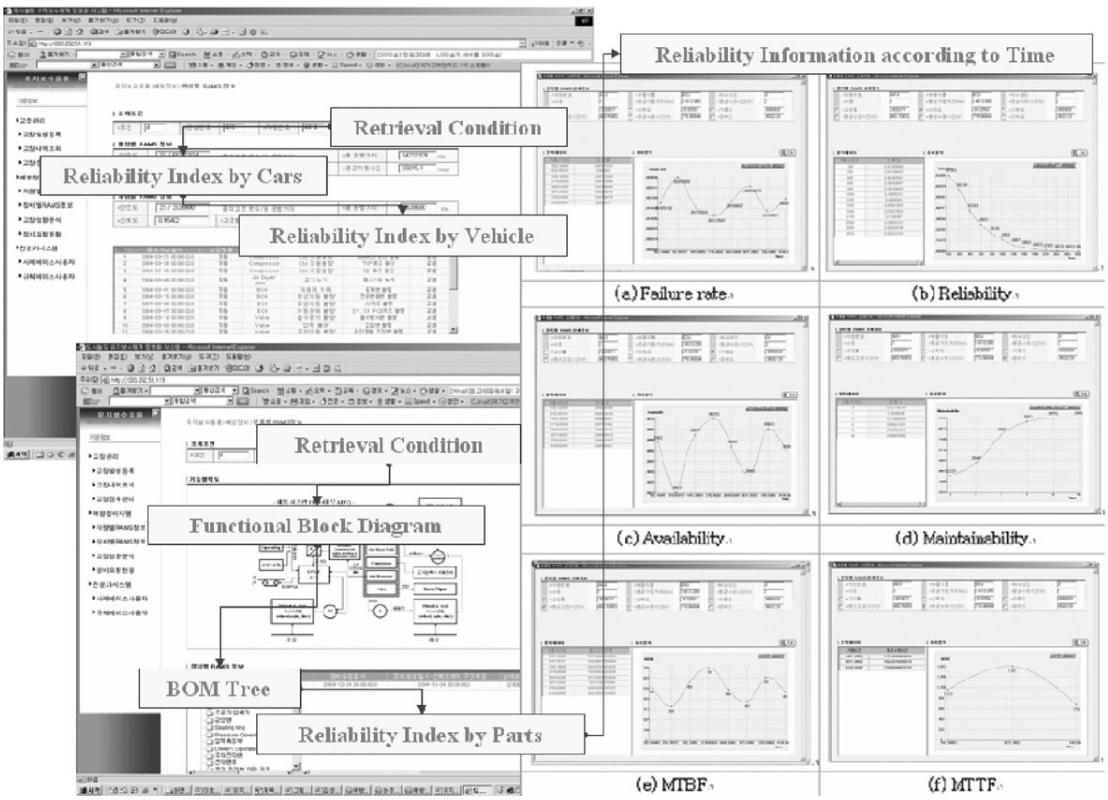


Fig. 7 GUI of web based maintenance system

the optimization and in/output data volume which is necessary for the approximation. Main devices are sorted by the effectiveness (Mettas, 2000) to the reliability, using the concept of the sensitivity function such as equation (17).

$$G=\left[\frac{\partial y}{\partial x_1}, \frac{\partial y}{\partial x_2}, \cdots, \frac{\partial y}{\partial x_n}\right]^T \tag{17}$$

If the equation (17) is applied for the brake system to sort out the main devices, it can define the effectiveness with the volume change of reliability in FBPC system regarding the volume change of reliability in each device as seen in equation (18).

$$\begin{gathered} I_R(i)=\frac{\partial R_{FBPC}}{\partial R_i} \\ 0<I_R(i)<1,\ i=1,2,\cdots,6 \end{gathered} \tag{18}$$

According to the Figure 8, the effectiveness's to improve the reliability in FBPC system are $I_R(BC)=0.978$, $I_R(V)=0.866$, $I_R(FB)=0.900$, $I_R(H)=0.382$, $I_R(R)=0.321$, and $I_R(AC)=0.134$ for each brake control, valve, brake friction, pneumatic horn, reservoirs, and air compressor consecutively. Shown in Fig. 8, pneumatic horn, reservoirs, and air compressor have remarkably less impact than brake control, valve, and brake friction. So, this research defaults the reliability of brake control, valve, and brake friction as main devices and design variable to improve the maintenance reliability of FBPC system.

4.2 Problem definition for reliability allocation using optimization technique

The problem is defined as the equation (19) when an inverse analysis method is used to optimize the maintenance reliability of FBPC system.

$$\begin{aligned} \text{Min} \quad & \Psi=(R_{FBPC}(X)-R_G)^2 \\ & X=(R_{BC}, R_V, R_{FB})^T, \\ \text{s.t.} \quad & 0.834<R_{BC}\leq 0.999 \\ & 0.909<R_V\leq 0.999 \\ & 0.896<R_{FB}\leq 0.999 \end{aligned} \tag{19}$$

where, $R_{FBPC}(X)$ is the reliability of FBPC system, which is calculated by the reliability evaluation system and R_G is the target reliability based on the maintenance standard for urban transit running currently. Also, X denotes 3×1 reliability matrix of all three of brake control, valve, and brake friction, all which construct FBPC system.

The optimization is to minimize error function of Ψ which is defined as the square of errors in system reliability, R_G, supported by both system reliability, R_{FBPC}, which is evaluated by the X matrix, the parameter and the maintenance standard. Each device, as a parameter, is set to move freely within the range between the predicted reliability, as the lower bound, at the planned time of 898 hrs by the maintenance standard and 99.9% as the upper bound.

The reliability of a subject system, the target function for a regular increment of a design variable is produced and trained according to the artificial neural network in order to introduce R_{FBPC} function which presents the reliability relationship between system and each device. It is not only because each step needs the reliability evaluation during the optimization but also because the maintenance historical data of reliability evaluation system made by the web can be introduced for the optimization after it is produced from the database.

In this research, the patterns which consist of 1,331 sets of data are used to train the neural network of Fig. 9. The reliability interval is broken into 6 sub-intervals of 0.865, 0.89, 0.915, 0.94, 0.965, and 0.99 according to the effectiveness analysis. Because of the nature of the sigmoid activation function, i.e. saturation function, the output variables should be scaled by the user, to be within the most active range of the sigmoid function. Scaling rule that minimum and maximum

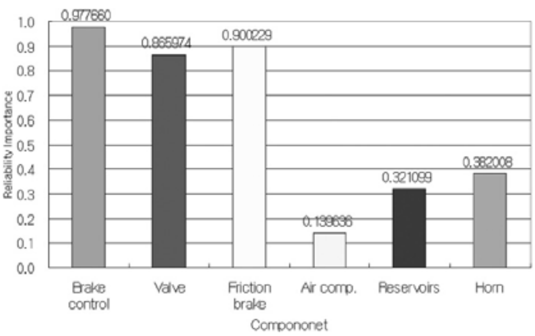


Fig. 8 Reliability importance of FBPC system

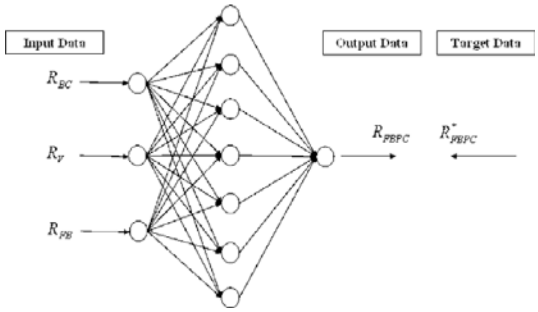


Fig. 9 Three-layer neural network with neuron arrangement of 3-7-1

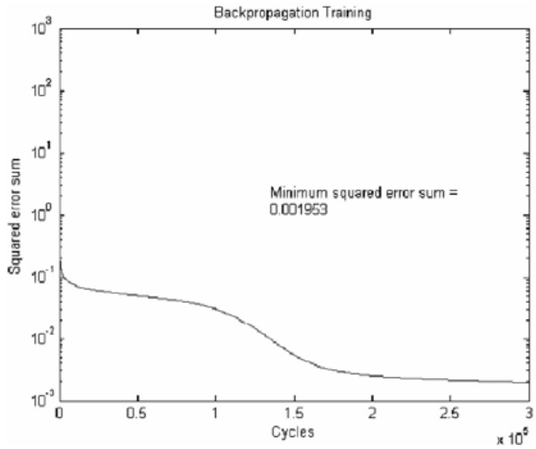


Fig. 10 Neural network training output

values are set to 0.1 and 0.9 is usually suggested. Through some trials, a network with neuron arrangement (input-hidden-output) of 3-7-1 trained with 100,000 iteration for the 1,331 patterns are concluded to be the best for our application. In addition, to attain the stable convergence in the training process the momentum coefficient is set to 0.9 and to speed up the convergence the adaptive learning rate is used. That is, if the error decreases the learning rate is increased by 1.05. Otherwise, the learning rate is decreased by 0.7.

Mean Square Error (MSE) is empolyed as a measuremenet of modeling performance. The mathematical expression can be described as follows :

$$MSE = \frac{\sum_{i=1}^{N}(e_i)^2}{N} \tag{20}$$

where, e_i denotes an error at pattern i and N is

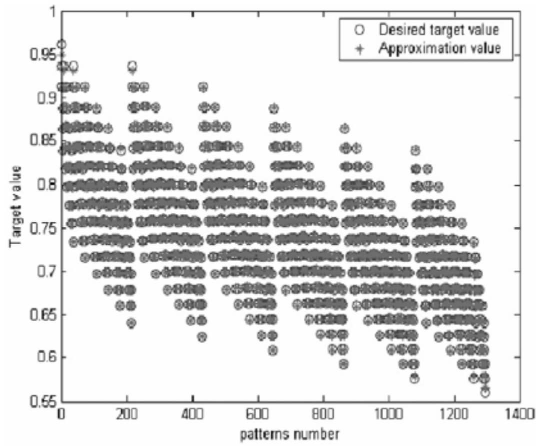


Fig. 11 Comparison of the estimated reliabilities from neural network to target values

the total number of pattern. As shown in Figure 10, the final MSE is 0.001953. The estimated reliabilities of FBPC system from network are compared to the target values as shown in Figure 11.

4.3 Optimization result for maintenance reliability allocation

For the defined optimization problem using artificial neural network, genetic algorithm is applied to compute the optimal reliability of main devices, design variables of R_{BC}, R_V, and R_{FB}, which construct FBPC system. The fitness function is set up, seen as equation (20), to transform for the calculating the maximum value.

$$fitness = \frac{1}{|R_{FBPC}(X) - R_G|^2} \tag{20}$$

The genetic algorithm for this research is set up : population size, $N=150$; crossover rate, $p_c=0.25$; and mutation rate, $p_m=0.01$. Also, each parameter is represented as a 44-bit binary number and roulette wheel selection method is adopted for the selection.

The optimization is performed with the reliability of both 0.90 and 0.95 to satisfy the maintenance standard. Figures 12 and 13 illustrate convergence history of the objective function for CASE 1 (R_G=0.90) and CASE 2 (R_G=0.95), respectively. The searches meet convergence after 79th and 97th generation for CASE 1 (R_G=0.90) and CASE 2 (R_G=0.95), respectively. The result of Table 4

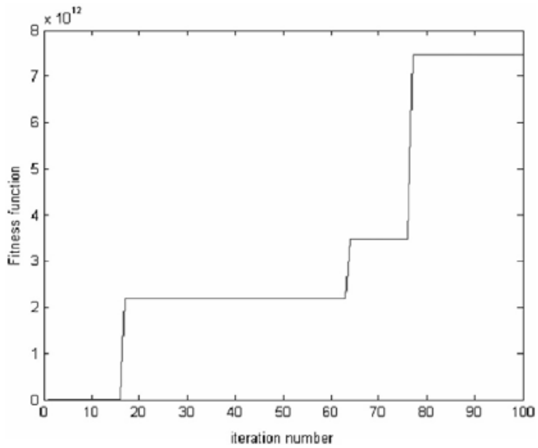


Fig. 12 Generation history of CASE 1 (R_G=0.90)

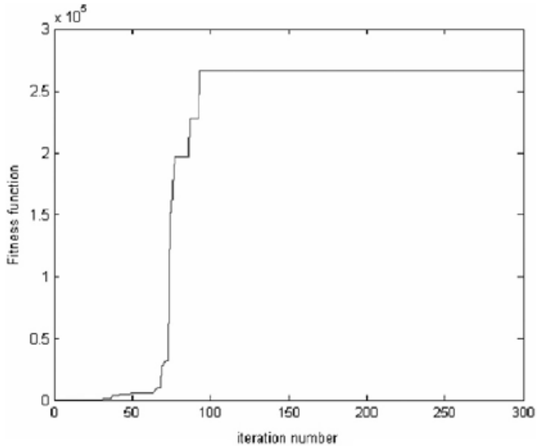


Fig. 13 Generation history of CASE 2 (R_G=0.95)

Table 4 Allocated maintenance reliability and cycle of FBPS system

	CASE 1 (R_G=0.90)		CASE 2 (R_G=0.95)	
	Optimum Result	Maintenance Cycle	Optimum Result	Maintenance Cycle
R^*_{BC}	0.9572	216.33 hrs	0.9783	108.50 hrs
R^*_{BC}	0.9783	205.23 hrs	0.9883	110.09 hrs
R^*_{BC}	0.9623	312.69 hrs	0.9829	140.34 hrs
	Result Value	Reference Value	Result Value	Reference Value
R_S	0.9009	0.9011	0.9505	0.9503
ER (%)	0.0222		0.0210	

shows that the maintenance reliability of main devices is estimated by the hybrid neuro-genetic technique. As seen in Table 4, the error rates are 0.0222% for CASE 1 and 0.021% for CASE 2. This can interpret that it is effective method to apply inverse analysis theory and neuro-genetic algorithm for the reliability.

4.4 Introducing the standard for the maintenance cycle

Since defects on urban transit happen accidentally, the reliability index follows the exponential distribution. Equation (21) shows the reliability function.

$$R(t)=\exp\left[-\int_0^t \lambda(t)\,dt\right]=\exp[-\lambda t] \quad (21)$$

where, t denotes the operating time for each device, and $\lambda(t)$ is a function of the failure rate. Equation (21) can be transformed to equation (22) when the MTBF, the reliability index of device which follows the exponential distribution, is introduced for failures.

$$R(t)=\exp\left[-\frac{t}{m}\right] \quad (22)$$

where, m is the average interval of failure, MTBF. Using equations (21) and (22), equation (23) is generated by equations (21) and (22) with the transformation to time domain after solving with reverse function.

$$t=-\frac{1}{\lambda}\log_e R=-m\log_e R \quad (23)$$

Equation (23) can be re-established with the maximum optimization, current failure rate, average life cycle, and the repairing time spending in order to calculate the repairing interval that can satisfy the result level of the optimized reliability of each device which consists of FBPC system.

$$T_i = -\frac{1}{\lambda_i}\log_e R_i^* = -m_i \log_e R_i^* \qquad i=1,2,\cdots,n \tag{24}$$

where, T_i is the repairing interval of a i-th device, λ_i is the i-th current failure rate, m_i is the i-th current MTBF, and R_i^* is the i-th optimized reliability. With equation (24), Table 4 shows the maintenance cycle for main devices to keep the target reliability of 0.90 and 0.95, respectively. In the maintenance cycle currently run at the maintenance stage for urban transit, brake system is in the regular inspection which is done every three days. Under the consideration of the operating time of 10 hours per a day, it is determined that the inspection and repairing is done in every 30 hours. This shows the reduction of maintenance cost and the safety acquirement from Table 4.

5. Discussion and Concluding Remarks

This research approached the historical maintenance data as system and then introduced the optimization method for device reliability allocation that can satisfy the maintenance standard. The optimization for maintenance reliability allocation with inverse analysis theory and neuro-genetic algorithm was applied for the brake system in urban transit and then it could calculate the optimized reliability. After applying this optimization method for generating the standard of reasonable maintenance, the conclusion could be obtained as follows :

(1) BOM, FBD, and RBD such as Table 1, Figure 4 were composed to evaluate the brake system in VVVF urban transit. FBPC system, the basis for the brake system, had 6 sub-categories and the functional relationships with each other sub-category were observed. As a result, the series relationship of reliability was drawn because the brake performance or the operation of urban transit had a negative effect if any failure in any sub-categories occurred.

(2) With five year historical maintenance data, the failure rate was 485.9×10^{-6}, MTBF 1,029 hrs when the reliability of the brake system in VVVF urban transit was analyzed. Also, the failure rate of each device in the brake system was shown in the Table 2. That failure rate and the web-based system enabled to obtain the 1,331 main reliability matrixes which were based on the time variance.

(3) According to the analysis on the reliability effectiveness of each device which consists of brake system, it was shown that the brake control ($I_R(BC)=0.978$), the valve ($I_R(V)=0.866$), and brake friction ($I_R(FB)=0.900$) had more impact on the brake system reliability than any other systems. This result can enable to reduce the input/output data volume and calculation cost and to define a subject for the maintenance cycle regulation.

(4) The formulization for the optimization was performed by the artificial neural network. The chosen main device was divided into 6 pieces according to the reliability interval and the change to the time variance is observed. Then the 1,331 reliability patterns were produced and these were used as the input/output points. As a result, the final MSE was shown as 0.001953, considerably stable value.

(5) The maintenance reliability allocation of main devices that satisfied the target value of the brake system was produced by the inverse analysis theory and neuro-genetic algorithm. The given reliability levels were 0.90 and 0.95 to meet the maintenance standard. As a result, the error in CASE 1 was 0.0222% and that in CASE 2 was 0.021%, shown in Table 4 as optimal reliability for main devices. Also, Table 4 showed the standard for the maintenance cycle that satisfied the reliability optimization, using the reverse function for the reliability.

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