J Electr Eng Technol Vol. 7, No. 6: 814-823, 2012
http://dx.doi.org/10.5370/JEET.2012.7.6.814

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

Application of Particle Swarm Optimization to the Reliability Centered Maintenance Method for Transmission Systems

Jae-Haeng Heo*, Jae-Kun Lyu*, Mun-Kyeom Kim† and Jong-Keun Park*

Abstract – Electric power transmission utilities make an effort to maximize profit by reducing their electricity supply and operation costs while maintaining their reliability. The development of maintenance strategies for aged components is one of the more effective ways to achieve this goal. The reliability centered approach is a key method in providing optimal maintenance strategies. It considers the tradeoffs between the upfront maintenance costs and the potential costs incurred by reliability losses. This paper discusses the application of the Particle Swarm Optimization (PSO) technique used to find the optimal maintenance strategy for a transmission component in order to achieve the minimum total expected cost composed of Generation Cost (*GC*), Maintenance Cost (*MC*), Repair Cost (*RC*) and Outage Cost (*OC*). Three components of a transmission system are considered: overhead lines, underground cables and insulators are considered. In regards to aged and aging component, a component state model that uses a modified Markov chain is proposed. A simulation has been performed on an IEEE 9-bus system. The results from this simulation are quite encouraging, and then the proposed approach will be useful in practical maintenance scheduling.

Keywords: Power transmission system, Reliability centered maintenance, Maintenance strategy, Particle swarm optimization

1. Introduction

A transmission system is composed of many different types of equipment, much of which was installed several decades ago, and so this equipment has deteriorated over time. Further deterioration may be unavoidable in the near future. As a result, the equipment performance will suffer and the equipment failure rate will increase. Accordingly, it is essential to find a suitable equipment model and a well-organized maintenance strategy that uses this equipment model. Time-Based Maintenance (TBM) is the most common method used for maintenance scheduling. Whereas this approach has the advantages of simple scheduling and high availability, it is not the most cost effective. In recent years, new maintenance scheduling techniques involving condition monitoring have been proposed [1-3]. The goal has been in the development of new maintenance strategies, such as the Condition-Based Maintenance (CBM) method, which can retain system reliability while reduce maintenance costs. Condition-Based Maintenance is driven by the actual condition of the equipment. However, it does not take into account on how the system is impacted by the failure of a specific piece of equipment. The Reliability-Centered Maintenance (RCM) method, on the other hand, not only considers the technical condition of a piece of equipment but also the importance of the equipment has to the whole system; it is expected to be the most cost effective method when compared to the traditional approach.

The RCM concept has been described in many studies [4-8]. The most of research focuses on the relationship between the reliability and cost on RCM models [4-6]. The model described in [4] determines a maintenance interval very similar to another maintenance method called TBM. The model described in [5] determines the inspection interval. However, the RCM framework should be required a variable failure rate that calculated on a yearly basis. Although the model described in [6] includes various maintenance activities, it decides on the maintenance schedule based only on the maintenance cost and associated probability. In [7], the authors presented the RCM method used for transmission systems. However, this particular study does not describe any method to quantify the impact of the maintenance on the reliability. The quantified impact of planned transmission outages on the overall system reliability has been focused in [8]. However, it does not take into account the state of the equipment, which varies over time. Consequently, these studies show the difficulty and the limitations found in the achievement of a maintenance strategy involving different kinds of aged and aging equipment.

For the development of a maintenance strategy that takes into account aged and aging equipment in a transmission system, this paper proposes a new approach using a modified Markov chain as an equipment model. It is represented by a chain of states that represent increasing

† Corresponding author: Department of Electrical Engineering, Dong-A University, Korea. (mkkim@dau.ac.kr)
* School of Electrical Engineering, Seoul National University, Korea. (jhheo78@snu.ac.kr; handyjack@snu.ac.kr, parkjk@snu.ac.kr)
Received: February 20, 2012; Accepted: May 17, 2012

levels of equipment deterioration. Since a transmission system is quite complicated, in that it consists of various types of equipment and loads, various factors, such as the equipment type, the equipment state, and the maintenance order have to be considered in the maintenance strategy of a transmission system. The basic problem addressed by a transmission system maintenance strategy is that it has a combinatorial explosion of choices and a very large search space. Solving this problem through analytical methods requires too much time and computational cost because of the vast search space and uncertainty. In such cases a heuristic approach can be used to find a feasible solution close to the optimal solution that reduces the simulation time and memory requirements through experience-based techniques. Among these heuristic approaches, Particle Swarm Optimization (PSO) is applied in this paper, in order to efficiently find the optimal maintenance strategies. We also propose a comprehensive model for the RCM that focuses on preserving the system functions and the system reliability. Using the proposed model, the optimal maintenance strategies derived through the PSO can be determined simultaneously based on the impact of the equipment maintenance to the system.

2. Modeling Equipment

A great deal of transmission equipment was installed several decades ago, and so has essentially deteriorated over time. Further deterioration is unavoidable. Equipment performance will be lowered and the equipment failure rate will increase. Consequently, conventional Markov models which are based on the assumption of constant transition rates (independent of time), should not be applied for the aging failure. In order to handle this problem, two methods are employed conventionally. One method is using the Weibul distribution. This has the advantage of representing all kinds of time varying failure rate, however, it needs a large historical data and the calculation time. Another method is modifying the Markov chain appropriately. It has a great advantage of performing the simulation. In this paper, in order to simulate the influence of the equipment deterioration, the operational state of the Markov model is represented by a chain of states related to the increasing levels of equipment deterioration. The equipment model using the modified Markov chain [9] is suitable for the RCM method.

2.1 Basic equipment model

In order to overcome the Markov model restrictions regarding constant transition rates (independent of time), the time dependent function of the transition rate (the bath-tub curve) is replaced by a step-by-step function with discrete increasing transition rate levels. In the modified Markov chain seen in Fig. 1, the operation state is divided into sub-states with an increasing level of wear (normal state N, deterioration states D1 to D2). State N represents a new system without degradation. The state transitions are governed by the transition rate λ_1 and λ_2 which are interpreted as the reciprocals of the mean times spent in the deterioration state. From failure states F, a repair transforms the system back to a working state by repair rate μ (the reciprocal of the mean value of the repair duration). M1 (weak maintenance) and M2 (strong maintenance) are the maintenance methods dependent on the deterioration state of the equipment (D1 or D2). D2 is different from F. D2 means that the equipment is still in service although the sensor has detected troubles in the equipment, however, the F state represents an out of order state of the equipment. If any maintenance methods are performed, the equipment state will become N by μ_1 or μ_2. Using the information taken from the real time sensors S, an inspector decides whether or not to perform maintenance. The decisions regarding d_{12}, d_{22}, d_{11}, and d_{21}, which are not a transition rate, need to be made in order to minimize the total expected cost which consists of the sum of the customer outage cost, the maintenance cost, the repair cost and the generation cost. In the cost estimation, the equipment state and the expected impact of the equipment state to the entire system are considered in order to make decisions. This is the core point of this model.

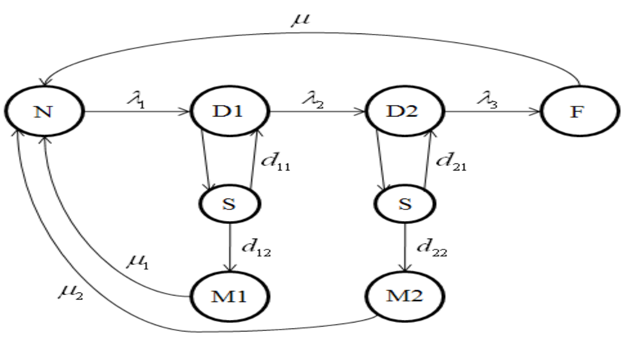

Fig. 1. The basic equipment state model

2.2 Applications to actual equipment

The equipment state model is adjusted by changing the number of deterioration states. The number of deterioration states is defined as the actual equipment aging stages and the possible maintenance methods. This enables the equipment state model to represent different kinds of equipment in the transmission system.

In this paper, an overhead-line, an insulator, and an underground cable have been selected as the study models. These three elements are the main components of transmission system; the failure of this equipment is related to the entire system failure. These components have different features and deterioration processes. Thus, the equipment state model needs to be adjusted in accordance with the equipment's characteristics. The deterioration states in this paper are defined on based of the inspection criteria used in the transmission utilities. The selection of the deterioration states may vary with the transmission utility company. Reasonable assumptions for the equipment state model were made for this study and are summarized below.

2.2.1 Underground cable

When inspecting a cable, an isothermal relaxation current analysis is used to calculate the aging factor. Isothermal relaxation current analysis is a non-destructive method that determines the aging status of a dielectric. The insulation status can be determined by measuring the relaxation current in the time domain [10].

The aging factor is determined by using the measured depolarization currents from laboratory and field aged cables. After the removal of the electric field, time dependant reactions follow whereby the dipoles tend to return to their random state over the duration of a few hundreds of seconds as a result of the thermal emission of the electrons. This is determined by the aging status of the power cable insulation.

The status of a cable can be classified into four states according to the aging factors taken from the isothermal relaxation current analysis. Table 1 shows the aging factors and the state criteria of the cables. The modified Markov chain modeling of cables is the same as seen in Fig. 1.

Table 1. The state criteria of underground cable

Aging factor	~1.85	1.85~2.60	2.60~	Failure
State	N	D1	D2	F

2.2.2 Overhead line

Three elements (line tension, line temperature, and line sag) contribute to an overhead line failure. Real time sensors monitor the condition of these three elements, and send a signal if they detect any problems in these elements. The equipment state model is defined according to these signals.

Table 2 shows the state criteria for the overhead lines. A number of signals are sent from the sensors that monitor the line tension, line temperature, and line sag; they are used to represent the states in this model: N for 0 troubled elements, D1 for 1 troubled element, D2 for 2 troubled elements, and D3 for 3 troubled elements. The equipment state model of the overhead line is the same as shown in Fig. 2.

Table 2. The state criteria of overhead lines

Tension	Temperature	Sag	State
O	O	O	N
O	O	X	D1
O	X	O	
X	O	O	
O	X	X	D2
X	O	X	
X	X	O	
X	X	X	D3
Failure			F

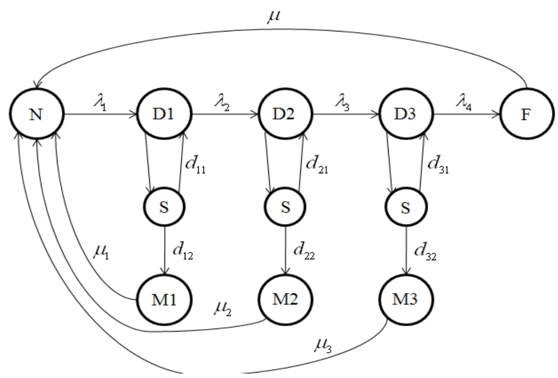

Fig. 2. The equipment state model of the overhead line

2.2.3 Insulator

For insulator inspection, the detection of a damaged spot or an arc discharge is needed. The state of the insulator is defined using information from the real time sensors for the above two elements. When either a damaged spot or an arc discharge is discovered the state of the equipment state model is changed. Table 3 indicates the state criteria for the insulator with the equipment state model of the insulator as illustrated in Fig. 3.

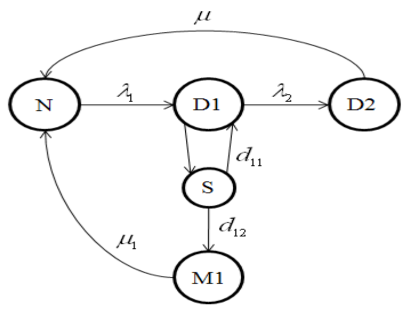

Fig. 3. The equipment state model of the insulator

Table 3. The state criteria of insulators

The trace of the arc or The damaged spot	State
O	N
X	D1
Failure	F

3. Particle Swarm Optimization on the Reliability Centered Maintenance

3.1 Overview of PSO

Kennedy and Eberhart first introduced Particle Swarm Optimization (PSO) in 1995 [11]. A PSO algorithm is based on the behavior of the particles of a swarm. Its roots are found in the simulation of the behavior of social systems, such as fish schooling and birds flocking [12].

The basic assumption of the PSO algorithm is that, birds find food by flocking rather than not individually. This leads to the assumption that information is owned jointly in flocking. Basically, the PSO was developed for a two-dimensional solution space. The position of each individual is represented by its X-Y axis position; its velocity is expressed by V_x in the x direction and V_y in the y direction. Modifications to the particle position are made by using the velocity and position information. The PSO algorithm for k-dimensional problem formulation based on the above concept can be described as follows; Let P is the 'particle' (position) and V its speed (velocity) in a search space. Consider i as a particle in the total population (swarm). The i-th particle position can be represented as P_i=(P_{i1}, P_{i2}, P_{i3}, … P_{iL}) in L-dimensional space. The best previous position of the i-th particle is stored and represented as $Pbest_i$=($Pbest_{i1}$, $Pbest_{i2}$, ... $Pbest_{ik}$). All of the $Pbest_i$ are evaluated by using a fitness function. The best particle among all of the Pbest becomes $Gbest$. The velocity of the i-th particle is expressed as V_i=(V_{i1}, V_{i2}, … V_{ik}). The modified velocity of each particle is calculated using the current velocity, the distance between the current position and $Pbest_i$ and the distance between the current position and $Gbest$. This can be formulated as:

$$\begin{aligned} V_{ik}^{(iter+1)} &= W * V_{ik}^{(iter)} \\ &+ c1 * rand1 * (Pbest_{ik}^{(iter)} - P_{ik}^{(iter)}) \\ &+ c2 * rand2 * (Gbest^{(iter)} - P_{ik}^{(iter)}) \end{aligned} \tag{1}$$

$$\begin{aligned} &P_{ik}^{(iter+1)} = P_{ik}^{iter} + V_{ik}^{(iter+1)} \\ &i = 1,2,3,.......Ps \quad k = 1,2,3,....L \end{aligned} \tag{2}$$

$$\begin{aligned} -(V_k^{\max}) \le V_{ik} \le V_k^{\max} \\ P_k^{\min} \le P_{ik} \le P_k^{\max} \end{aligned} \tag{3}$$

The use of a linearly decreasing inertia weight factor provides an improved performance in all of the applications. Its value decreases linearly from about 0.9 to 0.4 during a run. The suitable selection of the inertia weight provides a balance between the global and local exploration and exploitation, and results in less iteration on average to find a sufficiently optimal solution. Its value is set according to the following equation [13, 14]:

$$W = W_{\max} - \frac{W_{\max} - W_{\min}}{iter_{\max}} * iter \tag{4}$$

Here, W_{max} and W_{min} are both random numbers representing the initial weight and the final weight respectively.

In (1) the first term indicates the current velocity of the particle, and the second term represents the cognitive part of the PSO where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of the PSO where the particle changes its velocity based on the social-psychological adaptation of this knowledge.

3.2 Problem formulation

The total expected cost, which is the expectation value of summation of MC, RC, GC and OC, is shown in (5)

$$J = E\Big[\sum_{all\ years} \Big\{ \sum_{m \in NE} MC_m + \sum_{m \in NE} RC_m + \sum_{k \in NG} GC(PG_k) + \sum_{i \in NL} OC(LC_i) \Big\}\Big] \tag{5}$$

s.t.

$$\sum_{k \in NG} PG_k + \sum_{i \in NL} LC_i = \sum_{i \in NL} PD_i \tag{6}$$

$$PG_{\min} \le PG \le PG_{\max} \tag{7}$$

$$0 \le LC \le PD \tag{8}$$

$$\left| LF(S_j) \right| \le LF_{\max} \tag{9}$$

Here, GC is evaluated the function of the electrical output of each generator and the OC is calculated using amounts of load curtailment. PG_k is the electrical output of k-th generator and LC_i is amounts of load curtailment of i-th load. Power balance constraint is shown in (6). Eq. (7) and (8) are generation limits and load curtailment limits respectively. In (9), $LF(S_j)$ is the line flow vector for the j-th system state S_j and this equation express line capacity limit. The RC_m and MC_m are the repair cost and maintenance cost of m-th equipment respectively.

$$\underset{P \in \Theta}{Minimize}\ J(P) \tag{10}$$

In (10), the decision vector, P, minimizes the total expected cost. This decision vector depicts the optimal maintenance strategy for the equipment.

3.3 Particle representation

It is crucial to appropriately encode the particles of the population in the PSO in order to find the optimal maintenance strategy. The maintenance strategy of each pieces of equipment is chosen to represent the particle position in each dimension, and the positions in different dimensions constitute a particle, which is a candidate solution for the target problem. The position in each dimension is real-coded. The i-th particle P_i is represented as follows:

$$P_i=(P_{i1}, P_{i2}, P_{i3}, \ldots P_{ik}, \ldots P_{iL}) \quad i=1,2,3\ldots\ldots P_S \tag{11}$$

where L is the total piece count of the equipment in the transmission system, P_{ik} is the maintenance strategy of the k-th equipment in the i-th particle. Therefore, the number of dimensions for the population is $P_S \times L$.

For example, say there are eighteen pieces of equipment. Six of them are found in the overhead line, which has the state model shown in Fig. 2, three of them are found in the underground cable and the rests are for the insulator. The dimension of each particle, L, should be eighteen; the search space of the overhead line is [0, 1, 2, 3], the search space of the underground cable is [0, 1, 2] and the search space of the insulator is [0, 1]. 0 represents not doing any equipment maintenance, 1 means doing weak maintenance due to the state of the equipment being D1, 2 indicates carrying out strong maintenance due to the state of equipment being D2, similarly, 3 represents even stronger maintenance due to the state of equipment being D3.

If the i-th decision vector (particle) is shown in Fig. 4 [2,0,3,1,3,3,1,1,1,0,0,0,1,1,1,0,1,0], the first piece of equipment needs strong maintenance only when in the D2 state. The second one does not need any maintenance. The third one has a stronger maintenance that is carried out only when its state is D3. The fourth one needs to perform a weak maintenance action when the state is D1. Similarly, the maintenance strategies of the other pieces of equipment are represented by its respective particle.

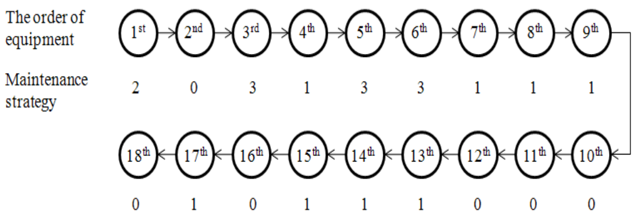

Fig. 4. The example of i-th particle

3.4 Algorithm step

Step 1. Randomly initialize the particles of the population and iteration counter (*iter*=0). Note that the velocity and position of each particle needs to be initialized in such a manner that each candidate solution (particle) locates within the feasible search space given by (3). Since the maintenance strategy particles are integers, their de-normalized value is rounded to nearest integer to determine the actual value.

Step 2. The procedure for the fitness function of each particle P_i with a state transition pattern used for the calculation of the total expected cost given by (5) is:

i) Specify the state of all the equipment by the grade of their deterioration.

ii) Estimate the failure patterns and the duration of the equipment residing in its present state chronologically using the sequential Monte Carlo Simulation [15]. For all of the equipment, random numbers are generated, and the time-to-state transition time and repair time are calculated chronologically. The duration of each piece of equipment for the present state is assumed to be distributed exponentially and to be expressed by the cumulative distribution function (CDF(t)) as shown in (12).

$$CDF(t) = 1 - \exp(\lambda t) \tag{12}$$

Where t is the transition time and λ ($\lambda_1, \lambda_2, \lambda_3, \lambda_4$) is the transition rate. The random variable T is given by:

$$T = -1/\lambda \ \ln(1-R) \tag{13}$$

where R is a uniformly distributed random number [0, 1].

iii) Transit the state of all of the equipment based on the derived failure patterns in a given time span.

iv) Calculate the total expected cost for i-th particle (P_i) in a given time span using the state of the equipment and the maintenance decision vector of the equipment. If the decision vector (particle P_i) is like that shown in Fig. 4, the *MC* is applied to the total expected cost each time the state of the first equipment transits to the D2 state, the state of the third one goes to the D3 state and the state of the fourth one transits to D1, based on the failure pattern. For the second component, the maintenance should be skipped only in accordance with the decision vector; otherwise it will increase the probability of equipment failure and probably cause a load curtailment. After applying the required maintenance, the *RC*, *OC* and *GC* are calculated using the system condition and the probability of failures.

Finally, the total expected cost is calculated. If there is no equipment failure in the transmission system, the *MC* and *GC* are added to the total expected cost. The MC differs depending on the methods, which vary with the deterioration states. If any equipment breaks down, but doesn't cause a load curtailment, the *RC* and *GC* are attached to the total expected cost. When a couple of equipment failures occur, causing a load curtailment, the *RC*, *OC* and *GC* are applied to the total expected cost.

v) Repeat ii)~iv) according to the population size (P_S).

The process of evaluating the total expected cost of each particle is portrayed in Fig. 5.

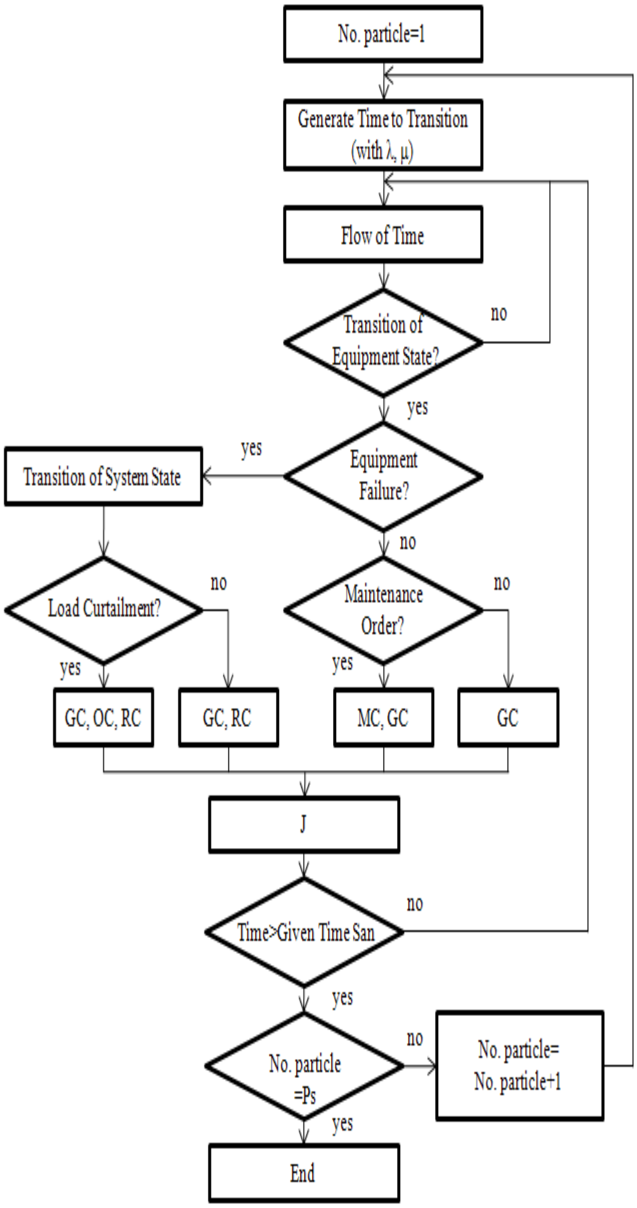

Fig. 5. The process of evaluating the total expected cost of each particle

Step 3. Compare the total expected cost of *Pbest* with the total expected cost of the current particle. If the total expected cost of the current particle is better than the total expected cost of *Pbest*, then set *Pbest* to the current position P_i.

Step 4. The best value among all the *Pbest* value, *Gbest*, is identified.

Step 5. New velocities for all of the dimensions in each particle are calculated using (1). The maximum velocity limit in the *k*-th dimension is computed as follows:

$$V_k^{\max} = \frac{P_k^{\max} - P_k^{\min}}{Per} \tag{14}$$

where *Per* is the chosen number of intervals in the *k*-th dimension. For all the examples tested using the PSO, $V_k^{\max}$ was set at 10-20% of the dynamic range of the variable on each dimension.

Step 6. The position of each particle is updated using (2).

Step 7. The time counter is updated *iter*=*iter*+1.

Step 8. If the number of iterations exceeds its maximum ($iter_{max}$) then go to Step 9. Otherwise, go to Step 2.

Step 9. Output the particle with the minimum total expected cost in the last generation. This particle includes the optimal maintenance strategy for all of the studied equipment.

The step by step procedure used to find the optimal maintenance strategies for the equipment and the minimum total expected cost is depicted by the flowchart seen in Fig. 6.

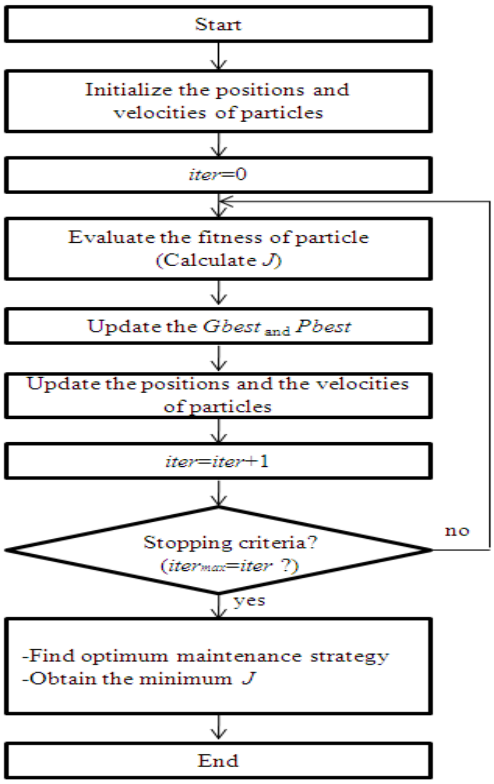

Fig. 6. The procedure to find optimal maintenance strategies with the PSO

4. Case Study

The effectiveness of the proposed maintenance strategy was demonstrated using an IEEE 9-bus system. In Fig. 7, 1 to 9 are the bus numbers, ①~③ represent the underground cable and ④~⑨ indicate the overhead line number. The insulators are also named ①~⑨. In reality, many insulators are installed between two buses; however only one insulator is assumed in order to simplify this study.

Any failure in the three components causes a

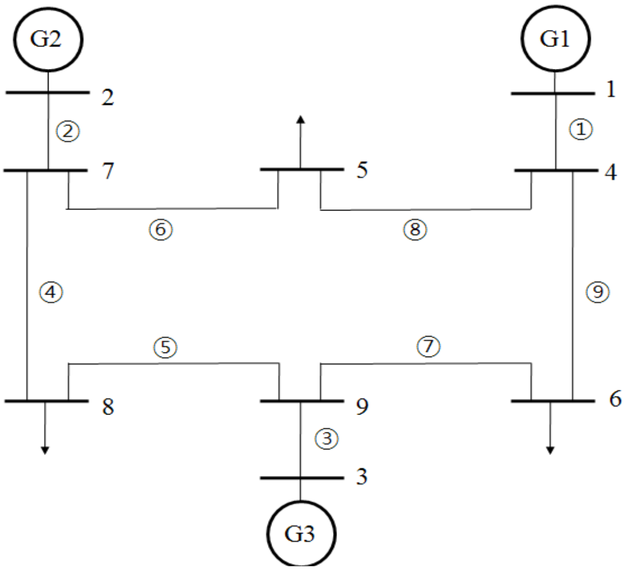

Fig. 7. IEEE 9-bus system

transmission line disconnection between two buses. The simulation data (bus data, line parameter, transition rate, repair rate, generation cost, maintenance cost, and outage cost) is shown in Table 4 to Table 9. Table 4 shows the bus data and Table 5 gives the line parameter. Table 6 and Table 7 show the transition rates and repair rates for the equipment respectively. Table 8 shows the generation cost per generator and Table 9 represents the maintenance cost and the outage cost.

This system has six lines, three underground cables and nine insulators. Since the underground cables have 2 deterioration states, the overhead lines have 3 deterioration

Table 4. The bus data for the IEEE 9-bus system

Bus Number	Type	PG(MW)	PL(MW)
1	Slack	0	0
2	Generator	163	0
3	Generator	85	0
4	Load	0	0
5	Load	0	125
6	Load	0	90
7	Load	0	0
8	Load	0	100
9	Load	0	0

Table 5. The line parameter for the IEEE 9-bus system

From	To	R	X	LF_{max}(MW)
4	1	0	0.0576	250
7	2	0	0.0625	250
9	3	0	0.0586	150
7	8	0.0085	0.072	300
9	8	0.0119	0.1008	150
7	5	0.032	0.161	250
9	6	0.039	0.17	250
5	4	0.01	0.085	250
6	4	0.017	0.092	250

Table 6. Transition rates for the equipment

	Transition rate (f/year)			
	λ_1	λ_2	λ_3	λ_4
Line	0.01	0.01	0.02	0.04
Cable	0.005	0.005	0.008	-
Insulator	0.02	0.04	-	-

Table 7. Repaired rates for the equipment

	Repair rate (f/year)			
	μ_1	μ_2	μ_3	μ
Line	0.0014	0.0014	0.0027	0.0027
Cable	0.0014	0.0014	-	0.0027
Insulator	0.0014	-	-	0.0014

Table 8. The generation cost per generator

Generator	PG_{min} (MW)	PG_{max} (MW)	GeneratorCost (k-KRW/MW)
G1	10	250	$0.11PG^2$+5PG+150
G2	10	300	$0.085PG^2$+1.2PG+600
G3	10	270	$0.1225PG^2$+PG+335

Table 9. The maintenance cost and the outage cost

Maintenance Cost(k-KRW)				
	M1	M2	M3	Repair
Line	1000	2000	3000	5000
Cable	3000	5000	-	8000
Insulator	500	-	-	3000
Outage Cost(k-KRW/MWh)=100				

Table 10. The initial state of equipment

Equipment number	Initial state	Equipment number	Initial state
Underground cable ①	D1	Insulator ①	N
Underground cable ②	D1	Insulator ②	N
Underground cable ③	N	Insulator ③	D1
Overhead line ④	D2	Insulator ④	D1
Overhead line ⑤	D2	Insulator ⑤	N
Overhead line ⑥	D3	Insulator ⑥	N
Overhead line ⑦	D3	Insulator ⑦	D1
Overhead line ⑧	D1	Insulator ⑧	D1
Overhead line ⑨	D1	Insulator ⑨	D1

states and the state of the insulators is expressed by 1 deterioration state, the dimension of each decision vector (particle) is 18. The initial state of the equipment is shown in Table 10.

The convergence characteristics for the PSO are shown in Fig. 8.

The parameters used are

Population size (P_s): 60

Generation number ($iter_{max}$): 500

Inertia weight W is set by Eq. (4),

Where W_{max}=0.9 and W_{min}=0.4

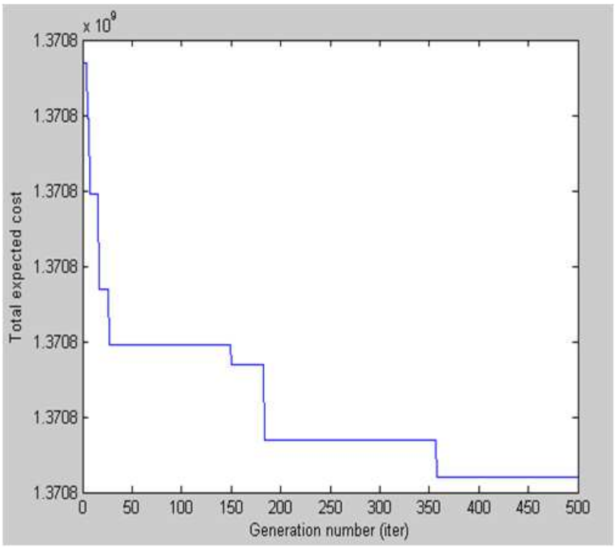

Fig. 8. The convergence characteristics for the PSO

Maximum velocity V_{max} is set by Eq. (14) where Per=10
Acceleration constant $c1=c2=2$

The x-axis represents the iteration number, and the y-axis represents the total expected cost. The minimum total expected cost is 1,370,774,395.6 k-KRW over a 30 year time span.

Table 11 shows the optimal maintenance strategy selected by the PSO, the failure frequency and the calculation time for the 30 simulation years. It shows that our method minimizes the total expected cost. This table shows the maintenance plan for all of the equipment. The PSO process took 265.62 seconds to converge to the optimal solution.

The optimal maintenance plan in the IEEE 9-bus system is suggested from the decision vector shown Table 11. For example, the optimal maintenance plan for cable ① is [Do M2], meaning that strong maintenance is performed whenever its state becomes D2. Stronger maintenance is executed for overhead line ⑨ [Do M3] when its state goes to D3. The maintenance strategy in which equipment is repaired after its failure is adopted for underground cable ③ and insulators ⑤, ⑥, ⑦ and ⑧. When maintenance actions are performed as prescribed by Table 11, the total expected cost is 1,370,774,395.6 k-KRW and equipment failure will occur once at insulator ⑦ over 30 years.

Table 12 shows the total expected cost of the proposed maintenance strategy and compares it to the conventional maintenance strategies which use the time-based maintenance and the condition based maintenance methods. T-1, T-2, T-3, and T-v are the time based maintenance methods. T-1 represents the total cost of 1 year of maintenance for all of the equipment. T-2 and T-3 show the total costs for 2 years and 3 years maintenance, respectively. T-v indicates the total expected cost when the lines are maintained every 3 years, the insulators are done every 2 years and the towers are done every 5 years. C-1, C-2, C-3 and C-4 are the conditional based maintenance methods. The C-1 method prescribes that every overhead line has the stronger maintenance (M3) performed when the state of the overhead line is D3, every underground cable has weak maintenance (M1) if the underground cable state is D1 and every insulator has weak maintenance (M1) when the state of the insulator transits into D1. In a similar manner, the C-2 method prescribes that every overhead line

Table 11. Optimal maintenance strategy for equipment in the IEEE 9-bus system

Equipment	When	How	Failure frequency
Cable ①	D2	Strong Maintenance	0
Cable ②	D1	Weak Maintenance	0
Cable ③	Nothing	Repair after failure	0
Overhead line ④	D2	Strong Maintenance	0
Overhead line ⑤	D1	Weak Maintenance	0
Overhead line ⑥	D2	Strong Maintenance	0
Overhead line ⑦	D1	Weak Maintenance	0
Overhead line ⑧	D2	Strong Maintenance	0
Overhead line ⑨	D3	Stronger Maintenance	0
Insulator ①	D1	Weak Maintenance	0
Insulator ②	D1	Weak Maintenance	0
Insulator ③	D1	Weak Maintenance	0
Insulator ④	D1	Weak Maintenance	0
Insulator ⑤	Nothing	Repair after failure	0
Insulator ⑥	Nothing	Repair after failure	1
Insulator ⑦	Nothing	Repair after failure	0
Insulator ⑧	Nothing	Repair after failure	0
Insulator ⑨	D1	Weak Maintenance	0
Total expected cost (J)	1,370,774,395.6 [k-KRW]		
Calculation time	265.62 [sec]		

Table 12. The Total expected cost of the proposed maintenance strategy, the TBM and CBM for the IEEE 9-bus system in 30-years

Maintenance Strategy	Total expected cost [k-KRW]
J (proposed maintenance strategy)	1,370,774,395
J-1	1,373,390,895
J-2	1,372,081,395
J-3	1,371,644,895
J-v	1,371,560,395
C-1	1,370,795,895
C-2	1,370,788,395
C-3	1,370,791,895
C-4	1,370,785,395

has weak maintenance (M1) performed, every underground cable has strong maintenance (M2) and every insulator has weak maintenance (M1). The C-3 method uses the (M2, M2, M1) maintenance strategy and C-4 uses (M3, M2, and M1).

J is lower than the time-based maintenance (T-1, T-2, T-3 and T-v) and the condition-based maintenance (C-1, C-2. C-3, and C-4). This illustrates that the proposed maintenance strategy, which considers the equipment failure characteristics, the effects of equipment failure, and the maintenance on the system is more cost effective than the existing conventional maintenance strategies for all of the equipment.

Fig. 9 and Fig. 10 show the comparison of the total expected cost between the proposed method and the time-based and condition-based methods for different simulation durations, respectively. The normalized total expected cost (p.u.) value determined by the total expected cost derived by the proposed method is used. The plot shows that the total expected cost of the proposed method is always lower than the time-based maintenance cost (T-1, T-2, T-3 and T-v) and the condition-based maintenance cost (C-1, C-2. C-3, and C-4).

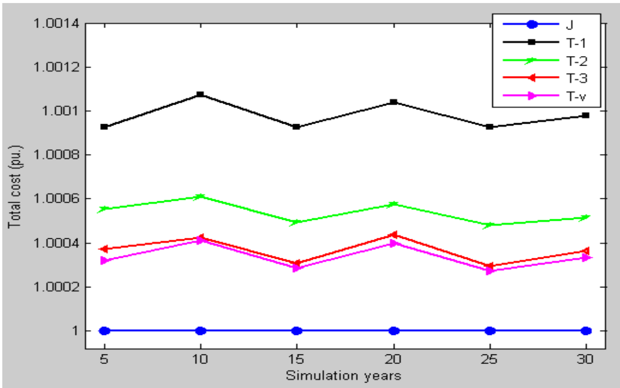

Fig. 9. The comparison of the total expected cost between the proposed method and the TBM.

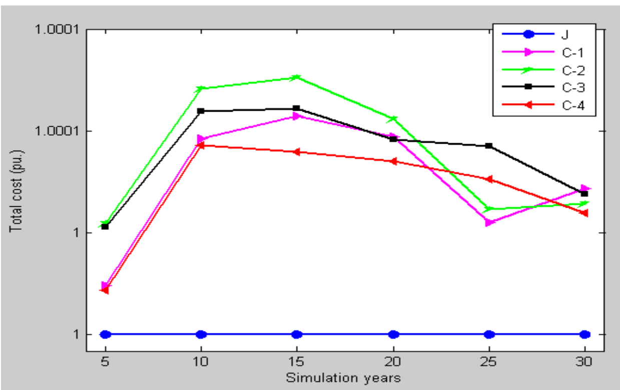

Fig. 10. The comparison of the total expected cost between the proposed method and the CBM.

5. Conclusion

A transmission system is composed of many different types of equipment, much of which was installed several decades ago, and so this equipment has deteriorated over time. Further deterioration may be unavoidable in the near future. it is essential to find a suitable equipment model and a well-organized maintenance strategy that uses this equipment model. This paper proposed the equipment model using the modified Markov chain to simulate the influence of the equipment deterioration and the operational state related to the increasing levels of equipment deterioration. Also we presented the RCM approach including this equipment model.

The RCM approach of transmission systems is an optimization problem that has a large search space and large uncertainties. This paper investigates the application of the PSO on the RCM method for transmission systems that has different kinds of aged and aging equipment. A numerical example shows that the proposed the RCM method that uses the PSO is more cost-efficient than the traditional maintenance methods (TBM and CBM). This proposed RCM model can determine the optimal maintenance strategy for all of the studied equipment.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (No. 2011-0000889). This work was also supported by the Human Resources Development of the Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Korea government Ministry of Knowledge Economy (No. 20114030200030).

References

[1] A Grall, C B´erenguer, L Dieulle, “A condition-based maintenance policy for stochastically deteriorating systems”, *Reliability Engineering & System Safety*, pp.167-180,Vol. 76, 2002.

[2] J. Nilsson, L. Bertling, “Maintenance management of wind power systems using condition monitoring systems-life cycle cost analysis for two case studies”, *IEEE Transactions on Energy Conversion* , pp.223-229, Vol.22 , No.1, 2007.

[3] D McMillan, G W Ault, “Condition monitoring benefit for onshore wind turbines: Sensitivity to operational parameters”, *IET Renewable Power Generation,* pp.60-72, Vol.2, No.1, 2008.

[4] L. Bertling, R Allan, R. Eriksson, “A reliability-centered asset maintenance method for assessing the impact of maintenance in power distribution system”,

IEEE Transactions on Power Systems pp.75-82, Vol.20, No.1, 2005.
[5] I P Siqueira., "Optimum reliability-centered maintenance task frequencies for power system equipments", *8th International Conference on PMAPS,* 2004.
[6] P A Kuntz, R. D Christie, S S Venkata, "A reliability centered optimal visual inspection model for distribution feeders", *IEEE Transactions on Power Delivery,* pp.718-723, Vol.16, No.1, 2001.
[7] M E Beehler, "Reliability centered maintenance for transmission systems", *IEEE Transactions on Power Delivery,* pp.1023-1028, Vol.12, 1997.
[8] W Li, J Korczynski, "A reliability based approach to transmission maintenance planning and its application in BC Hydro system", *IEEE Transactions on Power Delivery,* Vol.19, No.1, 2004.
[9] G P Park, J H Heo, S S Lee, Y T Yoon, "Generalized reliability centered maintenance modeling through modified Markov chain in power system", *Journal of Electrical Engineering & Technology,* pp.25-31, Vol.6, No.1, 2011.
[10] G Hoff, H G Kranz, "On-site dielectric diagnostics of power cables sing the Isothermal Relaxation Current Measurements", *IEEE/PES Panel on Diagnostic Measurement Techniques for Power Cables,* 2000.
[11] J Kennedy, R Eberhart, "Particle swarm optimization", *Proceedings of IEEE conference on neural networks Piscataway NJ,* pp.1942-1948, Vol.4, 1998.
[12] R Eberhart, Y Shi, "Particle swarm optimization: developments, applications and resources", *Proceedings of the Congress Evolutionary Computation,* pp.81-86, Vol.1, 2001.
[13] K Y Lee, M A El-sharkawi, "Modern Heristic Optimization Technique with Applications to Power Systems", *IEEE Power Engineering Society (02TP160)*, 2002.
[14] H Yoshida, K Kawata, Y Fukuyama, S. Takayama, Y. Nakanishi, "A particle swarm optimization for reactive power and voltage control considering voltage security assessment", *IEEE Transactions on Power System,* pp.1232-1239, Vol.15, 2000.
[15] R Billinton, R N Allan. *Reliability Evaluation of Power Systems*, Plenum Press, pp. 400-405.

Jae-Haeng Heo was born in Korea in 1978. He received his B.S. degree in Electrical Engineering from Dankook University, Seoul, Korea in 2005 and his M.S. degree in Electrical Engineering from Seoul National University, Seoul, Korea. He is currently working on his Ph.D. course in the Department of Electrical Engineering at Seoul National University. His research field of interest includes power system reliability.

Jae-kun Lyu was born in Korea, on 1982. He received the B.S. degree in electrical engineering from Shinshu University, Nagano, Japan in 2006. Currently he is working on the Integrated Master's and Doctor's Course in the Department of Electrical Engineering at Seoul National University. His research field of interest includes power system operation and reliability, renewable energy integration.

Mun-Kyeom Kim was born in Korea, on 1976. He received B.S. degree in Electrical Engineering from Korea University, Seoul, Korea in 2004 and M.S. and Ph.D. degrees in Electrical Engineering from Seoul National University, Seoul, Korea in 2006 and 2010, respectively. He worked as a post-doc in the institute of information technology in the department of electrical engineering at Seoul National University. He is currently a assistant professor in the Department of Electrical Engineering, Dong-A University, Busan, Korea in 2011. His research interests include the electric power network economics, power system reliability, and the real-time market design in smart grid

Jong Keun Park was born in Republic of Korea in 1952. He received B.S. degree in electrical engineering from Seoul National University, Korea in 1973 and his M.S. and Ph.D. degrees in electrical engineering from The University of Tokyo, Japan in 1979 and 1982, respectively. He worked as a Researcher at the Toshiba Heavy Apparatus Laboratory in 1982. He was a Visiting Professor with the Technology and Policy Program and Laboratory for Electromagnetic and Electronic Systems, Massachusetts Institute of Technology, Cambridge, in 1992. He is currently a Professor in the School of Electrical Engineering, Seoul National University. He is a senior member of the Institute of Electrical and Electronics Engineers (IEEE) and a fellow of the Institution of Electrical Engineers (IEE) and a member of the National Academy of Engineering of Korea and the Korean representative of the study committee SC5 "Electricity Markets and Regulation" in CIGRE. Also he was a President of Korean Institute of Electrical Engineers (KIEE) in 2010.