System-wide Bi-level Meta-heuristic Optimization Approach of CBM for Railway Train

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SUMMARY

This study proposes a strategy for CBM optimization for railway train system, which consists of multiple components with different characteristics such as materials and deterioration processes. The proposed strategy is designed based on a bi-level approach: component-level and system-level. It is a bottom-up approach, where component-level optimal activities are firstly derived and such activities are then combined with the constraints in the system-level optimization process. The constraints are the safety level and maintenance budget. In the first layer of the entire strategy, optimal and alternative (near-optimal) maintenance activities for each component are derived, and these are used as the inputs for the second layer: the system-level optimization. In the second layer, the problem is formulated as the combination of the inputs derived from the first layer and the constraints of safety level and maintenance budget of the system. Then, the best combination of optimal and alternative solutions for component-level maintenance is found. The evolutionary algorithm (EA), which is a meta-heuristic technique in searching optimal solution, is applied to the searching process for the best combination in the discrete search-space. As the proposed strategy is consolidated, it would become a strong tool for improving the operational stability of railway systems.

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INTRODUCTION

In several countries, big and small railway system failures have occurred with the increase of metro and inter-city train services, and railway users are facing inconveniences due to travel delays or cancellations. Railway system failures also bring economic losses. It increases the operational costs for the management agency, and it also negatively influences the shipping businesses. Safety is another and the most important issue related to such matter. In Korea, as an effort for improving the operational stability of railway systems, a discussion on the introduction of condition-based maintenance (CBM) is in progress. CBM is a concept of strategy that supports decision making process for maintenance, which is practiced based on condition information monitored by various sensors installed in the components of a certain system. The traditional maintenance decisions are mainly based on periodic replacements of system components without considering the deterioration rate, whereas CBM aims to take optimal maintenance actions that are determined by the conditions of multiple components of a certain system. This type of strategy supports the life-cycle analysis on a system and improves the maintenance efficiency, which is directly linked with promoting safety level and budge saving.

LITERATURE REVIEW

Regarding to the decision making in maintenance activities for a single facility, several studies aim to achieve the optimal maintenance activities for each state of the facility. Usually, the criteria of optimum is the minimum expected life-cycle, and many researchers (Carnahan et al., Madanat and Ben-Akiva) used dynamic programming [1, 2] to solve this optimization problem. Several studies in railway system have attempted to apply Markov chain for finding a component's deterioration model. Costello et al. [3] tried to develop a tail wear model using Markov process with New Zealand railway track wear data. Shafahi and Hakhamaneshi [4] also developed a cumulative damage model based on Markov process with Iranian railway track data, and they also found optimal decisions that minimize the cost of track maintenance by using a dynamic programming technique.

At the system level, many different components having intrinsic deterioration properties interact with each other, and they are influenced by external stimulus. The characteristics of each component should be considered when operators try to find the optimized maintenance plan. As system-level-optimization approaches, Robelin and Madanat [5] proposed a bottom-up approach, and Yeo et al. [6] and Gupta and Lawsirirat [7] presented methodologies for maintenance approach for certain infrastructure systems that consists of multiple facilities with heterogeneous characteristics.

The important features of CBM are predictive maintenance and real-time monitoring. Marseguerra et al. [8] considered a continuously monitored multi-component system and applied CBM optimization using genetic algorithm and Monte Carlo simulation. Barbera et al. [9] proposed a CBM model for a two-unit system in chemical industry using dynamic programming formulation design. Castanier et al. [10] proposed a decision rule structure for the CBM of a two-unit deteriorating system. Yam et al. [11] developed a predictive decision supporting system that uses the concept of CBM system as an aspect of fault diagnosis and a power of predicting components' states.

Particularly in a railway research area, several Reliability Centered Management (RCM) researches have been performed such as by Carretero et al. [12], Pedregal et al. [13] and Gonzalez et al. [14]. However, system-level optimization studies corresponding to the concept of CBM have rarely been performed.

CURRENT MAINTENANCE APPROACH IN KOREA

Up to the present, in Korea, a field of railway infrastructure maintenance are mainly based on the Time-Based Maintenance (TBM). TBM is a planned maintenance, which means that inspection and maintenance activities are performed based on a periodic schedule. Many of operating authorities manage their assets with Enterprise Resource Planning (ERP) system. In order to support TBM, an ERP system gathers and manages numerous historical databases related to system operation such as driving, breakdown, and maintenance. However, TBM has a disadvantage in considering different aging trends of various components. So, new maintenance concepts like condition-based maintenance (CBM) have attracted attention in terms of raising a system's safety level with efficient costing management. CBM means that operators conduct maintenance activities only when they need, namely, the performance of a component or system does not meet the satisfactory level. Such decision on conducting maintenance activities is made based on real-time monitoring and predicting the condition of an entire facility. In this study, we discuss how to predict the lives of components and system, and how to select a maintenance activity within budget constraints.

OPTIMIZATION APPROACH

A railway train consists of multiple components with different characteristics. In order to keep the train operable, the operator of the vehicle has to consider the condition of each of the various components and maintain the train system in the satisfactory condition within limited budget.

As shown in Figure 1, the methodology of in this study has two different processes: a component-level optimization and system-level optimization.

The component-level optimization finds the optimal and alternative activities at current condition in accordance with expected cost order. This study assumes that the railway train maintenance can be regarded as Markov chain problem, which has a memoryless characteristic meaning that the next future state depends only on the current state. Transition probability matrix is the basic component of a Markov chain that tries to obtain the deterioration model of a component. Transition probability matrix represents the probabilities that a certain condition changes to another condition in next time step. This matrix has an important role in the component-level optimization that finds a set of best and alternative maintenance activities.

In the system-level optimization, we assume that a railway train system consists of multiple components with different characteristics such as materials and deterioration processes. First, we solve the component level optimization and find best and alternative activities for all components. Next, we find the best combination across the components by choosing an activity among the optimal and alternative activities found in the component-level optimization. The budget limit in the maintenance activities should be considered as a constraint of the objective function.

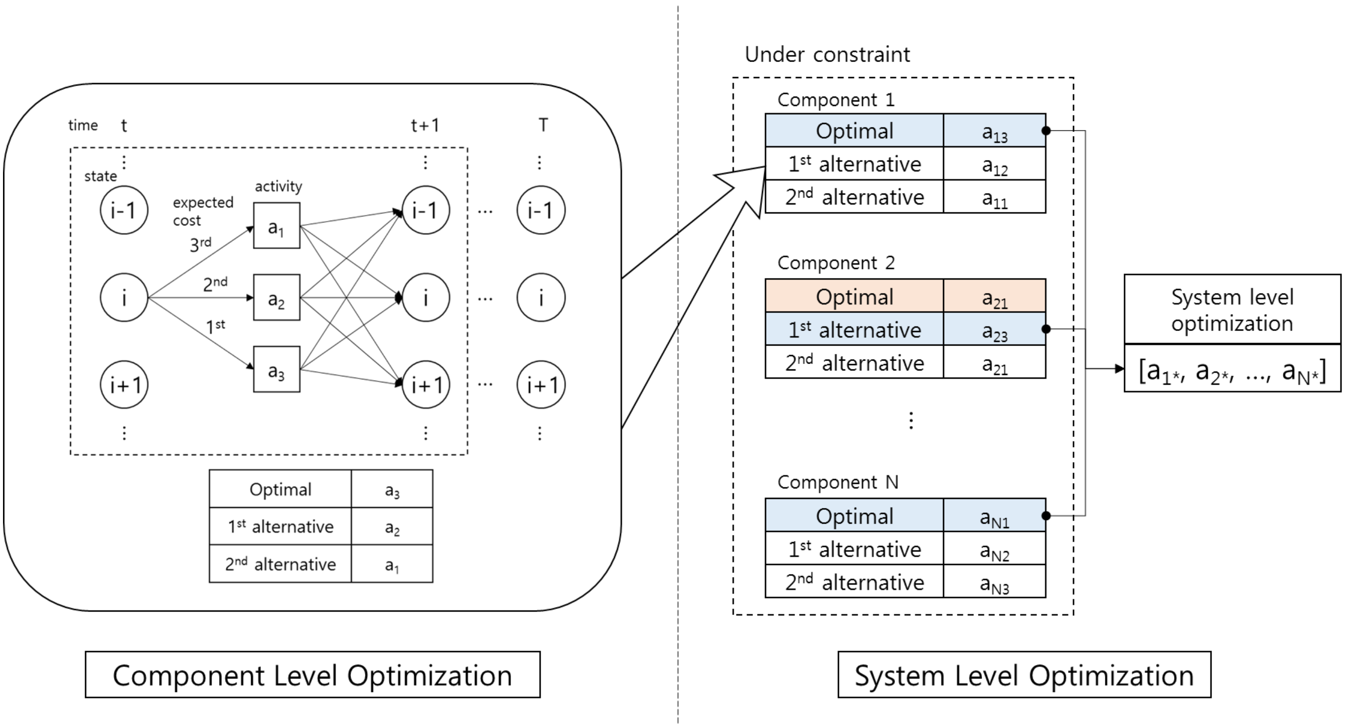

Figure 1: System-wide bi-level maintenance optimization approach

COMPONENT LEVEL OPTIMIZATION

In the component-level optimization algorithm, for each maintenance plan, the current states of the components and required maintenance costs are converted into the cost value, and the optimal and alternative maintenance activities for each component are determined. Figure 2 shows the flow chart of this algorithm.

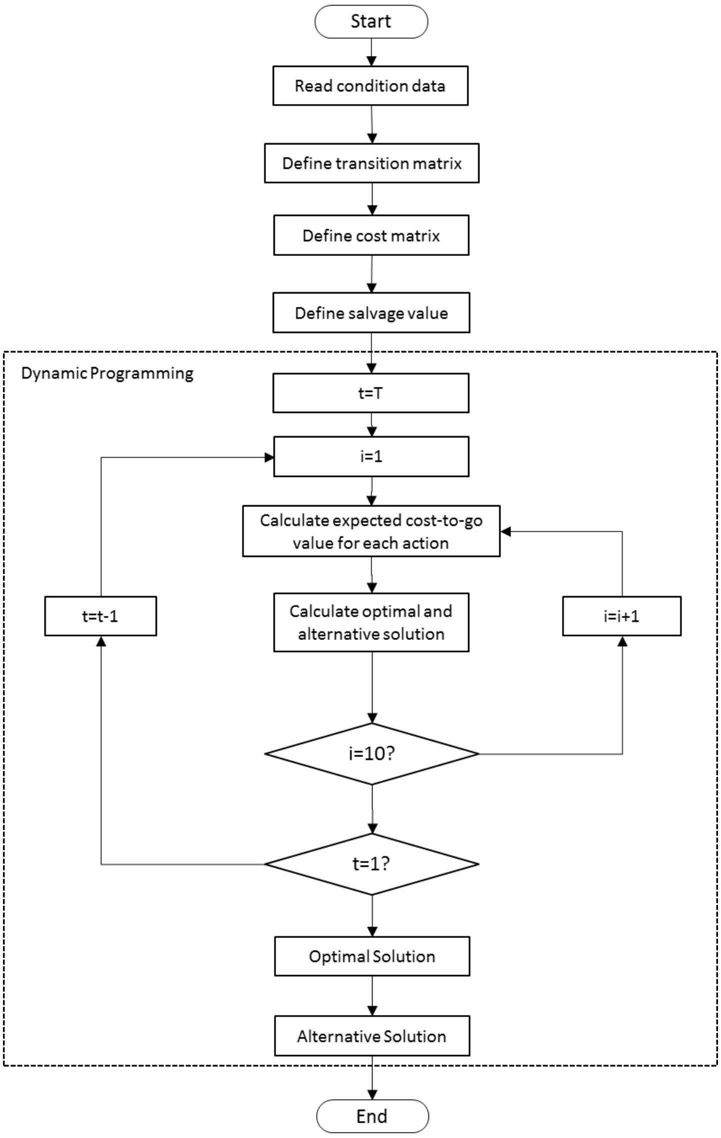

Figure 2: Flow chart of component level optimization algorithm

First, at 'Read condition data step', the algorithm obtains monitored or inspected condition data and analyzes the current condition level of a component. The condition level supports the algorithm in estimating the current performance level of the component. Next, the transition probability matrix and agency cost is determined. Also, the salvage value of a component for each state at time T, which is the planning horizon, is assigned. The transition probability matrix represents the probability of the performance transition for each maintenance activity, and it contains all necessary information to model the state change of a component in the process. The cost matrix corresponds the required cost value for each activity on certain component's condition at certain time. For every component, the value of cost matrix is derived by analyzing historical maintenance record data.

The optimal activity, a^*, and its expected cost-to-go from time t to T, V^*, can be solved with the dynamic programing formulation as shown in below.

$$a^*(i,t) = \arg\min_{a\in A}\{C(a,i) + \alpha \textstyle\sum_{j\in S} V(j,t+1)P_a(i,j)\} \quad (1)$$

$$V^*(i,t) = \min_{a\in A}\{C(a,i) + \alpha \textstyle\sum_{j\in S} V(j,t+1)P_a(i,j)\} \quad (2)$$

Where,

A: Set of feasible maintenance activities

S: Set of feasible state of component

$P_a(i,j)$: Transition probability from state i to state j under maintenance activity a

$C(a,i)$: Agency cost for activity a in state i

α: Discount amount factor = 1/(1+ r)

r: Discount rate

By iterating equation (1) and (2) from time T-1 to 1, the minimum expected total cost-to-go from the current time point to planning horizon T can be obtained. By computing the expected costs-to-go for each available maintenance activity for component state i at time t, we choose one activity that results the minimum expected cost-to-go, as the optimal activity. The activities that result second and third minimum expected costs-to-go are chosen as the first and second alternative activities. Then, the k^th alternative activity and its expected cost-to-go can be described by equations as follows.

$$a_{k+1}^*(i,t) = \arg\min_{a\in A-\{a_l^*, l\le k\}}\{C(a,i) + \alpha\sum_{j\in S} V(j,t+1)P_a(i,j)\},\ k = 0,1,2,\dots \quad (3)$$

$$V_{k+1}^*(i,t) = \min_{a\in A-\{a_l^*, l\le k\}}\{C(a,i) + \alpha\sum_{j\in S} V(j,t+1)P_a(i,j)\} \quad k = 0,1,2,\dots \quad (4)$$

With these equations, the optimal activity and optimal expected cost-to-go can be obtained when k=0.

SYSTEM LEVEL OPTIMIZATION

The objective of the system-level optimization is to find the combination of activities on each component that minimizes the expected cost-to-go of the entire system, such as train, while keeping the total agency cost with budget limit. The operator applies one activity to each component, and each activity may not be the optimal solution in terms of component level optimization.

Figure 3 represents the flow chart of such process. In order to perform the system-level optimization algorithm, the budget limit should be considered as the constraint. First, for every component, we proceed the component-level optimization algorithm, and determine the optimal and alternative maintenance activities. While considering the budget limit, the system-level optimization can be formulated as a constrained combinational optimization problem. We assume that all components are independent to each other.

Let $M_n = \{0,1,2,\dots\}$ be an alternative activity set for component n, where 0 represents the optimal and number i represents the i th alternative. The system-level optimal activity combination $[x_1^*, x_2^*, \dots, x_N^*]$, $x_n \in M_n$ will be determined given state s_n for component n. For component n given activity x_n at current time point, let $f_n^C(x_n)$ represents the expected cost-to-go function, and let $f_n^B(x_n)$ be the activity cost function. Note that $f_n^C(x_n) = V_{x_n+1}^*(s_n, 1)$ for all n, and $f_n^B(x_n) = C(a, s_n)$ for all n in the component level. Then, the combinational optimization problem can be described as follows.

Objective function: $\min(\text{TEC} = \sum_{n=1}^{N} f_n^C(x_n))$ *(5)*

Such that: $\sum_{n=1}^{N} f_n^B(x_n) \le B$ *(6)*

Where,

X: decision variables = $[x_1, x_2, \dots, x_n]$

TEC: the total system expected cost-to-go from current time point to planning horizon T

B: Budget of the current time point

There exist various methods for solving the constrained combinational optimization problem. Here, the evolutionary algorithm, one of meta-heuristic searching algorithms, is used to determine the system-level optimal solution. We determine evolution parameters and construct a new solution set by proceeding evolutionary computation. Continuously, we evaluate new solution set and check the optimality. We conduct evolutionary computation repeatedly until we get a satisfactory solution set, and decide the final solution, which is the combination of the maintenance activities, as the system-level optimization solution.

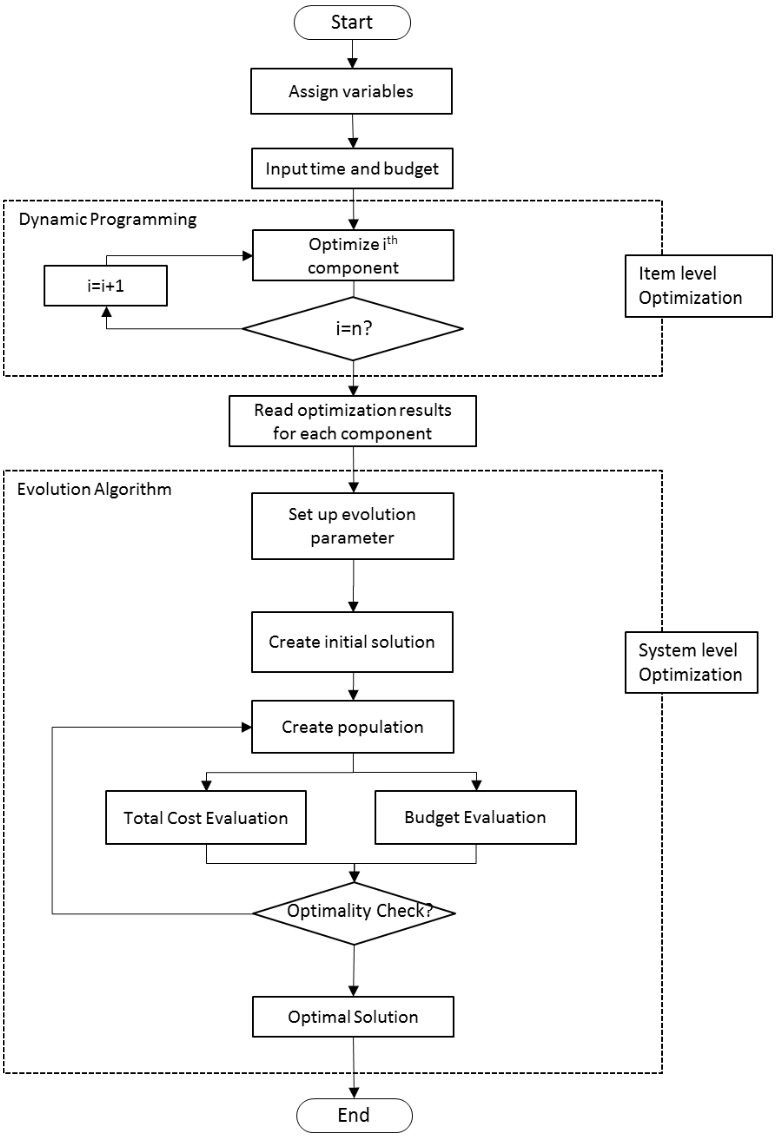

Figure 3: Flow chart of bi-level system level optimization algorithm

EXPERIMENTAL RESULTS

In order to evaluate the proposed bi-level approach, both the component and system level optimization algorithm are implemented using R statistical software. [15] To check the result of the system-level optimization algorithm, the optimization process has been performed with hypothetic values assuming the railway train consists of multiple components.

The planning horizon (T) and discount amount factor (α) are assigned as 40 years and 5 percent, respectively. The number of components is 60, and the state of the components are assigned from 1 to 10. The maintenance budget constraint is 700 (no unit). Table 1 shows the agency activity costs for each state and activity. Values in the table are used as the mean value to generate a hypothetical system for the experiment. As the constraint, the state lower than 4 is regarded as unacceptable safety condition.

Maintenance activity	Component state									
	10	9	8	7	6	5	4	3	2	1
	Acceptable							Unacceptable		
Do nothing	0	0	0	0	0	0	0	0	0	0
Minor Maintenance	0.5	3	8.5	16.5	23.5	43.5	40.5	47	48	50.5
Replacement	60	60	60	60	60	60	60	60	60	60

Table 1: Mean activity costs

The transition probability matrix provides the probabilities of state transition after maintenance activity is performed. For three maintenance activities, do nothing, minor maintenance and replacement, the transition probability matrices are used, respectively. These values are also used as the mean values for each component, and nonzero values are randomly generated while keeping the row sum to be 1. For the replacement activity, only the first column is set to be 1.

$$P_1 = \begin{pmatrix} 0.70 & 0.30 & & & & & & & & \\ & 0.77 & 0.23 & & & & & & & \\ & & 0.92 & 0.08 & & & & & & \\ & & & 0.91 & 0.09 & & & & & \\ & & & & 0.90 & 0.10 & & & & \\ & & & & & 0.79 & 0.21 & & & \\ & & & & & & 0.50 & 0.50 & & \\ & & & & & & & 1.00 & & \\ & & & & & & & & 1.00 & \\ & & & & & & & & & 1.00 \end{pmatrix}, P_2 = \begin{pmatrix} 0.69 & 0.31 & & & & & & & & \\ 0.69 & 0.31 & & & & & & & & \\ & 0.77 & 0.23 & & & & & & & \\ & & 0.92 & 0.08 & & & & & & \\ & & & 0.91 & 0.09 & & & & & \\ & & & & 0.90 & 0.10 & & & & \\ & & & & & 0.79 & 0.21 & & & \\ & & & & & & 0.50 & 0.50 & & \\ & & & & & & & 1.00 & & \\ & & & & & & & & 1.00 & 0.00 \end{pmatrix} \quad (7)$$

With these hypothetical data, the bi-level optimization algorithm is performed. Through 422 times of iteration, the algorithm has found the solution for the system, as in Figure 4. As the result, the algorithm can determine the maintenance activity set for the system while not exceeding the budget limit. (In one of experiment, total life cycle cost of the system and maintenance cost have been found to be 2482.701 and 698.9632, respectively.)

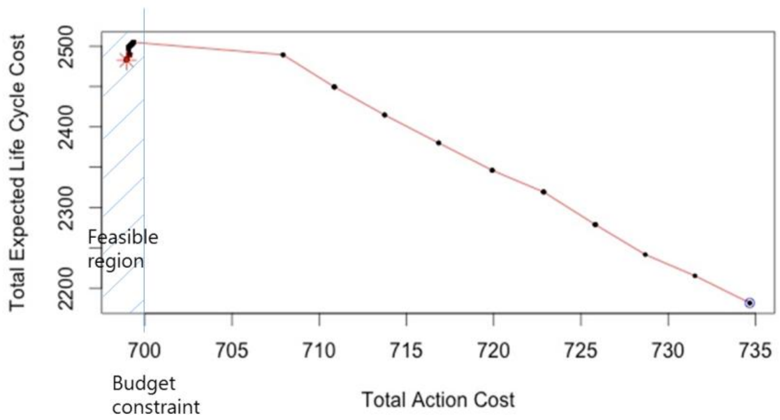

Figure 4: One of experimental optimal solution with hypothetical dataset

CONCLUSION

In this paper, we dealt with the railway train maintenance problem using Markov process, and proposed a system-wide bi-level optimization approach using meta-heuristic method. For multiple components with different characteristics, each component has their own characteristic function such as transition probability and agency cost, and a near optimal combination of maintenance activities can be found within budget limit. The proposed method is worthy of being applied to the railway maintenance, because it considers the life-cycle of railway assets. Also, it arranges preventive maintenance plan, and it supports in building a long-term strategy for safety management. Thus, this approach can support not only in supervising the safety level with detailed consideration on the characteristics of each component of a system, but also in improving the cost-effectiveness of maintenance activities on railway train and railway systems.

However, we could not yet consider the detailed characteristic of various components of the actual train system due to lack of real database. In order to introduce CBM for practical use, a variety of researches and supports has just begun in Korea. We expect to further evaluate and improve the proposed approach with actual data that can be used for the Markovian process in the method. Such process will lead us to derive more appropriate deterioration models for each component of an actual railway system. Additionally, this study considers a system composed of several independent components. To extend the usability of this method, we need to understand the interaction among components. For example, considering a certain case like that a same maintenance activity should be applied to both component A and component B, the connection state among components should be considered as another constraint. By investigating and complementing such things, this approach is expected to become a more reliable maintenance technique.

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