Dynamic Maintenance Scheduling with Fuzzy Data via Biogeography-based Optimization Algorithm and Its Hybridizations

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Received: 10 January 2020, Revised: 6 February 2020, Accepted: 12 March 2020

Abstract

A multi-objective maintenance problem of a plaza building is presented using a dynamic fuzzy maintenance scheduling model (DFMS). There are multiple component machines and jobs with different fuzzy processing time. Generally, it aims to simultaneously minimize total labor cost on regular, overtime and subcontract including equipment cost and minimize the makespan of all jobs, teams and consecutive time periods under fuzzy natures. Nature-inspired intelligence algorithms have become increasingly popular to implement complex problems. Some features of biogeography-based optimization algorithm (BBO) are unique among biology-based methods. This study applied the BBO and its hybridizations based on the variable neighborhood search (BBOVNS) and particle swarm optimization (BBOPSO) mechanisms to the DFMS. Analytical findings indicated that the proposed BBOPVNS is powerful in terms of dispersion effects. The proposed DFMS demonstrates an efficient compromise method and the overall levels of decision making satisfaction with the multi-objective problem.

Keywords: dynamic maintenance, fuzzy data, metaheuristic, biogeography-based optimization, variable neighborhood search, particle swarm optimization
DOI 10.14456/cast.2020.12

1. Introduction

In this case, this study is a major distributor of consumer goods. In the company's complex plaza, there are many machines and equipment requiring constant maintenance and repairs for full efficiency. Therefore, maintenance was found to reduce the likelihood of machine errors and prevent losses caused by machine and equipment damage. Furthermore, maintaining machines and equipment for functionality based on needs enabled the company to boost work efficiency to meet standards in the quantitative and qualitative aspects with safety and minimum losses. Maintenance need to incur the lowest costs possible.

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Thus, the agency needs to make suitable maintenance systems divided into two zones consisting of the office building and the complex. Buildings have many systems such as air conditioning systems, fire extinguishing systems, lighting systems and sanitation systems. Each system is important and has effects on work, safety and customer convenience when customers come to use services.

Therefore, the researcher's interest is studying the aforementioned problem using maintenance data from the case study company as an example. Existing problems in the Maintenance Department consist of differences in expertise and experience among technicians and engineers, repair and maintenance work diversity and differences in priority, urgency and working hours. This has made work schedule organization, work orders and repair and maintenance work assignments complicated with the effect of preventing repairs from being completed on time while incurring high costs. Therefore, the goals of this study were to reduce the number of work delays involved in daily repair and maintenance assignments, and to organize technicians' work schedules by using maximum cost-efficiency within the specified period to improve repair and maintenance efficiency.

Current problem situations in repair and maintenance agencies with work volume as shown in Table 1, which shows the work volume and types of repair and maintenance tasks for the company in one week. Tasks are assigned to four work teams. At present, work is not completed on time due to employees' work delays. The previous data from maintenance unit, overtime and subcontract cost accounted for 30-40%. Furthermore, some teams have received excessive assignments, thereby causing significant overtime costs and causing maintenance times to exceed specifications. In addition, outside contractors are needed to be hired to perform repairs.

A study of the repair work order distribution organization had the following conditions: Repair work did not have fixed characteristics. However, work was assigned twice per day at 7:30 a.m. and at 3:30 p.m. Each repair task has different time requirements for repair standards and different delivery times. Each repair work required one team of technicians responsible. Each repair work task had different score weights and differences in priority. Technicians must receive work assignments to be responsible for full-time work based on daily workloads with eight working hours per day. The company had four teams of technicians in the department who had different working hours.

In this paper, we introduce a recent metaheuristic tool to solve dynamic fuzzy maintenance scheduling optimization problems; the method has been referred as Biogeography-based Optimization Algorithm (BBO) which is inspired by the migration of species between different habitats, and the evolution and extinction of species. The sequential searching procedure of this algorithm mainly relies on the generation of new candidates. The source and number of new candidates can be determined by the users. Since real-world optimization problems are complicated, evolutionary algorithms or metaheuristics are powerful approaches to solve those optimization problems.

There are both single solution and population based algorithms have been developed. The first solution consists of Simulated Annealing (SA) and Tabu Search (TS) algorithms, while Firefly Algorithm (FA), Elephant Herding Optimization (EHO), and Virus Optimization (VO) are applied to multiple solutions with their own evolutionary heuristic tools. The well-performed metaheuristic tools balance among algorithm complexity of exploration and exploitation, computation time, and solution quality including problem complexity and difficulty. With wide applications and their good performance working with high dimensional problems, BBO is then compared with two widely used algorithms.

2. Materials and Methods

2.1 Problem description

Infrastructure systems in the plaza include all equipment and assets that help society function. These infrastructure services like air cool chiller, cooling tower, water pumps of primary and secondary chiller, pumps of transfer, booster, fountain, overflow, drainage, submersible pump, air blower pumps, fire pump and generator, AHU, pressurized, smoke and exhaust fans including load center and control building, are in demand. Engineers and maintenance professionals including subcontracting agencies need to monitor and maintain these existing infrastructures to extending their useful life and ensuring safety in the present as well as in the future. Based on the recent development of call centers reporting service requests, an allocation of maintenance resources properly target these user defined needs. However, with higher demands for services infrastructure with limited budgets, it is vital to maintain these infrastructure jobs over all period. Engineers and others who maintain these systems must develop more flexible ways to meet growing demand while using fewer resources via the fitted mathematical model.

2.2 Proposed model

The case study is conducted in the plaza company in Thailand. The maintenance plan is applied for 12 months. The maintenance workload is over its current capacity. There are 21 workers separated into three teams. Workers can be categorized to S6, S5 and S4 with the skill of worker of 0.5, 0.3 and 0.2, respectively. The summary of skill worker per team is greater than 1.5. There are 30 work groups. The works were assigned twice per day at 7:30 a.m. and at 3:30 p.m. Each repair task had different time requirements for repair standards and different delivery times. Regular working hours are 8 hours per day and overtime are 4 hours per day. Based on the current information, Table 1 shows the frequency (f), minimal (a), standard (m) and maximal (b) fuzzy processing times per unit (T) and number of machines (MC) used in the equipment. There are now nearly 200 items. However, based on the equipment used, they can be categorized into 26 and 4 jobs for main and head quarter buildings, respectively. In each team, regular and subcontract cost per hour are 700 and 1000 baht, respectively. Equipment cost per job is 2000 baht.

A mathematical model of dynamic fuzzy maintenance scheduling (DFMS) is presented in this section. The first step after identifying the problem in a mathematical model formulation is to establish the decision variables. Then an objective function is identified that should satisfy all related constraints on those decision variables (Table 2). The objective function for this model is to minimize total maintenance cost from all N-job (Z1) and to minimize total maintenance time or makespan from all M-team (Z2). The total maintenance cost consists of full-time worker salary, overtime payment and subcontract cost including equipment cost during planning periods in the planning horizon (T). There are some DFMS constraints related to full-time workers, part-time worker, tool or equipment, production, overtime, and subcontracting constraints. The number of full-time workers must be between the minimal and maximal limits. If it is lower than the minimal limit, the maintenance unit cannot proceed. Also, if it exceeds the maximal limit, some workers will be idle [1-2].

Table 1. Maintenance jobs categorized by equipments

Equipment	f	T			MC
		a	m	b	
Air Cool Chiller	2	2	2.5	3	2
Cooling Tower	2	2	2.5	3	4
Primary Chiller Water Pump	2	0.5	0.8	1	4
Secondary Chiller Water Pump	2	0.5	1	1.5	5
Condenser Water Pump	2	0.5	0.8	1	4
Transfer Pump	2	0.5	2	3	4
Booster Pump	2	0.5	1	1.5	2
Fountain Pump	2	0.5	1	1.5	6
Overflow Pump	2	0.5	1	1.5	4
Drainage Pump	2	0.5	1	1.5	10
Submersible Pump	2	0.5	1	1.5	15
Air Blower Pump	2	0.5	1	1.5	10
Fire Pump & Generator	2	0.5	1	1.5	5
AHU Building A	2	1.5	1	2	28
AHU Building B	2	1.5	1	2	36
AHU Building C	2	1.5	1	2	8
FCU Building A	2	1.5	2	2.5	16
FCU Building B	2	1.5	2	2.5	6
FCU Building C	2	1.5	2	2.5	8
FCU Parking	2	1.5	2	2.5	26
Pressurized Fan	2	1.5	2	2.5	6
Smoke Fan	2	1.5	2	2.5	4
Exhaust Fan	2	0.5	1.5	2	6
Load Center and Control Building A	2	1	2	3	9
Load Center and Control Building B	2	1	2	3	4
Load Center and Control Building C	2	1	2	3	2
Case A AHU	2	2	2.5	3	8
Case B PUMP	2	0.5	1	1.5	20
Case C Electrical Other	2	0.5	1	1.5	100
Case D Other	2	0.5	0.7	1	200

Table 2. Variables of the DFMS model

Variable	Symbol
Labor cost per hour for job j in period t	LC_{tj}
Working time per team for job j in period t	W_{tj}
Overtime cost for job j in period t	OC_{tj}
Overtime per team for job j in period t	WOH_{tj}
Subcontract cost per hour for job j in period t	SC_{tj}
Subcontract working time for job j in period t	SH_{tj}
Equipment cost for job j	EC_j
Makespan for team i in period t	MS_{ti}
Amount of overtime in period t	OT_t
Amount of subcontract in period t	SUB_t
Number of full-time workers	W
Skill Score for team i	SS_i

The limit is calculated from the total number of workers, working days, and working hours in each day that the overtime and subcontract can be applied. The total overtime and subcontract man-hours should be lower than the maximum limit. The number of skill levels per team should be higher than the minimal limit; otherwise the maintenance unit cannot function properly. Also, it should be below the maximum limit. The skill scores are the same for all teams. Finally, the total time man-hours should not over the maximum allowable limit. MAX W, MAX OT, MAX SUB, MAX SS and MAX T are the maximal number of workers, overtime, subcontract, skill score and maintenance time in the maintenance unit, respectively. MIN W, MIN SS and MIN T are the minimal levels of workers, skill score, and maintenance time in the maintenance unit, respectively.

$$\text{Min Z1} = \sum_{t=1}^{T}\sum_{j=1}^{N} LC_{tj} * W_{tj} + \sum_{t=1}^{T}\sum_{j=1}^{N} OC_{tj} * WOH_{tj} + \sum_{t=1}^{T} SC_{tj}SH_{tj} + \sum_{j=1}^{N} EC_j \quad (1)$$

$$\text{Min Z2} = \text{Max}\left(\sum_{t=1}^{T} MS_{t1}, \sum_{t=1}^{T} MS_{t2}, \dots, \sum_{t=1}^{T} MS_{tM}\right) \quad (2)$$

Subject to

$$\sum_{t=1}^{T} MS_{ti} = \sum_{t=1}^{T}\sum_{j=1}^{N/M} W_{tj}\,; i = 1, 2, \dots, M \quad (3)$$

$$\text{MIN W} \le W \le \text{MAX W} \quad (4)$$

$$OT_t \le \text{MAX OT} \quad (5)$$

$$SUB_t \le \text{MAX SUB} \quad (6)$$

$$\text{MIN SS} \le SS_i \le \text{MAX SS} \quad (7)$$

$$\text{MIN T} \le \sum_{t=1}^{T}\sum_{j=1}^{N} W_{tj} \le \text{MAX T} \quad (8)$$

2.3 Fuzzy natures

2.3.1 Fuzzy inputs

In this paper, each process time is uncertain, so triangular fuzzy number represented by a triplet [a, b, c] is used as presented in Figure 1. The level of membership function is defined as

$$\mu_{\psi_i}(x) = \begin{cases} 0, x < a \text{ or } x > c \\ \frac{x-a}{b-a}, a \le x \le b \\ \frac{c-x}{c-b}, b \le x \le c \end{cases} \quad (9)$$

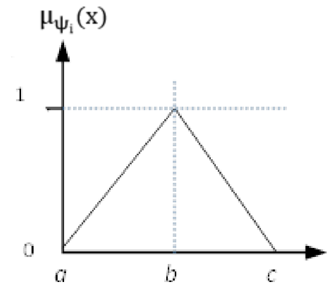

Figure 1. Fuzzy Maintenance Time

Next, the central gravity defuzzification can be applied to transform uncertain data of the fuzzy maintenance time (ψ_i) to crisp equivalent value using the approximated equation [3].

2.3.2 Fuzzy linear programming

In multi-objective functions, several conflicting objectives are considered. The problem is named Multiple Objective Decision Making (MODM) problem. There are many kinds of methods to solve this problem. Fuzzy linear programming (FLP) was applied in this research to make easiness of allowing vague aspirations of the DMs [4-7]. Generally, in MODM model all constraints are restricted as shown in the following

$$\begin{aligned} &\mathrm{MIN}\ Z_k = c_k^T x \\ &\text{Subject to } Ax \leq b;\ x \geq 0 \end{aligned} \tag{10}$$

In reality, input data are usually imprecise because of incomplete information. In order to solve this kind of problem, the fuzzy membership is then used. A symmetric fuzzy linear programming model can be represented by

$$\begin{aligned} &c_k^T x \lesssim Z \\ &Ax \leq b;\ x \geq 0 \end{aligned} \tag{11}$$

Here $\lesssim$ represents the fuzzified version of $\leq$ and has the linguistic interpretation "essentially smaller than or equal to". It is assumed to be linearly decreasing over the tolerance interval, p_k and k =1, 2, ..., K. Then, the membership function can be denoted by

$$\mu_k(x) = \begin{cases} 1 \text{ for } c_k^T x \leq Z_k^{PIS} \\ 1 - \frac{c_k^T x - Z_k^{PIS}}{p_k} \text{ for } Z_k^{NIS} \geq c_k^T x \geq Z_k^{PIS} \\ 0 \text{ for } c_k^T x \geq Z_k^{NIS} \end{cases} \tag{12}$$

; where $p_k = \left|Z_k^{PIS} - Z_k^{NIS}\right|, k = 1, 2, \dots, K$

Positive-Ideal Solution (PIS) and Negative-Ideal Solution (NIS) are used to construct the membership functions. Then, we arrive at the following problem:

$\mathrm{Max}_{x \geq 0} \mathrm{Min}_k \mu_k(x)$ or Equivalently

$$\text{Max } \lambda \tag{13}$$

Subject to

$\lambda \leq \mu_k(x); k = 1, 2, \ldots, K$

$Ax \leq b; x \geq 0$

$\lambda \in [0, 1]$

3. Biogeography-based Optimization Algorithm and its Hybridizations

Biogeography-based optimization (BBO) is one of the intelligence algorithm that was developed in 2008 by Simon [8-10]. Algorithm was inspired by the migration of species between habitats. Complex behavior via both exploration and exploitation strategies was simplified for purpose of evolutionary algorithm to solve global optimization problems. The characteristic of biogeography is close to natural selection. The species are fitter; they are better able to survive. When they survive longer, they are better to disperse and adapt. The BBO has distinctive characteristics which consist of the inter-habitat distance on migration; nonlinear migration relationships, mortality and reproduction rates on migration, predator/prey relationships, the different mobility measures of difference species on migration, geographical momentum during migration, habitat land area and habitat clusters on migration [11-13].

Complete candidates are firstly generated and each candidate is composed of features, or independent variables. Good and poor candidates correspond to a biological habitat that is well and poorly suited for life, respectively. It is possible for high-fitness candidates to share features with other solutions. The features of emigration and immigration are for high-fitness and low-fitness candidates, respectively. There are two main BBO operators of migration and mutation. The migration operator is to share search information among individuals. The mutation operator is applied to enhance the candidate diversity. The mutation operators of immigration rate and emigration rate of a habitat can be calculated by the linear migration function. More specifically, in the migration function when the number of species increases, fewer species can survive for immigration and more species tend to emigrate to other habitats, and vice visa [14].

Each candidate's migration rate from the deterministic curve is used to stochastically share features. The immigration rate is used to stochastically decide to immigrate the features. If a decision is made in favor of immigration, then a second random decision via a random number that is uniformly distributed between 0 and 1is generated; the emigrating solution is stochastically selected based on emigration rate. Mutation is a probabilistic function that can modify candidate features. An aim is to increase diversity among the population. BBO algorithm is defined as follows. One generation of the BBO algorithm, where N is the population size, Hk is the k^{th} candidate, H is the entire candidates, Hk(SIV) is the feature of Hk, z is a temporal solution, ub and lb are upper and lower bound of the search space, respectively [15-16]. The BBO and its hybridizations based on the variable neighborhood search or VNS [17-18] and particle swarm optimization or PSO algorithms [19-20] are summarized in Figure 2.

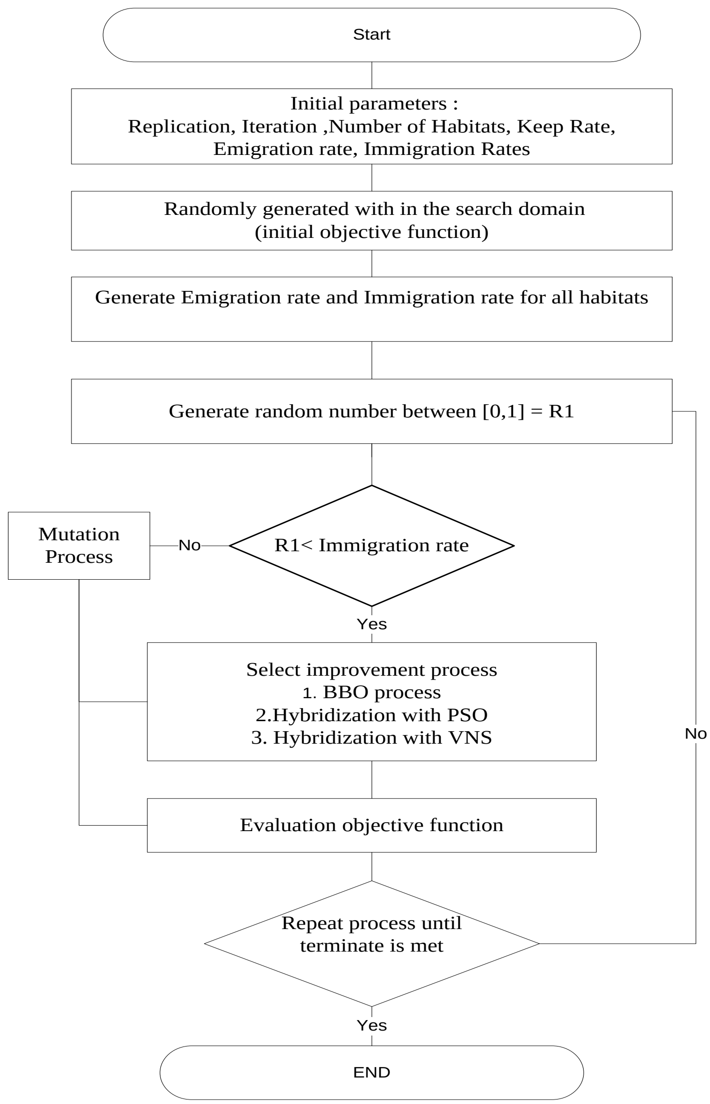

Figure 2. The BBO and its Hybridizations

4. Results and Discussion

In this research, the computational procedures previously described as the fuzzy natures of the dynamic fuzzy maintenance scheduling (DFMS) were performed in a computer simulation implemented in a Visual C#2008 program. The DFMS model presents an exceptional approach to solve the maintenance job scheduling problem with objective to manage breakdown and deterioration due to installation and to sustain performance by preventing unscheduled maintenance and considering uncertainties. The DFMS model was tested with 30 maintenance jobs. Fuzzy natures were used to assess the imprecision in a realistic scenario.

First, a finite interval of maintenance jobs applied the center of gravity defuzzification scheme to generate fuzzy variables and then randomized using the instantaneous probability characteristics of interval time per job. Secondly, the linear and continuous membership function of the objective functions was used to quantify the level of the fuzzy aspiration. The linear membership function was identified according to an analytical definition of membership functions. In BBO, a membership interval is calculated based on all responses in both total maintenance cost and total process time.

The BBO parameters of emigration probability, mutation probability and keep rate are set at 0.2, 0.1 and 0.2, respectively. VNS parameter of the neighbor range (k) equal 5. Both parameters of acceleration factors of c1 and c2 are set at 2. An upper limit on the maximal change of particle velocity (Vmax) is two. The operator balancing the global and the local search (ω) is set at 0.08. Maintenance job interval times were specified by fuzzy numbers and modelled using triangular membership function representations. Fuzzy defuzzification scheme via the center of gravity was used within a finite interval to obtain fuzzy variables. The fuzzy inputs randomized using the instantaneous probability characteristics were used to determine the stochastic measures of the DFMS model input.

Analyses and data visualizations were used to present the feasibility of the model. Minimal total cost and total time scenarios are calculated from all previous data with 100 iterations. A mathematical equation of the proposed model for this DFMS problem can be shown as followed with the corresponding functions of (3)-(8).

Max [λ]

$$\lambda \leq 1 - \left[\frac{Z1 - 733{,}822.31}{118{,}769.19}\right]$$

$$\lambda \leq 1 - \left[\frac{Z2 - 382.31}{68.38}\right]$$

When the performance of the BBO variants of BBO, BBOVNS and BBOPSO was compared, the BBOVNS showed better objectives (Table 3). Based on Z1, the BBOVNS method was the best with the higher level of λ (0.922), lower levels of cost (743,063.02 Baht) and job makespan (400.32 hours). To indicate the stability of the results, each algorithm was repeated 15 times. Moreover, median cost of a BBOVNS is lower than those of BBO and BBOPSO that minimum median value and indicates the stability of the results of this algorithm (Figure 3). The concept is the change of neighborhoods under the specific radius during searching for a better maintennce job scheduling (Table 4). However, there is no statistical significance on the differences of the speed of convergence and the parameter levels on the preliminary results when compared. Moreover, the best so far maintenance job scheduling brings no overtime and sub-contract items.

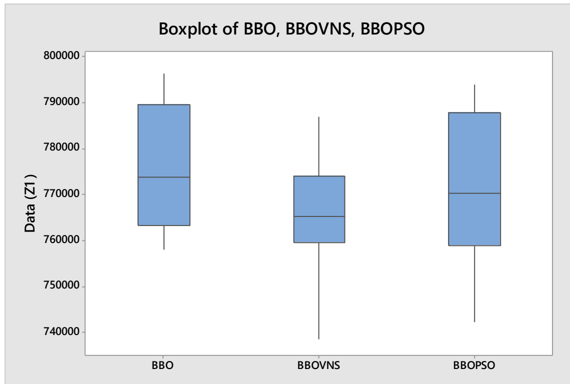

Figure 3. Performance Comparison based on Z1

Table 3. Numerical results of optimal fuzzy value of the objective function

Parameter	BBO	BBOVNS	BBOPSO
Z1 (Baht)	763377.409	743063.02	746322.81
Z2 (Hour)	428.86	400.318	401.531
Max λ	0.751	0.922	0.895

Table 4. Best-so-far maintenance job scheduling via the BBOVNS

	T1			**T2**	
	Team			**Team**	
1	2	3	1	2	3
26	18	5	5	14	10
22	25	21	19	26	7
29	13	19	25	17	4
6	23	28	24	20	23
7	10	30	3	9	1
14	8	15	8	22	28
3	2	27	21	27	12
17	24	4	30	6	29
20	9	16	16	2	18
12	11	1	13	15	11

5. Conclusions

The DFMS model is concerned with the determination of maintenance jobs of a plaza company on a specific time frame. The model aims to reduce the total maintenance cost, a fuzzy maintenance time, and total time. The application of a fuzzy goal programming and fuzzy variable was proposed in this study. The ultimate outcome was the plaza obtains the optimal maintenance plan with the total maximum levels of achieving the goal and uncertainty of job data that can be captured extensively. Recommended future works are exploration of the fuzzy properties of coefficients and related decision parameters for the DFMS problems.

In summary, hybridizations of the BBO can be applied to solve the DFMS problems with fuzzy natures on both variables and objectives. The BBO employs the particle swarm optimization algorithm to develop solution vectors with accuracy and convergence rate of the BBO. The effects of algorithm parameters on the BBO are presented and an approach for tuning these parameters is discussed in this paper. The hybridization via the VNS is an efficient search algorithm which can find admirable solutions when compared to other algorithms. This research provides a benchmarking scenario for managers in maintenance units to minimize cost for scheduling implementation activities. The future research can be the effect of metaheuristic parameters on convergence rate and comparison of this innovative BBOVNS with other metaheuristic methods.

6. Acknowledgements

Authors wishes to thank the Faculty of Engineering, King Mongkut's University of Technology North Bangkok and the Faculty of Engineering, Thammasat University for the financial supports. This research is partly funded by Research Unit in Industrial Statistics and Operational Research, Faculty of Engineering, Thammasat University.

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