Songklanakarin J. Sci. Technol.
43 (5), 1342-1350, Sep. - Oct. 2021

http://www.sjst.psu.ac.th

Original Article

Multi-objective periodic maintenance scheduling and optimization via krill herd algorithm

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Received: 1 July 2020; Revised: 9 October 2020; Accepted: 25 October 2020

Abstract

This study addresses a multi-objective programming model for optimizing periodic maintenance scheduling of department assets with a specified set of machines and instruments under a given planning time period. An aim is to minimize the overall variance of human resources and maintenance costs. The principle of the desirability function is incorporated into the optimization model while considering diminishing marginal utility concepts. The classic krill herd algorithm is modified via three swap mechanisms. After conducting a case study in the large retailer company in Thailand, one of the modified krill herd algorithms is proved to be highly effective in providing high quality solutions. This method is powerful to find out the desired degree of desirability and shows superior in learning preference structures with respect to the alternative solutions examined.

Keywords: preventive maintenance, multi-criteria optimization, desirability function approaches, swarm intelligence algorithms, modified krill herd algorithm

1. Introduction

Many companies apply preventive maintenance (PM) approaches to schedule maintenance with the aim of ensuring machine and equipment in efficient working condition. Maintenance is typically carried out based on time or usage. The benefits of PM include decreased equipment downtime, improved efficiency, reduced interruptions to critical operations, increased asset life, ensured workplace safety, and full compliance with Occupational Safety and Health Administration (OSHA) indications. On the other hand, disadvantages of PM exist such as high cost and labor requirements, and the need of corrective actions. To achieve the highest possible level of quality and safety, production equipment must be designed to achieve intended goals, mainly minimum cost and highest possible availability of production facilities (Paz & Leigh, 1994; Roberts & Escudero, 1983). There are many components for an effective maintenance. One of the most vital component is the planning and scheduling of technological and supervisory actions in the life cycle of any items (Silva *et al*., 1995).

The key objective of maintenance scheduling is to minimize labors, maintenance window, and time. On the other hand, a main concern is the scheduling in the facility machines inside buildings. An effective management of maintenance inside buildings has a substantial effect on the entire life cycle cost and energy use of building. Mathematical functions such as an integer, mixed integer or fuzzy linear programming models have been proposed to tackle maintenance planning and scheduling problems. The '*Just in*

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Time' method has been applied to schedule PM activities for optimal weight earliness and tardiness cost. A zero-one integer linear programming model was created and shown to significantly decreased maintenance cost by 16% (Gustavsson, Patriksson, Strömberg, Wojciechowski, & Önnheim, 2014). Metaheuristic methods also have proven to be highly efficient in maintenance scheduling problems. A hybrid genetic algorithm (GA) embedding a memetic function, a well-known metaheuristic technique, was able to decrease costs up to 20%, improving the results of a linear programming technique (Burke & Smith, 2000).

Metaheuristic methods are designed to provide a good solution in reasonable time for many complex problems. Currently, metaheuristic methods have been employed as an alternative method of the traditional mathematical-based approaches to identify solutions representing the global optimum or near-global optimum. Metaheuristics are highly flexible and adjustable towards getting good answers for complicated problems, which require fast and efficient decision-making. Metaheuristics can be divided into four groups. The first group contains evolutionary algorithms, and the best solution is designed to be the one associated with the last iteration of the whole population. Common techniques in this group include genetic algorithms and evolutionary algorithms, and differential evolution methods. The second group is composed by methods inspired by the interactions of a group of animals such as hunting search, ant system, krill herd, and monkey search algorithms. The third group contains algorithms inspired by physical phenomena, and contains methods such as simulated annealing, gravitational search algorithms and thermal exchange optimization. The last group relates to the human behavior algorithms, such as taboo search, harmony search, and tug of war optimization (Kaveh, 2017).

Metaheuristic is a method for obtaining reliable and efficient answers. Metaheuristic algorithms have been typically developed to imitate social or natural behavior of animals. They have been widely used in the production and logistics management. They help to shorten the time required for calculating solutions for large-scale problems. There is no strict requirement for the application of metaheuristic algorithms when solving the optimization problems (Aungkulanon, Luangpaiboon, & Montemanni, 2018). After having been tested on various benchmark functions, the krill herd algorithm (KHA) has shown excellent performance with simple structure, fewer parameters and great robustness against the parameter values.

In the literature, the two most common variants of maintenance planning problems are the free periodic maintenance scheduling (FPMS) and the periodic maintenance scheduling (PMS) problems. In this research, we address PMS problems to find cyclic maintenance scheduling activities over a certain time period for a given set of machines, with the aim of simultaneously optimizing the total variance of human resources and maintenance costs. An interactive desirability function is introduced, leading to a multi-objective decision making (MODM) problem. Metaheuristic algorithms are selected for solving the PMS with various constraints, model uncertainty, and the complexity of the real-world problems considered in this study.

The desirability function approach converts an objective function value to a desirability expressed as a value ranging from 0 to 1. The overall desirability, or OD, is achieved by aggregating individual desirability indices as a geometric mean or through an operator for aggregating the objective functions with minimal generalized distance between an achieved best-so-far solution and its ideal optimum. The decision maker (DM) needs to allocate the amount of resources to maintenance of a particular facility, or a section of it, for each of a given number of periods. There are some constraints related to the assignment of maintenance resources, which are limited in number and need to reach the minimum standards required by the facilities of each section. These can include the availability of skills or operators from different management policies.

In this study, we develop metaheuristic methods to solve the multi-objective periodic maintenance scheduling and optimization problem, with application to a large retailer. A krill herd algorithm (KHA) is initially proposed to obtain near optimal solutions. Subsequently, a variable neighborhood search algorithm is employed to escape from local minima by exploring more than one type of neighborhood search structure with systematic changes for the problem under consideration. The desirability function approach has been used in searching for the decision makers' preference structure for a satisfactory compromise of both the objectives considered. The benchmark problem considers the scheduling of a periodic preventive maintenance expressed as a mixed-integer non-linear mathematical programming model.

A set of cyclic maintenance operations is time-based, since a given set of machines are periodically fixed. Maintenance is compulsory after a periodic time interval on each machine according to a given planning period. Aim is to minimize the total variance of workforce levels over the time horizon and maintenance costs subject to various system constraints (Grigoriev, Klundert, & Spieksma, 2006; Mansour, 2011). The datasets used in this research experiments have been collected from a large retailer in Thailand, as explained in Section 2. The rest of this paper is arranged in the following order: Section 3 briefs the reader on the related algorithms; Section 4 describes computational results and analyses; Section 5 is conclusions and discussions.

2. Periodic Maintenance Scheduling and Optimization

Many large companies take a variety of aggregate production planning (APP) models to develop work processes including maintenance operations. The APP models for multiple products normally differ from those for one product only. This takes the APP to a higher level of complexity. An APP for each product category may be the best fit. It can lead to the most appropriate solution by dividing the workers into different groups based on the number of product types. Each group of workers is assigned to only one product type in each study period. More workers will be needed, if maximum capacity is reached. Workers will be laid off when they become redundant. The APP integration approach might consider different types of products, leading to a sharing of the company resources, especially human resources. This production line is designed to meet the needs of all types of products.

Workers can be transferred during the work process. There is no cost involved in the transfer of workers between lines. All workers are considered as a same resource that can be freely transferred between production lines. When got used to a job, if the worker is driven to another job, the productivity will be less than on the old job. This affects the overall productivity. The cost division, including the training department and the cost due to production waste, have applied the principles of maintenance management. The APP is highly beneficial for labor-intensive industries and can be apply to a variety of industries including maintenance management with a volume of production strictly depending on the labor hours.

The method we propose, based on PMS and optimization, aims to schedule a repeated maintenance plan for a set of machines for a given number T of planning periods, with some predefined goals. In this problem, during a predefined period, there is a set of m machines types, with a standard reference machine. Moreover, the experience of maintenance experts covers all the requirements of maintenance operations (Edwin & Curtis, 1990). The total number of maintenance activities for the standard unit is called the cycle length. The workforce levels are measured by the total man-hours. A cash flow (cost) is associated to each maintenance operation. For all machines a complexity parameter is given for the l^{th} machine of the k^{th} type. It represents the similarity between each machine with the standard reference unit, and estimates the work required for each machine. The maintenance labors are fixed and hired for the whole planning period.

This paper proposes a mixed-integer non-linear programming model for the PMS. A standard time-indexed model is formulated to find the global optimal solution. The notations of parameters and decision variables used in this mathematical programming model are listed in Table 1. The objective functions shown in Equation (1) and (2) minimize the standard deviation of costs and man-hours for all T planning periods. Equation (3) imposes that the summations of costs per period are not higher than a given cost budget. Equation (4) forces the total time of man-hours per period to be no more than those available for the given period j. Equation (5) regulates maintenance operation tasks, imposing them to follow the sequence of operations for the standard unit maintenance cycle. The variable domains are defined by Equation (6).

$$\text{Min } Z_1 = \left(\frac{\sum_{j=1}^{T}\left(\sum_{k=1}^{m}\sum_{l=1}^{m_k}\sum_{i=1}^{T}\alpha_{kl}mh_j x_{ijkl} - \left(\frac{1}{T}\right)\sum_{j=1}^{T}\sum_{k=1}^{m}\sum_{l=1}^{m_k}\sum_{i=1}^{T}\alpha_{kl}mh_j x_{ijkl}\right)^2}{T}\right)^{1/2} \quad (1)$$

$$\text{Min } Z_2 = \left(\frac{\left(\frac{1}{T}\right)\sum_{j=1}^{T}\left(\sum_{k=1}^{m}\sum_{l=1}^{m_k}\sum_{i=1}^{T}\alpha_{kl}c_j x_{ijkl} - \left(\frac{1}{T}\right)\cdot\sum_{j=1}^{T}\sum_{k=1}^{m}\sum_{l=1}^{m_k}\sum_{i=1}^{T}\alpha_{kl}c_j x_{ijkl}\right)^2}{T}\right)^{1/2} \quad (2)$$

Subject to

$$\sum_{k=1}^{M}\sum_{l=1}^{Mk}\sum_{i=1}^{T}\alpha_{kl}c_j\, x_{ijkl} - C_j \leq 0;\ \forall_j = 1,2,3,\ldots,T \quad (3)$$

$$\sum_{k=1}^{M}\sum_{l=1}^{Mk}\sum_{i=1}^{T}\alpha_{kl}mh_j\, x_{ijkl} - MH_j \leq 0;\ \forall_j = 1,2,3,\ldots,T \quad (4)$$

$$\sum_{j=1}^{T} jx_{ijkl} - y_{ikl} = 0;\ \forall_i = 1,2,3,\ldots,T;\ \forall_k = 1,2,3,\ldots,T;\ \forall_l = 1,2,3,\ldots,m_k \quad (5)$$

$$x_{ikl}, z_{ikl} \in \{0,1\};\ y_{ikl} \geq 0 \text{ and integer}; \quad (6)$$

3. Related Algorithms

A common problem encountered in engineering optimization is the selection of optimal decision variables that involves a simultaneous optimization of various characteristics. This problem is called a multiple objective optimization problem. The PMS is solved through various mathematical programming models. The decision maker (DM) searches for a compromise candidate with the greatest satisfaction in the presence of conflicting objectives. In this paper we will focus on the desirability function approach because it is highly popular. An interpolation of robustness concepts can be considered to determine better results. All prefer information of the DM can be extracted prior to solving the problem. All objectives are possibly combined into a single objective or desirability function, and optimized via the ideal balance among the desired objective values.

3.1 Desirability function approach

The desirability function approach (DFA) is typically designed to solve the problem of multiple objective optimization (Derringer & Suich, 1980; Kim & Lin, 2000; Geoffrion, Dyer, & Feinberg, 1972). The desirability function approach is one of the most common methods in engineering optimization. The DFA basically transforms an objective function into a scale-free function, called the desirability function ranging from zero to one (Zionts & Wallenius, 1976). Thus, the desirability function level presents the degree of desirability or satisfaction for the corresponding objective. If the smaller-the-better (STB) scenario is the objective that has to be minimized, the desirability function is defined as

$$d_i = \begin{cases} 1 & \text{for } F_i \leq F_i^{MIN} \\ \left[\dfrac{F_i^{MAX} - F_i}{F_i^{MAX} - F_i^{MIN}}\right]^{\alpha_i} & \text{for } F_i^{MAX} \geq F_i \geq F_i^{MIN} \\ 0 & \text{for } F_i \geq F_i^{MAX} \end{cases} \quad (7)$$

where F_i, F_i^{MIN} and F_i^{MAX} are respectively the candidate solution and the minimum and the maximum acceptable values of the i^{th} objective function. α_i is the parameter (α_i > 0) that determines the shape of the i^{th} desirability function (d_i). There are several ways to define the optimum considering multiple individual desirability functions but the most widely used method is to convert multiple desirability functions into a single desirability via the concept of geometric means (Korhonen & Laakso, 1986; Jeong & Kim, 2003).

Table 1. Index, parameters, and decision variables

Symbol	Parameter notation
i	Maintenance operation or MO, i = 1, 2, 3, …, T
j	Planning period, j = 1, 2, 3,…, T
k	Machine type, k = 1, 2, 3,.., M
l	Number of machine for each type, l = 1, 2, 3,…., m^k
c_j	Common MO cost of the *j*th period for each machine
C_j	Maximum cost at the *j*th period
α_{ki}	Complexity value for the *i*th machine of the *k*th type
mh_{ikl}	Operation time of workforces)man-hours(to handle the *i*th maintenance personnel for the *l*th machine number of the *k*th type and equals to h_j, c_{kl}
mh_j	Total man-hours to perform operation at the *j*th period for the standard machine
MH_j	Total man-hour cost at the *j*th period
M	Number of machine types
m_k	Number of machines per the *k*th type
T	Cycle length
x_{ijkl}	Decision variable with a binary value of 1 if the *i*th maintenance operation will be completed at the *j*th period of the *k*th machine type for the *l*th machine number and of 0 otherwise.
y_{ikl}	Integer decision variable for the finishing time of the *i*th maintenance operation, the *l*th machine number and the *k*th type.

3.2 Krill Herd Algorithm

The Krill Herd Algorithm (KHA) is inspired by grouping behaviors (Gandomi & Alavi, 2012). Krill creation is non-random. The krill breed in the study was the Antarctic krill, and this krill show learning capabilities in Nature. The Antarctic krill is equipped with great performance in feeding, reproduction, defense against hunters and adaptation to the environment (Moodley, Rarey & Ramjugernath, 2015). During the past decades, many researchers have been interested in studying and understanding the characteristics of the krill ecosystems and its dispersal. When krill forms a herd, optimized krill herd configurations are observed, by considering factors and making positive modifications or selecting only the best results to form groups or herds with outstanding features (Jensi & Jiji, 2016).

The KHA was applied to solve various problems in many settings such as electric and power system (Mandal, Roy, & Mandal, 2014; Mukherjee & Mukherjee, 2016; Niveditha, Sujatha, & Kumar, 2018; Pulluri, Naresh, & Sharma, 2017), Wireless and network system (Singh & Sood, 2013), Neural network training (Kowalski & Łukasik, 2015), Production Scheduling and Text Clustering (Abualigah, 2019; Abualigah, Khader, & Hanandeh, 2018a). Hybrid methods involving KHA may occur from combining various techniques to find the best answers within the possible answers and normally lead to fast answers (Ren *et al*., 2016). Hybrid KHA, embedding other algorithms such as chaotic, artificial bee colony and particle swarm optimization significantly increased performance of the original KHA (Bolaji, Al-Betar, Awadallah, Khader, & Abualigah, 2016). On the basic KHA process, the objective function is to maximize the number of krill closest to food sources. Each krill's position depends on three factors: the presence of other individuals, an ongoing foraging activity and a random diffusion (Abualigah, Khader, & Hanandeh, 2018b, 2018c).

Generally, there are various mechanisms to develop and improve the KHA. The first mechanism is relating to parameters setting. The selection of KHA parameter levels is a challenging task, like for all metaheuristic algorithms since there is no general rule to determine the optimal ones. Experimental trials are normally employed to find the best values. However, this matter brings the research into new variants of the KHA by introducing some evolutionary elements to make some of these parameters dynamically adapted. The second mechanism is about hybridizing the KHA with other metaheuristic algorithms. These hybrid approaches consist of integrating some elements of other metaheuristic algorithms into the KHA structure and integrating some KHA components into other metaheuristic algorithms' structure.

The objective of the modified krill herd algorithm (MKH) is to increase the chance of finding new better solution (Goldberg, 1989). According to these modifications, we add three position processes swaps to the basic KHA, on the basis of the variable neighborhood search method or VNS (Hansen & Mladenovic, 2001). The swap process is then adopted to create a new point which helps our purposed method to escape from local optima in the KHA memory (Imran, Salhi, & Wassan, 2009; Qi *et al*., 2016). These novel hybridizations are merged to boost the performance of the original KHA for determining the best solution retrieved so far. A number of individuals form the population are randomly selected. Each of the chosen solutions randomly exchanges two elements in their designated arrays. The swap process is considered according to a given swap rate. In this paper, three modifications movements are generated after the application of the genetic operator in the KHA process. If a new candidate is worse than the memory solutions, the modification process will be run to create a new solution to enhance the algorithmic procedures. On the first modified krill herd algorithm (MKH1), the process is to randomly pick two job positions from all and swap the respective positions. The second modified krill herd algorithm (MKH2) randomly selects four positions from the tasks and swap them. The third modified krill herd algorithm (MKH3) randomly search six positions and swap them. The modified krill herd algorithm can be summarized as shown below, where also some further formal details are provided.

4. Computational Results and Analyses

A large department store is a collection of retailing business consisting of a wide variety of stores, restaurants, banks, and services. The air control system is one of the main components of supporting system in a department store for cooling air and ventilation. A primary equipment in an air control system includes chiller, AHU, water and air change pumps, fire protection, lighting and piping system. Engineers and maintenance staff as well as subcontractors need to monitor and maintain equipment to extending service life and ensuring safety. In our case study, the initial interview with a department store's staff demonstrated the need of strategies for allocation of maintenance resources under extreme situation of high demands for maintenance services and limited budget. Engineers and staff from the maintenance department require innovative approaches to meet a growing demand while using fewer resources. The solution is developed using a fitted mathematical model.

The case study is conducted at a large retail store in Thailand. The purposed planning covers for 12 months. The workload is over the current capacity. There are 21 workers separated into three teams. Workers are categorized as S6, S5 and S4, with skills classified as 0.5, 0.3, and 0.2, respectively. The sum of the skills of the workers of each team is greater than 1.5. There are 30 task groups. The cycle length is of two times. The tasks were assigned into two shifts 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. Standard working times are eight hours per day and overtime is set for four hours worked in excess of the regular working hours. Table 2 shows the type of tasks and their related equipment, number of machines used from the equipment, required man-hour and cost. Labor cost for regular are 700 Baht per hour and subcontract are higher at 1,000 Baht per hour. The equipment cost per task is 2,000 Baht. In this research, the work content for all equipment could be estimated by referencing to typical maintenance processes such as scheduled and unscheduled maintenance visits, component monitoring, job scheduling and routing, labor time collection, cost collection, inventory management, and maintenance document management. It turns to be the complex parameter (α_{ki}) and it is set at 1 throughout. The boundary of desirability function is shown in Figure 2 and both $\alpha_i^{'}s$ are set at 1.

MKH algorithm
Initialize algorithm parameters:
N^{max} : maximum speed
v_f : foraging speed
D^{max} : maximal speed of diffusion
ω_n : inertia weight
ω_f : inertia weight
C_r : crossover probability
M_u : mutation probability
S : krill member
I^{max} : maximum iteration value
Rep^{max} : maximum replication value

Start
While (Rep< Rep^{max}) do.
For i = 1 to S (all n krill);
For j=1 to n (n krill)
Rank the krill member from fitness value F(X)
j=j+1
End for j;
i=i+1
End for i;
Sort the n krill, where n ∈ (1, 2, . . ., S)
While (I< I^{max}) do.
For k = 1 to S do
Perform the three motion
Update each krill
krill operators: Crossover and mutation
k=k+1
End for I;
Rank the krill member and find the current best;
Apply three swap process mechanisms;
I=I+1
End while I:
End while Rep:
Postprocess results
End procedure.

Figure 1. Pseudo code of the MKH Metaheuristic

In this research, the mixed-integer non-linear programming model for the PMS previously described is developed using the Visual C# program. The PMS model is an approach to determine a practical objective of balancing the workforce levels and maintenance costs over T consecutive time periods via non-linear mathematical functions based on their standard deviations. The PMS model was tested with 30 maintenance jobs. The KHA parameters of Rep^{max}, I^{max}, S, ω_n, ω_f, v_f, M_u, C_r, N^{max} and D^{max} are set at 20, 2000, 40, 0.9, 0.9, 0.02, 0.2, 0.2, 0.01 and 0.005, respectively.

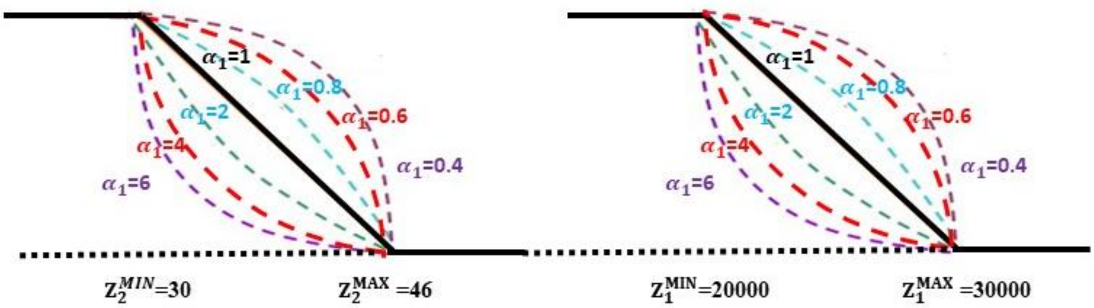


Figure 2. Boundary of Z_1 and Z_2

Table 2. Maintenance jobs categorized by equipment

Type	Equipment	No. of Machines (m_k)	Required man-hours (mhj)	Cost (Cj, Baht)
1	Air Cool Chiller	2	2	2,800
2	Cooling Tower	4	2	5,600
3	Primary Chiller Water Pump	4	0.5	1,400
4	Secondary Chiller Water Pump	5	0.5	1,750
5	Condenser Water Pump	4	0.5	1,400
6	Transfer Pump	4	0.5	1,400
7	Booster Pump	2	0.5	700
8	Fountain Pump	6	0.5	2,100
9	Overflow Pump	4	0.5	1,400
10	Drainage Pump	10	0.5	3,500
11	Submersible Pump	15	0.5	5,250
12	Air Blower Pump	10	0.5	3,500
13	Fire Pump & Generator	5	0.5	1,750
14	AHU. Building A	28	1.5	29,400
15	AHU. Building B	36	1.5	37,800
16	AHU. Building C	8	1.5	8,400
17	FCU. Building A	16	1.5	16,800
18	FCU. Building B	6	1.5	6,300
19	FCU. Building C	8	1.5	8,400
20	FCU. Parking	26	1.5	27,300
21	Pressurized Fan	6	1.5	6,300
22	Smoke Fan	4	1.5	4,200
23	Exhaust Fan	6	0.5	2,100
24	Load center and control Building A	9	1	6,300
25	Load center and control Building B	4	1	2,800
26	Load center and control Building C	2	1	1,400
27	Case A AHU	8	2	11,200
28	Case B PUMP	20	0.5	7,000
29	Case C Electrical Other	60	0.5	21,000
30	Case D Other	75	0.5	26,250

Minimal overall standard deviation of man-hours and costs to generate planning maintenance schedule over all T periods scenarios are analyzed from the previous data with 20 iterations. A complexity parameter (α_{ki}) for the i^{th} machine of the k^{th} type is given for all machinery and equipment in a retail store, are evaluated through the similarities between the machines of interest and the pre-defined standard unit in the management plan. Therefore, a job content for each maintenance of machinery and equipment by maintenance workers employed throughout the year can be estimated by referring to the machine complexity parameters. Guidelines or corrective actions for facility maintenance are compiled to determine the allocated costs for each machine over the entire T planning period.

Table 3 summarizes the experimental results, reporting maximal, minimal, mean, standard deviation (stdev.), individual desirability, and overall desirability levels. In general, the KHA and its variants do not consume large memory and CPU time compared with the proposed mathematical model. When the KHA variants MKH1, MKH2 and MKH3 were compared, it emerged that the MKH1 could find solutions better than all remaining algorithms in terms of the means on both objectives. Moreover, the median cost of a MKH1 is minimal, which represents the stability of the results of this algorithm (Figure 3). However, means are not significant difference ($p<0.05$). Moreover, the best so far maintenance job scheduling was provided by the MKH2 variant: it brings the lowest cost and man-hours in each month, as shown in Table 4.

The maintenance schedule obtained from applying the mixed-integer non-linear programming model differs from the current schedule by smoothing the workforce levels and maintenance costs through T. On the best-so-far maintenance scheduling obtained via the MKH2, disassembly, repair and assembly bring expenses or delayed service operation. However, if the large retail store has a well-supported and robust plan, with another machine working temporarily as a backup in the event that a current machine is unavailable, the service process can therefore be continued. However, changing to another machine may result in a change in the machine sequences as well as the material handling distance during the change as well. Production flexibility helps the ability to respond to unpredicted changes that might occur and helps to maintain production efficiency, as well as increasing the competitiveness of nowadays industry.

5. Conclusions and Discussion

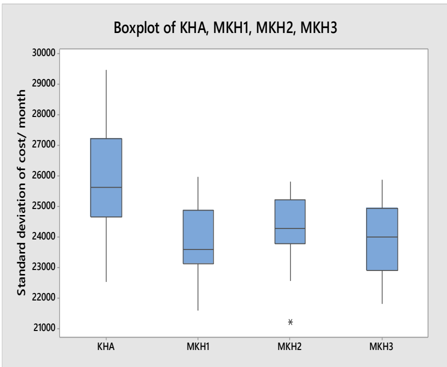
A multi-objective optimization algorithm with different desirability functions is introduced to determine the optimized solutions via the modified krill herd algorithm. To do this, we generate candidate solutions of the periodic maintenance scheduling problem from a large Thai department store as a case study. The study focuses on predetermined sequences of maintenance operations on various machine types for specific planning periods. An aim is to minimize variance levels-based performance measures on the total man-hours and cost for all the planning horizons with

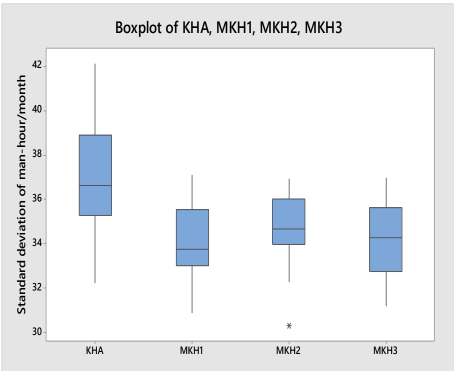
Table 3. Statistical performances categorized by algorithms

Stdev based performance	KHA		MKH1		MKH2		MKH3	
	Cost	Man-hours	Cost	Man-hours	Cost	Man-hours	Cost	Man-hours
Max	29,472.38	42.10	25,969.28	37.10	25,836.86	36.90	25,888.54	36.98
Min	22,546.34	32.20	21,616.36	30.88	21,225.40	30.32	21,825.54	31.18
Mean	25,829.96	36.90	23,874.16	34.10	24,280.16	34.68	23,986.32	34.26
Stdev.	1,798.92	2.56	1,179.92	1.68	1,116.94	1.60	1,343.42	1.92
Desirability	0.75	0.86	0.84	0.94	0.88	0.98	0.82	0.93
Max OD	0.86		0.94		0.98		0.93	

Table 4. Best-so-far of cost and man-hour via the MKH2

Performance	Planning Period					
	1	2	3	4	5	6
Cost per month	42,000	45,500	46,200	42,350	40,950	38,500
Man-hour per month	60	65	66	60.5	58.5	55
Tasks	3,24,2,21,26,29	9,14,4,27,13	10,23,8,15,7	5,20,6,11,28	16,30,18	1,17,19,22,25,12





Figre 3. Performance comparison based on Z_1 and Z_2

equal weights. Thereafter a modified krill herd algorithm is employed to find the best so far setting.

The resulting variable neighborhood with swap mechanisms seems the best choice. The results show the efficiency of our proposed KHA on solution quality and the CPU working time. The comparisons confirm that the MKH2 variant is more reliable than previous works when considering the overall desirability levels. On preliminary studies, MKH2 seeks to improve the operation of strength and the time required for the optimization of highly complex functions involving multiple dimensions. The MKH2 variant might then serve as a starting point for the design of innovative new future algorithms. The KHA could be expanded through hybridization with existing alternative techniques. Variants of algorithm parameter settings could be tried to get a better understanding of their benefits. The maintenance planning can include other maintenance strategies as reliability-based approaches.

Acknowledgements

First author would like to thank the Faculty of Engineering, King Mongkut's University of Technology North Bangkok. For the second author, this work was supported by Thammasat University Research Unit in Industrial Statistics and Operational Research and the research funding from Faculty of Engineering, Thammasat University.

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