Application of Krill Herd (KH) Algorithm for Production Scheduling in Capital Goods Industries

Hathaithanok Puongyeam, Pupong Pongcharoen*, and Srisatja Vitayasak

***Abstract*—** Production scheduling is one of the essential business operations particularly in capital goods company preferring to reduce inventory by delivery of goods based on limited time whilst simultaneously accomplish high resource utilisation. The capital goods industry manufactures complex products with highly customised and manufactured in low volume on the make/engineer-to-order basis. Effective production scheduling must be met the customer due dates as well as minimised the total earliness and tardiness penalties cost. This paper presents the application of the Krill Herd (KH) algorithm and proposes the Modified Krill Herd algorithm (MKH) for solving production scheduling problem. The computational experiments were carried out using various sizes of scheduling problem obtained from a capital goods company. The analysis on the computational results indicates that the MKH algorithm significantly performed better than the conventional KH algorithm for all problems.

***Keywords*—**Krill Herd Algorithm, scheduling, capital goods

I. Introduction

IN commercial context, businessman makes an attempt at extracting the maximum output or profit from a limited amount of usable resources. Production scheduling can be defined as the allocation of available resources over time to perform a collection of tasks that best satisfy some set of criteria [1]. Scheduling is one of the core business operations particularly in manufacturing industry since companies seek to deliver products on just in time basis as well as achieve high resource utilisation. Scheduling is a combinatorial optimisation problem and classified as non-deterministic polynomial (NP) hard problem [2], meaning that the number of computations need to find solution increase exponentially with problem size.

The business activities of capital goods companies are the design, manufacturing and structuring of large products such as turbine generators, cranes and boilers [3], each of which need a large number of operations on machines and operating cost. These products have extremely complex and deep product construction with many levels of assembly, which gives increase assembly precedence constraints. The customer demand is highly variable and uncertain.

Centre for Operation Research and Industrial Applications (CORIA), Faculty of Engineering, Naresuan University, Pitsanulok, Thailand 65000.

KH algorithm [4], introduced by Gandomi and Alavi, is a novel biologically-inspired algorithm. These branches are population-based stochastic search algorithms working with best-to-survive criteria [5]. One of the noticeable advantages of KH algorithm is that the derivative information is not necessary because it uses a stochastic random search rather than a gradient search and the other important advantage of KH algorithm is its simplicity, therefore, it is very easy to implement [6].

The objectives of this paper were to: propose the Modified Krill Herd algorithm (MKH) for scheduling capital goods; investigate the appropriate parameter setting of the proposed method using statistical tools for experiment design and analysis; and compare the performance of the MKH algorithm with the ordinary KH algorithm in terms of the quality of the solutions achieving within the same amount of search and computational time need to solve four industrial cases.

The remaining sections of this paper are structured as follows. The next section shortly presents the particularities and the assumptions of scheduling problem for manufacturing capital goods. Section 3 and 4 explain the KH algorithm and proposed the MKH algorithm to solve the complex scheduling problems adopted from a capital goods industries. Section 5 presents the experimental design and provides a statistical analysis on the experimental results. These are followed by the conclusions in section 6.

II. Production scheduling problem

A. Capital Goods Industry

Sequencing usually determines the order of operations or jobs to be performed on processor(s) or resource(s). The sequencing process is sometimes constrained by precedence relationship and assembly precedence. Scheduling is defined as the allocation of resources over time to execute an assemblage of jobs [7].

The production scheduling problem in capital goods industry is one of the most important and complicated problem in machine scheduling. This problem is characterised as NP-hard. The high complexity of the problem makes it hard to find the optimal solution within reasonable time in most cases. The main products have deep and complex product structures, typically with eight levels of assembly [3]. This

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type of scheduling problem has been solved by various metaheuristics e.g. Artificial Bee Colony [8]-[9], Bat Algorithm [10]-[11], Firefly Algorithm [12], Genetic Algorithms [13, 14], Particle Swarm Optimisation [15], Shuffled Frog Leaping [16].

A typical product structure of a capital goods is shown in Fig. 1. Each node represents the final product that requires many assemblies. The branch nodes correspond to the components, each of which needs manufacturing operation on different machines.

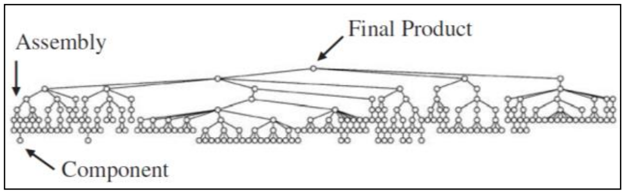

Fig. 1 A product structure of a capital goods [3].

B. Equations

The scheduling objective function that is used in this work is give as in (1). [17, 18]

$$\text{Total cost} = \sum\sum Pe\,(E_{jk}+E_k) + \sum Pt\,(T_k) \qquad (1)$$

Subject to:

$ST_{ijkm} \geq R_m \qquad \forall_{i,j,k,m} \qquad (2)$

$FT_{ijkm} = ST_{ijkm}+SU_{ijkm}+TT_{ijkm} \qquad \forall_{i,j,k,m} \qquad (3)$

$C_{jk} \geq FT \qquad \forall_{i,j,k,m} \qquad (4)$

$E_{jk} = (D_{jk}-C_{jk})/\text{Sh} \qquad \forall_{i,k} \qquad (5)$

$E_k = (D_k-C_k)/\text{Sh} \qquad \forall_{k} \qquad (6)$

$T_k = (C_k-D_k)/\text{Sh} \qquad \forall_{k} \qquad (7)$

$ST_{ixkm}-ST_{ijkm} \geq SU_{ijkm}+PT_{ijkm}+TT_{ijkm} \qquad \forall_{i,j,k,m;i\in S(x)} \qquad (8)$

$ST_{gjkm}-ST_{ijkm} \geq SU_{ijkm}+PT_{ijkm}+TT_{ijkm} \qquad \forall_{i,j,k,m;g=i+1} \qquad (9)$

$X_{ijkmabcm}+X_{abcmijkm} = 1 \qquad \forall_{a,b,c,i,j,k,m} \qquad (10)$

$X_{ijkmabcm} \in (0,1) \qquad \forall_{a,b,c,i,j,k,m} \qquad (11)$

$E_{jk}, E_k, T_k \geq 0 \qquad \forall_{i,k} \qquad (12)$

$ST_{ijkm}, R_m \geq 0 \qquad \forall_{i,j,k,m} \qquad (13)$

$FT_{ijkm}, ST_{ixkm}, SU_{ijkm}, PT_{ijkm}, TT_{ijkm} \geq 0 \qquad \forall_{i,j,k,m} \qquad (14)$

The following notation is introduced for using in the model.

Notions:

i = operation i^{th} (i = 1, 2, …, O)

j = part or component j^{th} (j = 1, 2, …, C)

k = final product k^{th} (k = 1, 2, …, P)

m = machine m^{th} (m = 1, 2, …, M)

E_k = earliness duration of product k^{th}

E_{jk} = earliness duration of component j^{th} in product k^{th}

T_k = tardiness duration of product k^{th}

$X_{ijkmabcm}$= 1 if operation i^{th} for component j^{th} in product k^{th} precedes operation a^{th} for component b^{th} in product c^{th} on machine m^{th}; and 0 otherwise

R_m = ready time of machine m^{th}

C_k = completion time of product k^{th}

C_{jk} = completion time of component j^{th} in product k^{th}

D_k = due date of product k^{th}

D_{jk} = due date of component j^{th} in product k^{th}

SU_{ijkm}= setup time of operation i^{th} for component j^{th} in product k^{th} on machine m^{th}

ST_{ijkm}= start time of operation i^{th} for component j^{th} in product k^{th} on machine m^{th}

PT_{ijkm}= processing time of operation i^{th} for component j^{th} in product k^{th} on machine m^{th}

FT_{ijkm} = finishing time of operation i^{th} for component j^{th} in product k^{th} on machine m^{th}

TT_{ijkm}= transfer time of operation i^{th} for component j^{th} in product k^{th} on machine m^{th}

Pe = earliness penalty (currency unit per day)

Pt = tardiness penalty (currency unit per day)

$S(x)$ = set of child items of item x

Sh = working hour per shift (minutes per shift)

III. Krill Herd Algorithm (KH)

The KH algorithm is based on the simulation of the herding behaviour of krill individuals. It is a new general stochastic optimisation approach for the global optimisation problem. The minimum distances of each individual krill from food and from highest density of the herd are considered as the objective function for the krill movement. The KH approach repeats the implementation of the three movements: movement induced by other krill individuals (N_i); foraging activity (F_i); and random diffusion (D_i) [4],[19].

In KH method, the Lagrangian model [4] is used within predefined search space as Eq. (15)

$$\frac{dX_i}{dt} = N_i + F_i + D_i \qquad (15)$$

A. Movement induced by other krill individuals (N_i)

In movement affected by other krill individuals, the direction of motion (α_i) is approximately computed by the following three factors: (a) target effect (target swarm density), (b) local effect (a local swarm density), and (c) a detestable effect (repulsive swarm density). For a krill individual, this movement can be defined as Eq. (16) and N^{max} is the maximum induced speed, ω_n is the inertia weight of the motion induced in [0,1], and N_i^{old} is the last motion induced [4].

$$N_i^{new} = N^{\max}\alpha_i + \omega_n N_i^{old} \qquad (16)$$

B. Foraging activity (F_i)

The foraging motion comprises two main components that are the current food location and the previous experience about the food location. For the krill individual, this motion can be formulated as Eq. (17-18), where v_f is the foraging speed. ω_f is the inertia weight of the foraging motion in [0,1]. F_i^{old} is the last foraging motion. β_i^{old} is the food attractive and β_i^{best} is the effect of the best fitness of the krill individual so far [4].

$$F_i = V_f \beta_i + \omega_f F_i^{old} \qquad (17)$$

Where

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{18}$$

C. Physical diffusion (D_i)

For the krill individuals, as a matter of fact, the physical diffusion is a random process. This motion includes two components: a maximum diffusion speed and oriented vector. It can be formulated as follows:

$$D_i = D^{max}\left(1 - \frac{I}{I_{max}}\right)\delta \tag{19}$$

Where

D^{max} is the maximum diffusion speed. δ is the random directional vector and its arrays are random numbers [-1,1]. I is the actual iteration number and I_{max} is the maximum number of iterations [4].

Begin
Step 1: Define population size (S) and iteration (I_{max})
Step 2: **Initialisation**. Set the iteration counter I = 1; initialise the population (X_i); i = 1, 2, 3…, S krill individuals randomly and each krill corresponds to a potential solution to the give problem; set the foraging speed V_f, the maximum diffusion speed D^{max}, and the maximum induced speed N_{max}.
Step 3: **Fitness evaluation**. Evaluate each krill individual according to its position.
Step 4: **While** the termination criteria are not satisfied **or I < I_{max}** Iteration **do**
Sort the population/krill from best to worst.
for i = 1: S (all frill) **do**
Perform the following motion calculation.
Movement induced by other krill individuals
Foraging activity
Physical diffusion
Implement the genetic operators.
Update the krill individual position in the search space.
Evaluate each krill individual according to its position.
End for *i*
Sort the population/krill from best to worst and find the current best.
I_{max} = I+1.
Step 4: **end while**
Step 5: Post-processing the results and visualization.
End.

Fig. 2 Pseudo code of KH algorithm adopted from [6]

IV. MODIFIED KH ALGORITHM (MKH)

To some extent, all meta-heuristic algorithms strive towards making balance between randomisation global search and local search [20]. The KH algorithm is one of the effective optimisation methods containing both exploration and exploitation mechanisms for seeking the best solution [6], [21]. However, sometimes it may not escape some local best solution in search space solution so that it cannot be optimal solution. MKH algorithm combines the exploitation of employed bees (for global best artificial bee colony algorithm: GABC [22]) with the exploration of KH algorithm productively, therefore, it can generate the promising candidate solutions. KH algorithm can explore the search space effectively and efficiently but sometimes it may escape some local optima [21]. For KH algorithm, the search depends completely on random search [23], a method has been proposed which escape randomness and irregularity to search space .

In this work, the MKH algorithm was developed that increases the number of local best solutions. The pseudo code of MKH algorithm applied to solve the production scheduling problem is shown in figure 3. It can be formulated as follows [22]:

$$ch_{i+1} = \sin(\pi ch_i),\ ch_i \in (0,1),\ i = 0, 1, 2, \ldots, S \tag{20}$$

$$V_{i,j} = X_{best,j} + D_i\ (X_{Cr,j} - X_{Mu,j}) \tag{21}$$

Where

$X_{Cr,j}$ is the food location and position individual krill for crossover operator.

$X_{Mu,j}$ is the food location and position individual krill for mutation operator.

The KH algorithm based scheduling program was coded in modular style using a general purpose programming language called TCL/TK programming language. A personal computer with Intel Core 2 Quad Processor 2.66 GHz CPU and 4.00 GB RAM was used to determine the simulation time required to execute a computational run.

Begin
Step 1: Define population size (S) and iteration (I_{max})
Step 2: **Initialisation**. Set the iteration counter I = 1; initialise the population (X_i); i = 1, 2, 3…, S krill individuals by equation (20) and each krill corresponds to a potential solution to the give problem; set the foraging speed V_f, the maximum diffusion speed D^{max}, and the maximum induced speed N_{max}.
Step 3: **Fitness evaluation**. Evaluate each krill individual according to its position.
Step 4: **While** the termination criteria are not satisfied **or I < I_{max}** Iteration **do**
Sort the population/krill from best to worst.
for i = 1: S (all frill) **do**
Perform the following motion calculation.
Movement induced by other krill individuals
Foraging activity
Physical diffusion
Implement the genetic operators.
The new food location and position individual krill in search space by equation (21)
Update the krill individual position in the search space.
Evaluate each krill individual according to its position.
End for *i*
Sort the population/krill from best to worst and find the current best.
I_{max} = I+1.
Step 4: **end while**
Step 5: Post-processing the results and visualization.

Fig. 3 Pseudo code of MKH algorithm adopted from [6],[22]

V. EXPERIMENTAL DESIGN AND ANALYSIS

In this work, the computational was developed using a two-step sequential experiment. The first experiment was aimed to investigate the impact of parameters' setting on the KH algorithm performance. A sequential experiment was planned to study the performance

Comparison of the proposed MKH algorithm with ordinary KH algorithm in terms of the penalty cost of the best so far (BSF) solution, average BSF solution and average action time (min.) acquired.

This work considered four different problem sizes: small, medium, large and extra-large. The characteristics of scheduling problems are shown in Table 1.

TABLE I

THE CHARACTERISTICS OF THE SCHEDULING PROBLEMS [24]

Problem Sizes	Characteristics of scheduling problem				
	No. of Products	No. of Components	Machining/ assembly operations	No. of Machines	Level of product structure
Small	2	6	25/9	8	4
Medium	2	8	57/10	7	4
Large	2	12	118/17	17	4
Extra-large	1	46	229/39	25	6

A. KH's screening experiment

The first experiment was aimed to statistically examine the suitable parameter setting of the KH algorithm via the statistical design and analysis. The one-quarter fraction factorial experimental design (2^{k-2}) shown in table 2 was applied to this work.

TABLE II

EXPERIMENTAL FACTORS AND ITS LEVELS

Factors	Levels	Values	
		Low (-1)	High (1)
P/I	2	25/100	100/25
ω_n	2	0.1	0.9
ω_f	2	0.1	0.9
D^{max}	2	0.002	0.010
Crossover	2	0.1	0.9
Mutation	2	0.1	0.9

P/I = population×iteration, ω_n = the inertia weight of the motion induced in the range [0,1], ω_f = the inertia weight of the foraging motion in the rand [0,1], D^{max} = the maximum diffusion speed.

From table 2, there were six factors, each of which was determined at two levels. The previous factors were the combination of the several parameters, *P/I*, ω_n, ω_f, D^{max}, Crossover and Mutation executed an important function on the amount of search in solution space conducted within the KH algorithm. The several parameters increased in the probability of finding the best solution but required longer computational time. In this work, the amount of search (a combination of *P/I*) for the problem was predetermine at 2,500.

The one-quarter fraction factorial (2^{6-2}) experimental design [25] was utilised for the screening experiment, which shortened the number of computational runs by 75% per replication, was carried out with five replications using different random seed numbers. This experiment was based on the extra-large scheduling problem. The computational results acquired from 80 (2^4x5) runs were analysed using a general linear model from of analysis of variance (ANOVA). Table 3 shows an ANOVA table consisting of Source of Variation, Degrees of Freedom (DF), Sum of Square (SS), Mean Square (MS), F and P values. A factor with P values less than or equal to 0.05 was considered statistically significant with 95% confidence interval.

TABLE III

ANOVA ON THE KRILL HERD (KH) PARAMETER

Source	DF	SS	MS	F	P
P/I	1	3.46320E+12	3.46320E+12	14.03	**0.000**
ω_n	1	2486450000	2486450000	0.01	0.920
ω_f	1	2486450000	2486450000	0.01	0.920
D^{max}	1	7430512500	7430512500	0.03	0.863
Crossover	1	7430512500	7430512500	0.03	0.863
Mutation	1	34569612500	34569612500	0.14	0.709
Error	64	1.76185E+13	2.75289E+11		
Total	79	2.15337E+13			

From ANOVA table, it can be seen that the combination of *P/I* were statistically significant with 95% confidence interval. The main effect plots on all KH algorithm's parameters considered is shown in figure 4. The statistical analysis suggested that the best schedules were obtained from the KH algorithm when the *P/I* combination was set at 25/100. The remaining KH parameters were statistically insignificant in this particular problem with 95% confidence interval.

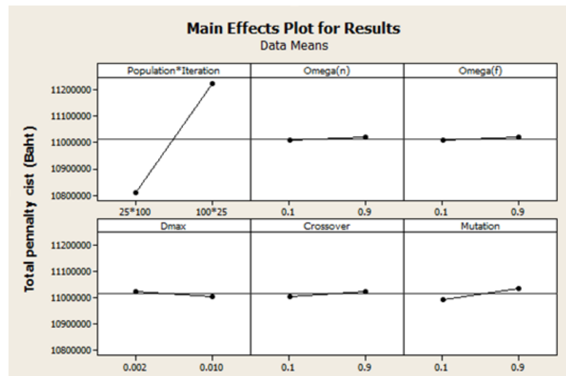

Fig. 4 Main effect plots of the KH algorithm.

B. Performance comparison of KH and MKH

This experiment was to compare the results obtained from the KH algorithm with the results obtained from the MKH algorithm. The computational experiment on the KH algorithm based scheduling program for each problem size using conventional KH algorithm and MKH algorithm was carried out with 30 replications with assigned different random seed numbers. The computational results acquired from a total of 240 runs were analysed in table 4.

According to the statistical analysis on the average and standard deviation of the computational results acquired, from different settings of the KH algorithm parameters shown in table 3, it can be seen that the KH algorithm's parameters *P/I*, ω_n, ω_f, D^{max}, crossover and mutation were advised at 25/100, 0.1, 0.9, 0.010, 0.9 and 0.1 respectively.

TABLE IV

TOTAL PENALTY COST INVOLVED WITH THE PRODUCTION SCHEDULES ACQUIRED FROM EACH PROBLEM SIZE

[CURRENCY UNIT ($\times 1000$)].

Problem size	Method	BSF solution	Average BSF	Standard Deviation	Average run time (min.)	T-value	P-value
Small	KH MKH	15 15	16.367 15.183	1.017 0.245	1.00 1.00	6.20	0.00
Medium	KH MKH	54.5 52	58.367 56.083	1.306 1.486	2.80 2.07	6.32	0.00
Large	KH MKH	245.5 249.0	291.0 278.667	13.743 10.753	5.13 5.07	-3.87	0.00
Extra Large	KH MKH	10,280.0 9,721.0	11,727.08 10,675.53	563.932 508.214	18.33 17.56	7.59	0.00

The purpose of experimental results shown in table 3 was to compare the performance of the proposed MKH algorithm with ordinary KH algorithm in terms of the quality of solution acquired and computational time needed for using the suitable parameters in the previous experiment.

From table 4, it can be seen that the penalty cost of the BSF solution from both MKH algorithm and KH algorithm were marginally different for the medium size and extra-large size problems. The proposed MKH algorithm produced BSF schedules with lower penalty cost than the conventional KH algorithm for the medium size and extra-large size problems. In terms of the average Best-so-far (BSF), schedules obtained from MKH have lower average BSF penalty cost than those results obtained from the ordinary KH algorithm for all problem sizes. Likewise, the average execution time (min.) taken by the MKH algorithm were marginally quicker than the conventional KH algorithm.

The P-value correlative with two sample analysis was applied to analyse the statistical difference between two groups of results acquired from both algorithms. The average penalty cost connected with the production schedules acquired from the MKH algorithm were significantly lower than that acquired by the conventional KH algorithm (with a 95% confidence interval). This was the case for all problem sizes. The computational experiments indicated that the MKH algorithm performance can produce schedules with lower penalty cost than those acquired from ordinary KH algorithm for small, medium, large and extra-large size problems with up to 8%, 4%, 4% and 10% respectively. The average execution time (min.) taken by the conventional KH algorithm were longer than that taken by the MKH algorithm with up to at 35%, 1% and 4% for medium, large and extra-large size problems respectively.

VI. Conclusions

This work explains the development of production scheduling tool, in which the Modified Krill Herd (MKH) algorithm was applied to solve production scheduling in capital goods industry. This paper demonstrated the use of the experimental design and analysis tools to investigate the appropriate parameter setting before sequentially conducting a comparative study on the performance of the proposed methods. The general liner model form of the analysis of variance (ANOVA) indicated that all the KH parameters except the coefficient rate were statistically significant with a 95% confidence interval. The main effect plots and P-value suggested that the *P/I* parameter should be set at 25/100. The performance of the MKH algorithm was better than that of the ordinary KH algorithm in terms of both qualities of solutions obtained and average computational time.

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References

[1] S. Graves, "A Review of Production Scheduling," Operations Research, vol. 29, pp. 646-675, 1981. http://dx.doi.org/10.1287/opre.29.4.646

[2] J. King and A. Spachis, "Scheduling: Bibliography & Review," International Journal of Physical Distribution & Logistics Management, vol. 10, pp. 103-132, 1980. http://dx.doi.org/10.1108/eb014469

[3] C. Hicks and P. Pongcharoen, "Dispatching rules for production scheduling in the capital goods industry," International Journal of Production Economics, vol. 104, pp. 154-163, 2006. http://dx.doi.org/10.1016/j.ijpe.2005.07.005

[4] A. H. Gandomi and A. H. Alavi, "Krill herd: A new bio-inspired optimization algorithm," Communications in Nonlinear Science and Numerical Simulation, vol. 17, pp. 4831-4845, 2012. http://dx.doi.org/10.1016/j.cnsns.2012.05.010

[5] Tang and Wu, "Biologically inspired optimization: a review," Transactions of the Institute of Measurement and Control, vol. 31, pp. 495-515, 2009. http://dx.doi.org/10.1177/0142331208094044

[6] G. Wang, et al., "Incorporating mutation scheme into krill herd algorithm for global numerical optimization," Neural Computing and Applications, vol. 24, pp. 853-871, 2014/03/01 2014.

[7] Baker, "A review of: "Introduction to Sequencing and Scheduling."," International Journal of Production Research, vol. 13, pp. 654-654, 1975/01/01 1975.

[8] P. Pansuwan, et al., "Identifying Optimum Artificial Bee Colony (ABC) Algorithm's Parameters for Scheduling the Manufacture and Assembly of Complex Products," in Computer and Network Technology (ICCNT), 2010 Second International Conference on, 2010, pp. 339-343.

[9] P. Pongcharoen, et al., "Artificial Bee Colony with Random Key Technique for Production Scheduling in Capital Goods Industry " in 2012 2nd International Conference on Industrial Technology and Management (ICITM 2012), 2012, pp. 66-70.

[10] P. Musikapun and P. Pongcharoen, "Solving Multi-Stage Multi-Machine Multi-Product Scheduling Problem Using Bat Algorithm " in 2012 2nd International Conference on Management and Artificial Intelligence, 2012, pp. 98-102.

[11] S. Chansombat, et al., "A Modified Bat Algorithm for production scheduling in the Capital Goods Industry," in 22 International Coference on Production Research, 2013.

[12] N. Rukwong, "Application of Firefly Algorithm for solving production scheduling," 2010.

[13] P. Pongcharoen, "Genetic algorithms for production scheduling in capital goods industries.," International Journal of Production Economics, vol. 104, pp. 154-163, 2001.

[14] P. Pongcharoen, et al., "Applying designed experiments to optimize the performance of genetic algorithms used for scheduling complex products in the capital goods industry," Journal of Applied Statistics, vol. 28, pp. 441-455, 2001/03/01 2001.

[15] C. Kaweesirikon, Particle Swarm Optimisation for prodution scheduling, 2007.

[16] S. Chompooming, "Shuffled Frog Leaping Algorithm for production scheduling in capital goiods industries," 2009.

[17] Pongcharoen, et al., "Determining optimum Genetic Algorithm parameters for scheduling the manufacturing and assembly of complex products," International Journal of Production Economics, vol. 78, pp. 311-322, 2002. http://dx.doi.org/10.1016/S0925-5273(02)00104-4

[18] Pongcharoen P., et al., "The development of genetic algorithms for the finite capacity scheduling of complex products, with multiple levels of product structure," European Journal of Operational Research, vol. 152, pp. 215-225, 2004. http://dx.doi.org/10.1016/S0377-2217(02)00645-8

[19] G.-G. Wang, et al., "Stud krill herd algorithm," Neurocomputing, vol. 128, pp. 363-370, 2014. http://dx.doi.org/10.1016/j.neucom.2013.08.031

[20] X.-S. Yang, et al., Metaheuristics in water, geotechnical and transport engineering: Newnes, 2012.

[21] G.-G. Wang, et al., "An effective krill herd algorithm with migration operator in biogeography-based optimization," Applied Mathematical Modelling.

[22] W. Gao, et al., "A global best artificial bee colony algorithm for global optimization," Journal of Computational and Applied Mathematics, vol. 236, pp. 2741-2753, 2012. http://dx.doi.org/10.1016/j.cam.2012.01.013

[23] W. Gaige, et al., "Lévy-flight krill herd algorithm," Mathematical Problems in Engineering, vol. 2013, p. 14, 2013.

[24] P. Pongcharoen, et al., "Determining optimum Genetic Algorithm parameters for scheduling the manufacturing and assembly of complex products," International Journal of Production Economics, vol. 78, pp. 311-322, 2002. http://dx.doi.org/10.1016/S0925-5273(02)00104-4

[25] D. Montgomery, Design and analysis of experiments, 4th ed. ed. New York, N.Y. :: John Wiley & Sons, 1997.