A hybrid optimization approach for sustainable process planning and scheduling

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Abstract. Process planning and scheduling are important stages in manufacturing, and good strategies can significantly improve the energy performance of manufacturing to achieve sustainability. In this paper, an innovative optimization approach has been developed to facilitate sustainable process planning and scheduling. In the approach, honey-bee mating and annealing processes are simulated to optimize multi-objectives including energy consumption, makespan and the balanced machine utilization. Experiments on practical cases show that the optimization results from this approach are promising in comparison with those from a genetic algorithm, a honey bee mating optimization algorithm, ant colony optimization and a simulated annealing algorithm, respectively.

Keywords: Honey bee mating optimization, Simulated annealing, Sustainable manufacturing, Process planning, Scheduling

1. Introduction

With the rapidly growing production demands, manufacturing has become one of the largest energy consuming sectors [50]. Statistics has shown that the greenhouse gas emitted from the usage of energy sources such as electricity, coal, oil and gas during manufacturing accounts for more than 37% even 50% of the world's total greenhouse gas emissions [38]. In order to balance the multi-faceted dimensions of economic growth and environmental protection, a series of regulations and guidelines, such as the European standard EN 16001:2010 [10], life-cycle carbon labeling outlined by the life-cycle assessment frameworks of the ISO 14040: 2006 and ISO 14044: 2006 [19, 20], and the Publicly Available Specification 2050: 2008 (PAS 2050) [47], have been developing. For manufacturing companies, based on the regulations and guidelines, energy efficiency can be improved and the greenhouse gas emission level can be minimized so as to embrace "Competitive Sustainable Development" and shoulder "Extended Producer Responsibilities (EPR)" [24] effectively. Meanwhile, energy saving is also increasingly vital for customers in choosing products. For instance, a survey indicated that 67% of UK consumers are more likely to buy a product with a lower life-cycle energy consumption and 44% would switch to such a greener product even if the brand/model is not their first choice [54]. Therefore, these economic, environmental and competitive factors are motivating manufacturing companies to take measures to minimize their energy consumption and achieve sustainable manufacturing.

A large number of studies [49] have indicated that careful process planning and scheduling for manufacturing systems will realize great energy savings. That is, process planning and scheduling are critical functions not only to minimize cost, improve adaptability, responsiveness and robustness but also to enhance the sustainability of manufacturing processes. Therefore, effective process planning and scheduling is imperative to achieve sustainable manufacturing.

In order to realize sustainable manufacturing by optimizing process planning and scheduling, a multi-objective optimization problem of minimizing overall energy consumption, makespan and machine utilization in a job shop is considered in this paper. An in-

novative optimization approach for sustainable process planning and scheduling is presented. In this approach, a 5-phase energy consumption model and an effective hybrid honey-bee mating optimization and simulated annealing (HBMO-SA) algorithm are developed to optimize the overall energy consumption in process planning and scheduling.

This research is a comprehensively extended version from a previous work of authors [31], and significant improvements are reflected from the following aspects. First, a detailed literature survey is given. Second, a model of integrated process planning and scheduling for dynamic manufacturing is presented in detail. Finally, the developed HBMO-SA approach is benchmarked with other classic heuristic algorithms to demonstrate its merits and effectiveness.

The remainder of this paper is organized as follows. In Section 2 related work is reviewed. In Section 3, process planning and scheduling are first represented and then its energy consumption model is presented. Then, the HBMO-SA approach is presented in Section 4. In Section 5, case studies and comparisons with other heuristic algorithms are given. Finally, a conclusion is drawn in Section 6.

2. Related works

In recent years, both sustainable manufacturing and process planning and scheduling have attracted many researchers' attention. This section presents a review of the related work from the viewpoint of sustainable manufacturing and heuristic algorithms applied to sustainable manufacturing applications.

2.1. Sustainable manufacturing

The research works focusing on sustainable manufacturing can be viewed from four different perspectives, i.e., machining process, machine design, eco-product development and manufacturing system.

(1) Machining process

Most of the research works were dedicated to quantifying the energy consumed in machining. Some research works focus on developing machine specific models of unit process energy consumption. In the existing models, the most representative one was developed by Gutowski et al [13]. The specific energy consumption (SEC) of machining processes was modeled as a function of the process rate by analyzing the unit process energy for the processes in an exergy framework [13]. However, in the model, the specifications for the fixed power P_0 and the constant k were not given. Taking up the missing specification in the model of Gutowski et al., researchers developed some improved energy consumption models such as the unit process energy consumption model created by Li and Kara [25], the SEC model provided by Diaz et al [8] and the energy consumption model for milling processes developed by Li et al [28].

Different from the research works on modeling unit process energy consumption, some other research works concentrated on modeling the total energy consumption in machining. For instance, Diaz et al. modeled the total energy consumption in machining as a function of average power and the processing time [8]. However, the impact of machine tools, work-piece materials and cutting variables were neglected. Mori et al. presented an energy consumption model which involved the energy consumption of several processes: positioning and acceleration the spindle, returning the spindle to the tool change position after machining and stopping the spindle [36]. He et al. divided the total energy consumption of Numerical Control (NC) machining into five parts, i.e. the energy consumption of spindle, axis feed, tool change system, coolant pump, and the fixed energy consumption. Each part can be estimated by the corresponding power characteristics and the parameters extracted from the NC codes [14]. However, this model can only be used to help NC code designers make decisions regarding energy-efficient NC programs because it is based on the NC programming but ignores some other energy factors consumed by chillers, swarf conveyors and lubrication of machines etc. Aiming at predicting direct electrical energy requirements in machining tool-paths, Balogun and Mativenga divided the energy states of machine tools into three categories: basic, ready and cutting states, where the energy is demanded to activate required machine components, making the axis and tool to be ready for action and remove work-piece material respectively [4]. However, this model is limited because the energy consumed by the machine axis has not been taken into account. Duflou et al. [9] studied the energy efficiency on the machining factory level. However, the energy consumption of preparation phase in scheduling is neglected.

(2) Machine design

The research works focus on developing and designing more energy-efficient machines and equipment. The most representative work is the standard on energy saving for machine tools drafted by the

International Standard Organization (i.e. ISO/WD14955-1) [21]. Two informative annexes related to environmentally relevant improvements and well tried mechanical and electrical components are listed in the standard.

(3) Eco-product development

The related works concentrate on modeling and reducing the embodied product energy (EPE) during manufacturing to support energy efficient manufacturing. A modeling framework was introduced by Seow et al. to represent the total energy required to manufacture a unit product [44]. Another model was built by Kara et al. to assess the impact of global manufacturing on the EPE [26].

(4) Manufacturing system

The energy efficiency of a manufacturing system is improved mainly by two methods. One is simulation based method which improves the energy efficiency by simulating electricity consumption and the process chain [16]. The other is optimization based method which improves the energy efficiency by optimizing the single machine scheduling [37] and the flow shop scheduling [5].

From the literature survey, it can be observed that energy consumption and sustainability are related to the different stages of product development and manufacturing life-cycle. Hence, as an important sector of manufacturing, process planning and scheduling is of great importance for energy saving.

2.2. Algorithms for process planning and scheduling

In the past decade, a number of research works appeared to develop heuristic algorithms [46]. Among these algorithms, GA is the most popular one [2, 3, 15, 22, 32, 55]. It was used to generate the feasible sequences of operations and identify the optimal tool sequence in process planning for machining (e.g., milling). It is proved that GA has a good global search capability [6, 23, 33, 35, 40, 42, 43]. However, the algorithm is liable to be trapped in a local optimum. SA is another algorithm widely used in process planning and scheduling. It was applied to search the optimal solution in process planning and scheduling [29]. SA can identify a good solution quickly but may fluctuate around the local optima due to the lack of the memory mechanism. Additionally, several swarm intelligence algorithms such as ACO [12], particle swarm optimization (PSO) [17, 18, 45, 48, 52, 53] and HBMO [51], were applied to process

planning and scheduling. Compared with the other most known heuristic algorithms such as GA, SA and ACO, HBMO has a better performance in computational effectiveness and stability.

HBMO is a swarm intelligence algorithm which was developed by modeling the mating behavior of honey bee swarm. It is known that the intelligent behaviors of bees include mating, foraging, dance, nest site selection and so on. Hence, different intelligence algorithms can be obtained by modeling different behaviors of honey bee swarm. For instance, the artificial bee colony (ABC) algorithm [41] was developed by simulating foraging behavior of honey bees. Different from these algorithms, HBMO is inspired by the mating behavior of honey bees.

After HBMO was first presented by Abbass [1] to address the propositional satisfiability problems, the algorithm was applied to various domains. Koudil et al. [27] applied HBMO to solve partitioning and scheduling problems in code design. Curkovic and Jerbic [7] used HBMO to address the non-linear diophantine equation benchmark problem. Haddad et al. applied HBMO to optimize reservoir operation and distribution systems. Amiri and Fathian [11] improved HBMO to solve a real-world problem of an Internet bookstore market segmentation, and then, applied the algorithm in clustering. Marinakis et al. [34] used a hybrid algorithm combining HBMO and Greedy randomized adaptive search procedure to solve the vehicle routing problem. Niknam et al. [39] presented an improved HBMO for multi-objective placement of renewable energy resources. Wen et al. [51] first applied HBMO to address process planning problem and obtained a good process plan with minimal global machining cost in reasonable time.

Although HBMO can be used to solve optimization problems and good solutions can be obtained quickly, it often converges to local optima. Therefore, an improved HBMO method is required to overcome this shortcoming.

3. Sustainable Process Planning and Scheduling Approach

3.1. Representations for process planning and scheduling

Process planning and scheduling, which bridges Computer Aided Design (CAD) and Manufacturing Execution Systems (MES), is a critical function to minimize cost, improve adaptability, responsiveness,

robustness and sustainability of manufacturing processes.

The major considerations in process planning include: (1) generating machining operations based on the features of a part to meet desired functional specifications and achieve good manufacturability, (2) identifying machining resources applicable to the operations, and (3) determining the set-up plan and operation sequence according to some criteria such as makespan, energy efficiency and so on. Therefore, a process plan for a part can be represented by a series of machining operations, applicable resources for the operations, set-up plans, operation sequence, etc. A set-up can be generally defined as a group of operations that are manufactured on a single machine with the same fixture.

Based on the generated process plans of parts, the scheduling task is to assign the parts and their machining operations to specific machines to be executed in different time slots, targeting at a good shop floor performance, such as the shortest makespan, the most balanced machine utilization, the least total tardiness, etc. A Gantt chart has been popularly used to represent a schedule of a group of parts, illustrated in Fig. 1. In the Gantt chart, the order in which the parts and their operations are carried out is laid out and the dependencies of the tasks are managed. The X axis of the Gantt chart represents time. Each row in the Y axis represents a machine and the specific arrangement for the operations of the parts on the machine. A machine is comprised of a number of time slots, which can be further classified into idle time slots, preparation time slots for machining operations (further including the set-up time, the machine change time, or the tool change time), and machining time slots of operations.

As a consequence of the above, a part can be manufactured by different process plans. A group of alternative process plans can be generated using two strategies: processing flexibility and operation sequencing flexibility. Processing flexibility refers to the possibility of performing an operation on alternative machines with alternative set-ups or tools. Operation sequencing flexibility corresponds to the possibility of interchanging the sequence in which the operations are performed. For a group of parts, alternative schedules can be created based on scheduling flexibility, which relates to the possibility of arranging different schedules to manufacture the parts and the operations.

3.2. Energy consumption modeling for process planning and scheduling

It has been known that there are a group of machines in the machining resources. Following the process planning and scheduling solution, one or more operations will be executed on the same machine. For a machine, its power profile is illustrated in Fig. 2, which consists of startup phases, idle phases, preparatory phases, working phases, and shutdown phases.

Hence, the energy consumption of a machine can be separated into the corresponding five segments.

The energy consumption during the startup phase can be computed as:

$$E(M_i).startup = \int_{T_i}^{T_{i\_1}} P_{startup}(M_i)dt \tag{1}$$

where $E(M_i).startup$ represents the energy consumed during the startup phase, $P_{startup}(M_i)$ represents the power demand of the i-th machine during the startup phase, T_i and T_{i_1} stand for the start and end time of the startup phase.
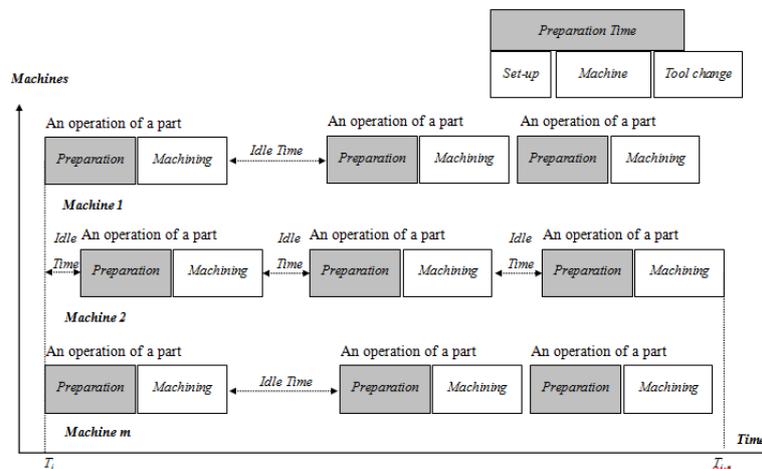

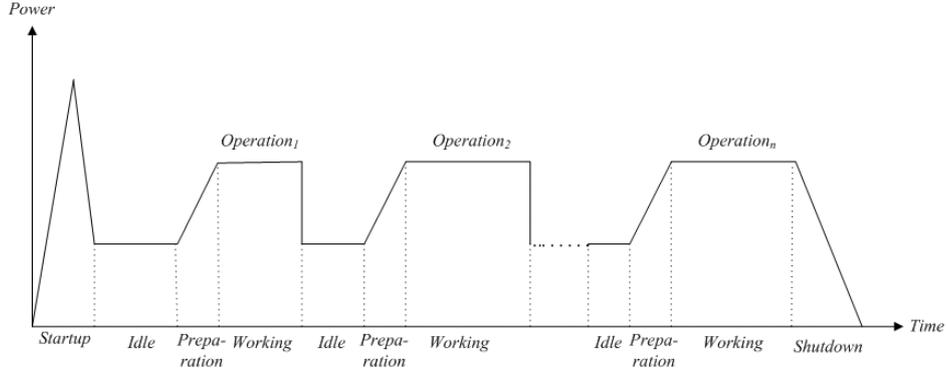Fig. 1. A Gantt chart for scheduling parts and machining operations.

Fig. 2. Different phases of energy consumption for a machine.

The energy consumption during the idle phase can be formulated as:

$$E(M_i).idle = P_{idle}(M_i) \times T_{idle}(M_i) \tag{2}$$

where $E(M_i).idle$ stands for the energy consumption of the idle phase, $P_{idle}(M_i)$ is the power demand of the i-th machine during the idle phase, which is the sum of the power demand of all the components in the machine and usually a constant value. $T_{idle}(M_i)$ stands for the total idle time of the i-th machine and can be represented as:

$$T_{idle}(M_i) = \sum_{j=1}^{n} T_{j,j+1} \tag{3}$$

where n stands for the number of the operations to be executed on the i-th machine, $T_{j,j+1}$ stands for the idle time between the j-th and $(j+1)$-th operations to be executed on the i-th machine. $T_{j,j+1}$ can be obtained by the following pseudo codes.

If $T_j.end < T_{j+1}.start$ then
// The j-th operation ends before the $(j+1)$-th
// operation and the machine will be idle.
$$T_{j,j+1} = T_{j+1}.start - T_j.end$$
Else // There is no waiting.
$$T_{j,j+1} = 0$$
Endif

Here, $T_j.end$ and $T_{j+1}.start$ stand for the j-th operation's end time and $(j+1)$-th operation's start time respectively. Let O be the operation in the process plan, which shares the same part with the $(j+1)$-th operation and is followed by the $(j+1)$-th operation. $T_{j+1}.start$ does not equal to O's end time because O and the $(j+1)$-th operation may be executed on different machines or tools. That is, the time consumed by changing machines should be considered. Thus, $T_{j+1}.start$ can be represented as:

$$T_{j+1}.start = T_O.end + T_{machinechange} + T_{toolchange} \tag{4}$$

where $T_O.end$ and $T_{machinechange}$ and $T_{toolchange}$ stand for O's end time and the time needed for changing machines and tools respectively.

The preparatory phase mainly consists of two activities: machine change and tool change. The energy consumption of the preparatory phase is just the energy consumed during these activities, which can be computed as:

$$E(M_i).preparation = \sum_{j=1}^{n} \int_{T_{i\_2}}^{T_{i\_3}} P_{preparation}(M_i)dt \tag{5}$$

where $E(M_i).preparation$ represents the energy consumed during the preparatory phase, n stands for the number of the operations to be executed on the i-th machine, T_{i_2} and T_{i_3} stand for the start and end time to prepare the j-th operation, $P_{preparation}$ is the power needed during the preparation for the j-th operation, which can be the sum of P_{idle} and the machine change power or the tool change power.

The energy consumption during the working phase can be represented as:

$$E(M_i).working = \sum_{j=1}^{n} E_j(M_i).working \tag{6}$$

where $E(M_i).working$ stands for the energy consumption of the working phase, n stands for the number of the operations to be executed on the i-th machine, $E_j(M_i).working$ stands for the energy consumption of the j-th operation to be executed on the i-th machine. $E_j(M_i).working$ can be computed as:

$$E_j(M_i).working = V_j \times SEC \tag{7}$$

where V_j is the volume of the material removed by the j-th operation, SEC is the energy consumed by removing 1 cm^3 material. SEC can be computed by using the following formulation [25].

$$SEC = C_0 + \frac{C_1}{MRR} \qquad (8)$$

where the coefficient C_0 is related to the work-piece material, tool geometry and spindle drive characteristics; C_1 depends on how the machine tool is designed including its motor and transmission system; *MRR* stands for material removal rate for the working phase, which is influenced mainly by four types of factors, i.e., tool conditions, work-piece material, cutting parameters and cutting environment. For C_0 and C_1, multiple machines' corresponding coefficients were provided by Kara and Li [25]. *MRR* can be obtained using the cutting volume and time.

The energy consumed during the shutdown phase can be computed as:

$$E(M_i).shutdown = \int_{T_{i\_4}}^{T_{i\_5}} P_{shutdown}(M_i)dt \qquad (9)$$

where $E(M_i).shutdown$ represents the energy consumption of the shutdown phase, T_{i_4} and T_{i_5} stand for the start and end time for switching off the *i-th* machine respectively, $P_{shutdown}(M_i)$ stands for the power consumption of the *i-th* machine during the shutdown phase.

Based on the energy consumption of the above phases, the total energy consumption of a machine can be represented below:

$$E(M_i) = E(M_i).startup + E(M_i).idle + E(M_i).preparation +$$
$$E(M_i).working + E(M_i).shutdown \qquad (10)$$

where $E(M_i)$ stands for the total energy consumption of the *i-th* machine.

Therefore, if there are *m* machines to be used in the process planning and scheduling, the overall energy consumed by all the machines to machine all the parts is:

$$E_{Group} = \sum_{i=1}^{m} E(M_i) \qquad (11)$$

3.3. Process planning and scheduling criteria

The energy consumption for a process planning and scheduling, as an essential criterion, has been defined above. Some other criteria based on time to evaluate the performances of process plans and schedules are defined in the following, which consists of the makespan and the balanced level of the machine utilization. In order to present the criteria, two assumptions are made. One is the number of machine (*m*). The other is the number of operations (*n*) to be executed on the machine.

Makespan means the maximum interval time spent to machine all the parts. It can be defined in the following:

$$Makespan = \underset{i=1}{\overset{m}{Max}}(T(M_i)) \qquad (12)$$

where $T(M_i)$ is the total utilization time of the *i-th* machine, which is composed of multiple startup, idle, preparation and working phases. That is, $T(M_i)$ can be represented as:

$$T(M_i) = T(M_i).startup + T(M_i).preparation +$$
$$T(M_i).idle + T(M_i).working \qquad (13)$$

where $T(M_i).startup$, $T(M_i).preparation$, $T(M_i).idle$, and $T(M_i).working$ stand for the time of the corresponding phases. Let O_{ij} be the *j-th* operation to be executed on the *i-th* machine.

$$T(M_i).startup = \sum_{j=1}^{n}(O_{ij}.Startup \times O_{ij}.Startup\_Index) \qquad (14)$$

where $O_{ij}.Startup$ represents whether the *i-th* machine is started up, $O_{ij}.Startup\_Index$ is the time index for each start up.

$$O_{ij}.Startup = \begin{cases} 0 & \text{if the } i-th \text{ machine has been started up} \\ 1 & \text{if not} \end{cases} \qquad (15)$$

$$T(M_i).preparation = \sum_{j=1}^{n}(O_{ij}.MC\_T + O_{ij}.TC\_T) \qquad (16)$$

where $O_{ij}.MC\_T$ and $O_{ij}.TC\_T$ represent the time for machine change and tool change respectively.

$T(M_i).idle$ can be computed by using Eq. 3. $T(M_i).working$ is just the time used to execute all the operations on the *i-th* machine. Thus, it can be computed as:

$$T(M_i).working = \sum_{j=1}^{n}(O_{ij}.Working\_T) \qquad (17)$$

where $O_{ij}.Working\_T$ represents the time used by the *i-th* machine to execute the *j-th* operation.

The standard deviation concept is introduced here to evaluate the balanced machine utilization.

$$\chi = \frac{\sum_{i=1}^{m} T(M_i)}{m} \qquad (18)$$

$$Utilization\_level = \sqrt{\sum_{i=1}^{m}(T(M_i) - \chi)^2} \qquad (19)$$

Based on the above functions, the weighted additive utility function is used to solve multi-objective optimization problem. The total weighted performance criteria (TWPC) can be described as:

$$TWPC = w_1 E_{Group} + w_2 Makespan + w_3 Utilisation\_level \qquad (20)$$

where w_1, w_2 and w_3 are the weights. The value of each weight is between 0 and 1, and the sum of them equals to one.

4. Hybrid HBMO-SA algorithm

4.1. Overview

HBMO is a recently developed evolutionary algorithm. It is inspired by the process of real honey-bee mating and has been applied in some combinatorial optimization problems such as the traveling salesman problem, vehicle routing problem and the process planning problem. Furthermore, all the results have shown that better local optimum solutions can be found quickly using HBMO. However, it has also been observed that HBMO is liable to converge to local optima. Fortunately, SA can be used to compensate for this shortcoming because it can accept some probability. Consequently, in this paper, the strengths of HBMO and SA are combined to achieve the global optimization effectively.

The proposed HBMO-SA consists of two phases: HBMO-phase and SA-phase. In the HBMO-phase, the honey-bee mating process is simulated to generate a population. Good chromosomes in the population are then selected as the initial current process plans and schedules for the SA to search the optimal or near-optimal process plans and schedule. The flowchart of the proposed hybrid HBMO-SA is shown in Fig. 3.

In the hybrid HBMO-SA, the encoding scheme for each individual consists of four parts: operation sequencing, machine sequencing, tool sequencing and tool approaching direction (TAD) sequencing. In the operation sequencing, each position corresponds to an operation number. That is, the *i-th* element of the operation sequence represents the operation that will be executed. The second part is machine sequencing where the *i-th* position corresponds to the machine number used by the *i-th* operation. The third part is tool sequencing that is just the tool number used by the corresponding operation. The fourth part is TAD sequencing used by the operations.

In addition, the reciprocal of the objective function is chosen as the fitness function (cf. equation 21) to follow the rule that the individual with a greater fitness has a higher chance to be chosen. The fitness function for a solution is as follows:

$$Fitness = \frac{1}{TWPC} \tag{21}$$

4.2. Honey-bee mating algorithm: Phase 1

The HBMO algorithm has been developed by simulating the honey-bee mating process. In the mating process, the queen flies far from the nest. During the mating flight, the strong drones catch up with the queen and mate with her. After the queen's spermatheca is full of sperms, she will fly back to the nest and lay eggs. Each time the queen lays eggs, she randomly retrieves a sperm from her spermatheca to fertilize the eggs and a set of broods are generated. Then, the works will take care of and improve the broods (e.g. feeding them with royal jelly). If a brood is better than the queen, it will be the new queen and starts its mating flight. The final queen obtained after all the mating flights is just the optimization result.

As a consequence of the above, the HBMO algorithm should contain a number of different procedures which correspond to the different phases of the honey-bee mating process. The HBMO algorithm can be described as follows:

Step 1: Initialization consists of the following steps:

Step 1.1: The parameters of HBMO, including size of queen's spermatheca, number of drones, workers, number of mating flights, the queen's flight speed at the *t-th* mating *Speed(t)* and its drop coefficient α, are initialized respectively.

Step 1.2: The population of the honey bees (i.e., initial solutions) is created to configure the initial hive. In the proposed algorithm, the initial population, where each individual is composed of the operation sequence, and the selected machine, tool and TAD, is generated using a GA. Then, the reciprocal of the objective function is used as the fitness function and the fitness values of all members are calculated by Eq. 21. According to the fitness values, the queen (i.e. the best schedule in the initial population) with the maximum fitness value is selected. All the other members of the population are used as drones.

It should be pointed out that the GA used to generate the initial population is the basic version of GA. It consists of three operators: selection, crossover and mutation. The roulette-wheel selection is used as the selection operator to choose individuals for crossover and mutation. The two-point crossover is implemented to crossover the first parts of two chromosomes. A specified probability is then used in the mutation operator to judge whether the mutation will be executed. If the probability is greater than a random number, the machine, tool and TAD used by the corresponding operation will mutate.

Step 2: Drones are selected to mate with the queen. A drone mates probabilistically by using an annealing function as follows:

$$e^{\frac{-|\Delta f|}{Speed(t)}} > r \tag{22}$$

where Δf is the difference between the fitness of the drone and queen, which can be evaluated by using the Eq. 21, r is between 0 and 1 and randomly generated, $Speed(t)$ is the queen's flight speed at the t-th mating , the queen's flight speed decays with the mating according to the following equation:

$$Speed(t+1) = \alpha \times Speed(t) \tag{23}$$

where α is between 0 and 1.

Based on this probabilistic rule in Eq. 22, the strong drones with the great fitness value are selected and their sperms are stored in the queen's spermatheca. This selection procedure will not stop until the queen's spermatheca is full.

Step 3: A brood is generated by crossovering the queen's genotype with the sperm selected from the queen's spermatheca. The crossover operator includes the following steps:

Step 3.1: A crossover position P is chosen randomly. The queen and the selected sperm are separated into left and right parts from the crossover point.

Step 3.2: Both the right part of the queen and the left part of the selected sperm are copied to generate a brood.

Step 3.3: The brood is checked to find out those genes that are redundant or lost.

Step 3.4: The redundant genes in the brood are replaced with the lost ones. The machines, tools and TADs are adjusted according to the operations. The new brood is obtained.

Step 4: For each brood, a worker (i.e. a local search heuristics) is chosen randomly to improve it. If the improved brood (i.e., the new solution) has a greater fitness than that of the current queen, it will replace the queen. All the other broods will take part in the next mating flight as drones. The improvement is achieved by three operators: mutation, adjacent swapping and shift.

- The mutation operator is achieved mainly by two steps. First, an operation in the current solution is selected randomly. Then, the corresponding machine and tool are renewed from the candidate lists.
- The adjacent swapping is realized by exchanging two adjacent operations in the current solution. Meanwhile, the corresponding machines, tools and TADs are exchanged.
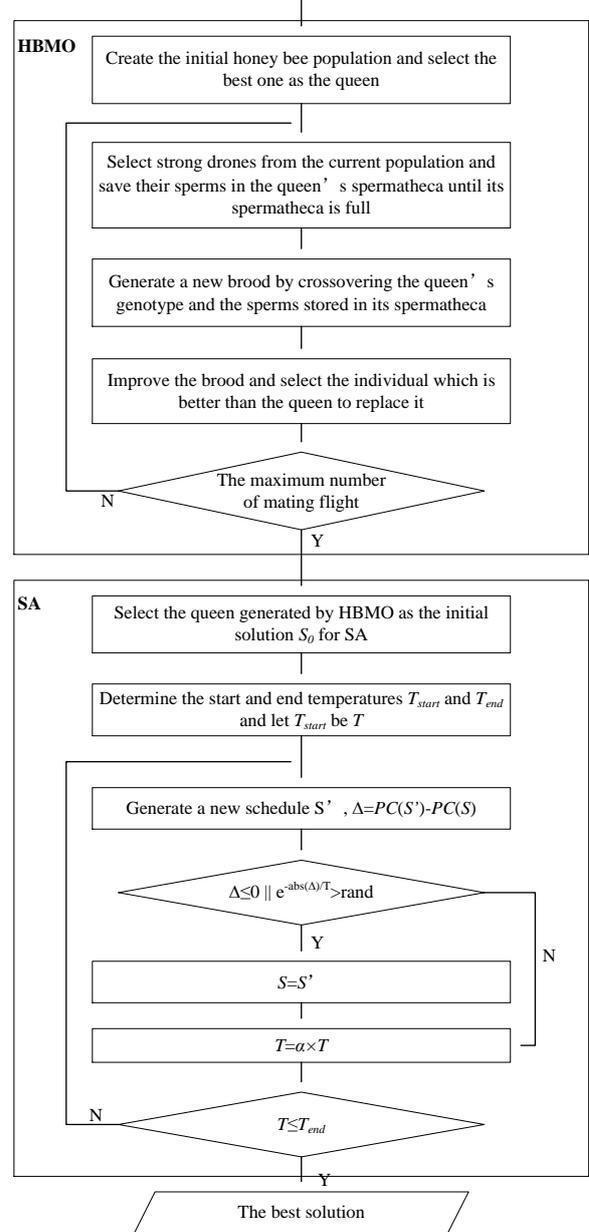

Fig. 3. Flowchart of the hybrid HBMO-SA algorithm.

- The shift operator is done by removing an operation from its present position to insert it at another position. The machine, tool and TAD used by the operation will also be removed to the corresponding positions.

Based on the above operators, four workers are generated. The first three workers correspond to mutation, adjacent swapping and shift respectively. The fourth worker simultaneously employs two operators: mutation and adjacent swapping.

Step 5: If the number of mating flight is still not more than the maximum which has been defined in step1.1, a new mating flight will begin. That is, Steps 2-4 will be repeated until the number of mating flight reaches the largest number.

4.3. Simulated annealing: Phase 2

In the second phase of the hybrid HBMO-SA approach, the SA algorithm is used to jump out of local optima and achieve a better localized search. Its processes are described as follows.

Step 1: The individual with the maximum fitness value is first selected from the populations generated by HBMO. The selected individual is used as the initial current schedule S_0 for the SA.

Step 2: The start and end temperatures T_{start} and T_{end} are determined. T_{start} is taken as the current temperature T.

Step 3: A new temporary schedule S' is generated by using two types of mutation strategies which are listed as follows:

- Two operations in the current schedule S are chosen randomly and exchanged. The machines, tools and TADs used by the operations are exchanged too.
- An operation in S is selected. Then, the machine, tool and TADs used by the selected operation are changed by referring the candidate list.

Step 4: One of the performance criterion functions defined above is used to compute the difference between the performance criteria of S' and S. Let PC represent a performance criterion.

$$\Delta = PC(S') - PC(S)$$

If $\Delta \le 0 \parallel e^{-abs(\Delta)/T} > rand$ $// 0 < rand < 1$

  $S = S'$

End

$T = \alpha \times T$ $// 0 < \alpha < 1$

Step 5: Steps 3-4 will be repeated until $T <= T_{end}$.

5. Case studies and discussions

In this section, three groups of parts from practical manufacturing are presented to validate the effectiveness and feasibility of the proposed approach. In the case studies, the machines tested by Kara and Li were used as the machining resources [25]. The experiments were performed on the Windows 7 operating system with Intel Dual-core CPU at 2.10 GHz and 3.00GB of main memory. The simulation was carried out by using the Matlab programming language.

In order to select the appropriate parameters, a number of different alternative values of the proposed algorithm's parameters were tested. The selected parameters of HBMO are: size of queen's spermatheca equals to 60, number of drones equals to 100, number of mating flights equals to 400, the initial *speed(t)* and α in equation (23) are 1000 and 0.85 respectively. For the SA, the selected parameters are: the start and end temperatures T_{start} and T_{end} equal to 1000 and 3.5116e-025 respectively, and α equals to 0.9.

It should be pointed out that some assumptions [29, 30] that are commonly used in most of the previous research works regarding scheduling were still taken for this study. The assumptions include:

- Parts are independent, and part preemption is not allowed;
- The sequence of the operations of each part complies with manufacturing constraints;
- All parts, machines and tools are available at time zero simultaneously;
- Each operation is performed on a single machine, and each machine can only execute an operation at a time;
- Machines are continuously available for production;
- If a machine or a tool is broken down, or a new part is inserted, the algorithm can re-start and generate new process plans and a schedule due to the efficient optimization performance of the algorithm;
- The time for a set-up is identical and independent of specific operations. The time for a machine change or a tool change follows the same assumption.

5.1. Case study 1

The first case consists of three parts which are shown in Fig. 4. This group of parts has 38 machining features.

For the parts, various experiments were conducted for three different conditions.

- $PC_1 = Makespan$

  where PC_1 represents the first performance criterion (to achieve the minimum makespan).

- $PC_2 = Energy\_Consumption$

  where PC_2 represents the second performance criterion (to achieve the minimum energy consumption).

- The third performance criterion is used to optimize energy consumption and the balanced utilization simultaneously, and thus consists of both of them. It can be represented as:

$$PC_3 = w_1 \times Energy\_Consumption + w_3 \times Utilization\_Level$$

where PC_3 stands for the third performance criterion, and w_1 and w_3 stand for the weights of the two criteria. Both w_1 and w_3 are set 0.5 in the experiments to take the energy consumption and utilization into account simultaneously.

The proposed HBMO-SA was conducted 15 times under different conditions respectively to verify its performance. The average convergence curves of HBMO-SA under different conditions are illustrated in Fig. 5, 6 and 7 respectively. It can be observed that the HBMO drops fast in the first phase of the proposed algorithm and converges to an intermediate solution. Based on this intermediate solution, a further optimization is obtained by the SA in the second phase.

To explore the relation between energy consumption and the other two performance criteria, i.e., energy consumption vs makespan and energy consumption vs balanced utilization of machines, were obtained under Condition 2 respectively. As shown in Fig. 8(a), they follow the similar trends since the numbers of machine changes and tool changes and the reduced idle time under Condition 2 contribute to both energy consumption and makespan. However, it is not the linear relation since the energy consumption is also affected by other factors such as power, material removal rate, etc. In Fig 8(b), the energy consumption and the balanced utilization of machines were obtained under Condition 2. Energy saving can be achieved through the intensive utilization of energy efficient machines. It is conflicted with the criterion for the balanced utilization of machines. Therefore, the targets for the lower energy consumption and the more balanced utilization of machines are in contradiction, which is clearly reflected in Fig 8(b).

The algorithm was further compared with four popular evolutionary algorithms: HBMO, SA, ACO and GA. In GA, the operators including selection, crossover and mutation are used to improve the populations gradually [32]. The number of generations equals to 1000, the crossover and mutation rates equal to 0.8 and 0.6 respectively. SA's parameters mainly include the start and end temperatures and factor α [29]. T_{start} and T_{end} equal to 1000 and 1.7479e-043 respectively, and α equals to 0.9. An ACO algorithm was modelled based on the behavior of ant seeking a path between their colony and a source of food [12]. Its parameters include the number of ants n, evaporation factor ρ, and weight parameters α and β. n equals to 100. ρ equals to 0.1. α and β are 1 and 2 respectively. For HBMO, the number of mating flights is 1000, and other parameters are the same as the corresponding ones used by the hybrid HBMO-SA. Fig.9 shows the comparisons among the proposed algorithm, HBMO, SA, ACO and GA under condition 2. All the algorithms were executed for 15 times. The results obtained by the proposed algorithm were better than those obtained by other algorithms. In addition, the CPU time consumed by the proposed algorithm and HBMO were 126s and 287s respectively. The proposed algorithm showed a better performance in efficiency since the inner loop in the SA adopted in its second phase iterates only 1 times to obtain a better efficiency than the HBMO under the fore-mentioned parameters. In addition, the comparisons among HBMO-SA, HBMO, SA, GA and ACO under Condition 1 are displayed in Table 1. From the results of Table 1, HBMO-SA got smaller makespan in mean, maximum and minimum. The comparison studies in this case showed that HBMO-SA exceeds HBMO, SA, GA and ACO in effectiveness and stability.
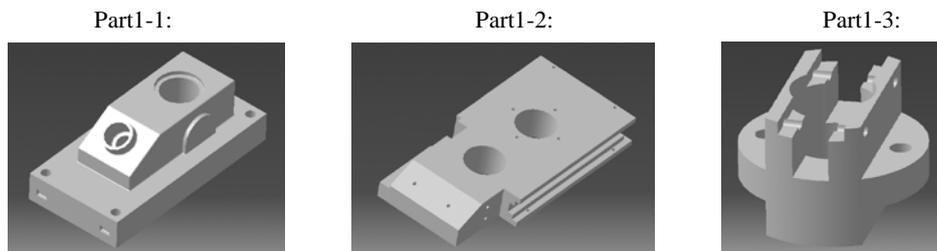
Part1-1:   Part1-2:   Part1-3:
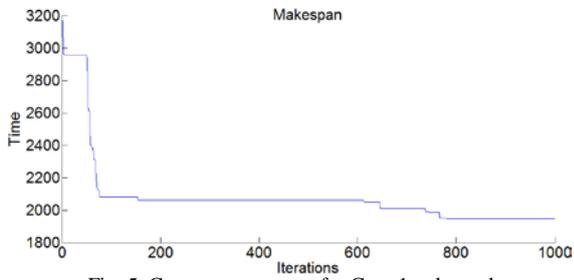

Fig 4. The first group of parts.

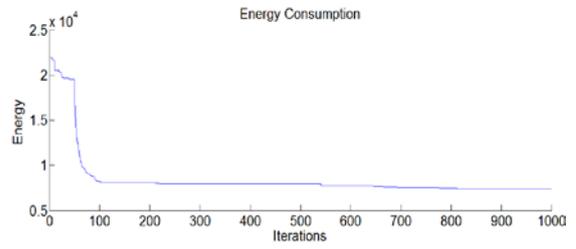Fig. 5. Convergence curve for Case 1under makespan.

Fig. 6. Convergence curve for Case 1 under energy consumption.
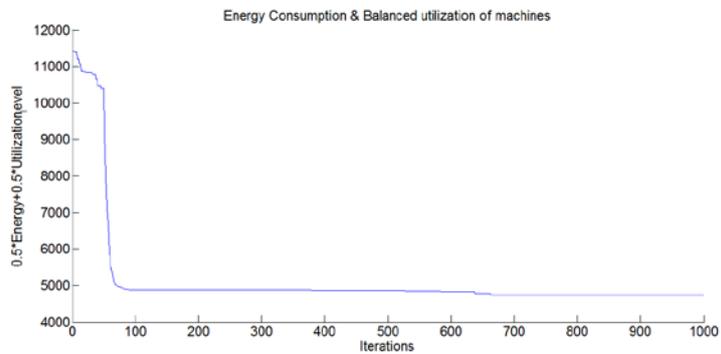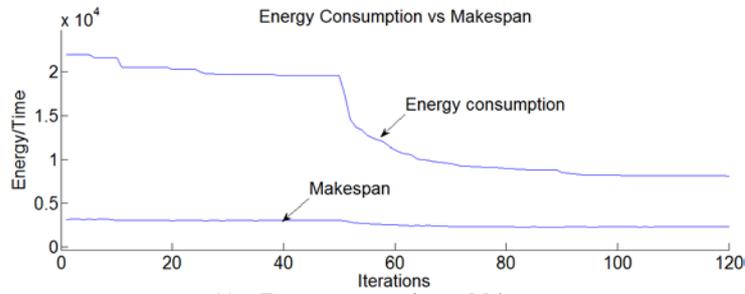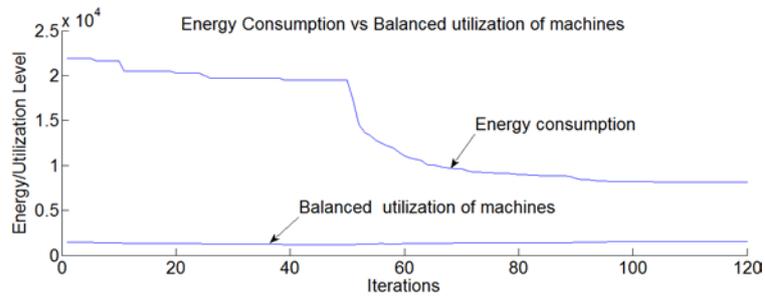

Fig. 7. Convergence curve for Case 1 under energy consumption and utilization level.

(a) Energy consumption vs Makespan

(b) Energy consumption vs Balanced utilization of machines

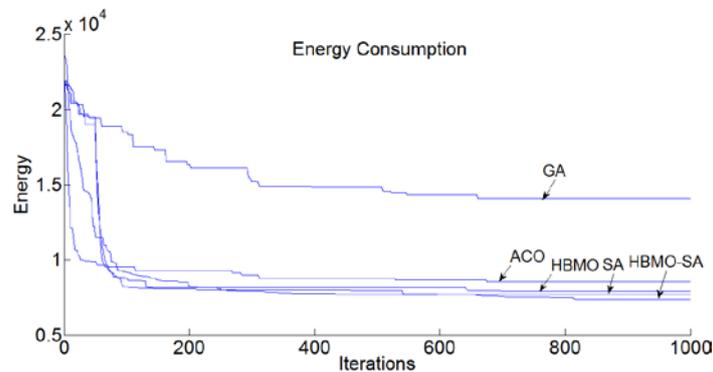Fig. 8. The comparison of two criteria for Case 1 under the same condition.

Fig. 9. The comparisons of the five algorithms for Case 1 under energy consumption.

Table 1

Comparison studies of five algorithms for case study1 under makespan

	HBMO-SA	HBMO	SA	GA	ACO
Mean	1945.1	2172.7	2147.7	2442.8	2928.5
Maximum	2002.4	2392.8	2317.4	2554.5	3128.2
Minimum	1893.6	1985.1	1980.1	2278.8	2743.7

5.2. Case study 2

The second case study employed another three parts (c.f. Fig. 10) to further validate the proposed approach. The parts have 48 machining features.

The above three conditions in Condition 1 were taken into ac-count again. All the algorithms were conducted for 15 times under these conditions. The optimization results are shown in Fig. 11 and 12. The trend was similar to that in Case study 1. As illustrated in Fig. 13, the similar trend between energy consumption and makespan, energy consumption and the balanced utilization of machines were verified again. In addition, through further trials on other groups of parts, the algorithm was verified to have the stable performance and good optimization results.

The comparisons among the proposed algorithm, HBMO, SA, ACO and GA under condition makespan are shown in Fig. 14. From the results, it can be observed that HBMO converged to a good solution more quickly than other algorithms. The local optima can be avoided by SA. The hybrid HBMO and SA adopted in the approach of this paper combined the advantages of HBMO and SA, and thus can achieve better optimized results.
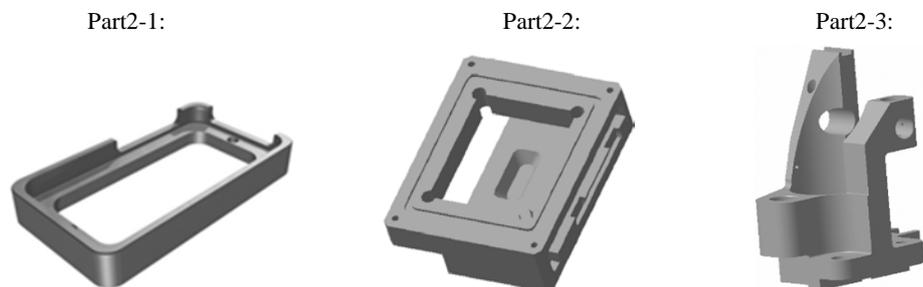
Part2-1:   Part2-2:   Part2-3:

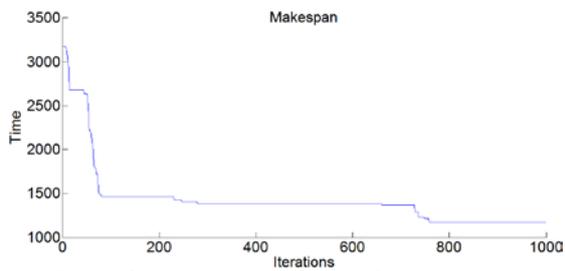
Fig 10. The second group of parts.

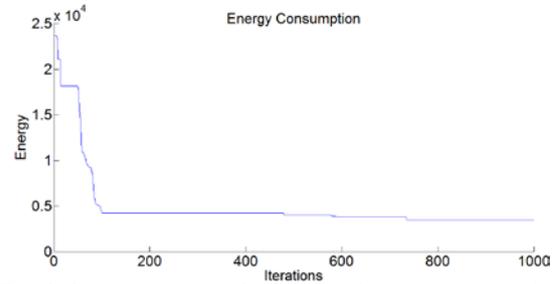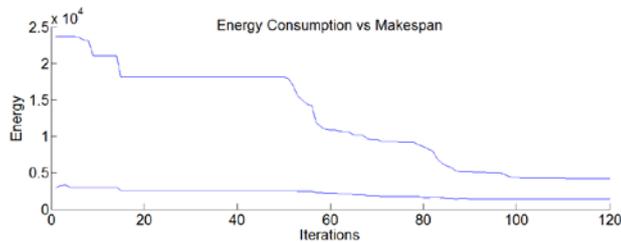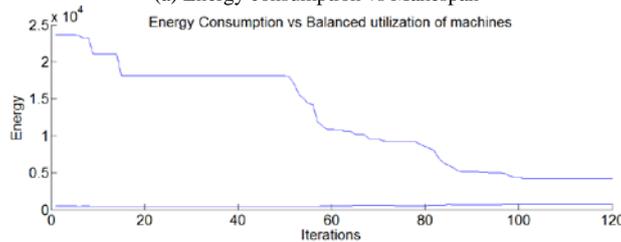Fig. 11. Convergence curve for Case 2 under makespan.

Fig. 12. Convergence curve for Case 2 under energy consumption.

(a) Energy consumption vs Makespan

(b) Energy consumption vs Balanced utilization of machines

Fig 13. The comparison of two criteria for Case 2 under the same condition.
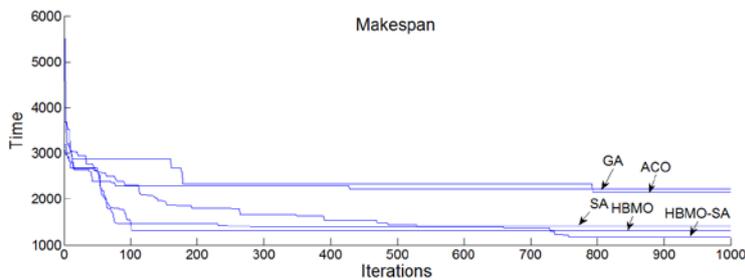

Fig 14. The comparisons of the five algorisms for Case 2 under makespan.

5.3. Case study 3

The third case study utilized the parts shown in Fig. 15. This group of parts consists of 48 machining features.

The proposed algorithm was executed for 15 times under the above three conditions defined in Case study 1 to verify its performance of the parts. The optimization results are shown in Fig. 16 to 19.

It can be observed that the results for this group of parts followed the similar trends for the parts in the above two groups. It was verified again that the presented algorithm had the stable performance and good optimization results. The comparison results shown in Fig. 20 also demonstrated that HBMO-SA had a good performance in solving process planning and scheduling problem.

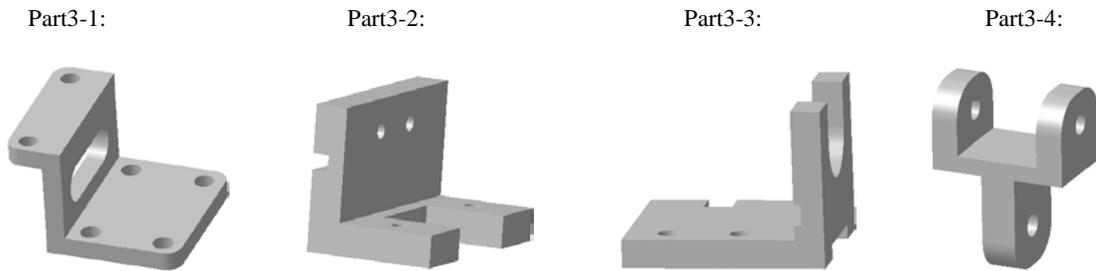Part3-1:   Part3-2:   Part3-3:   Part3-4:
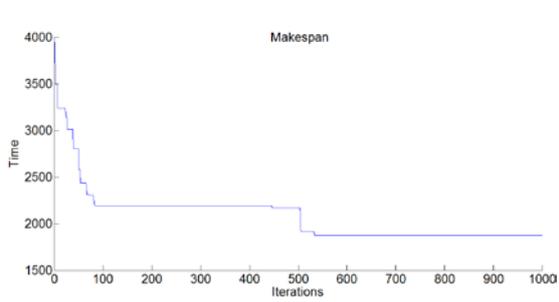

Fig 15. The third group of parts.

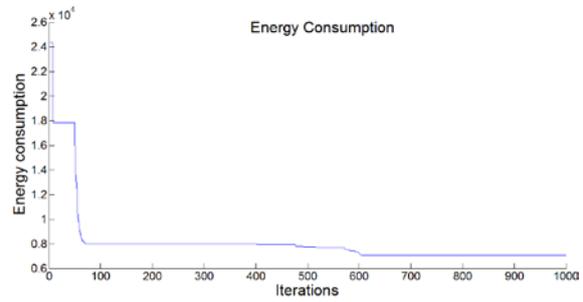Fig. 16. Convergence curve for Case 3 under makespan.

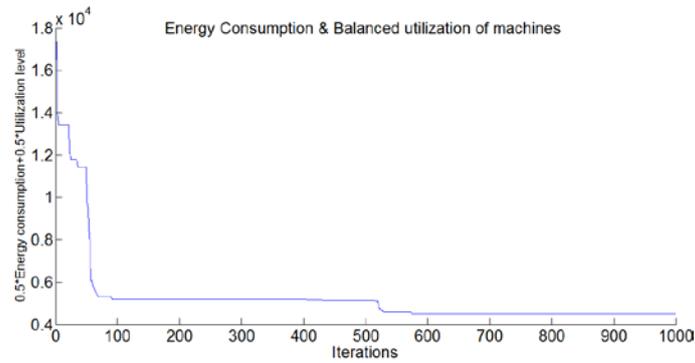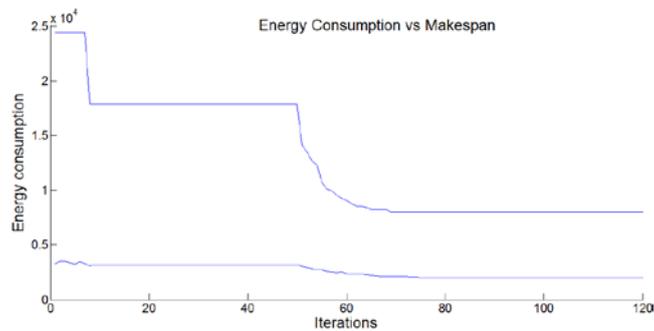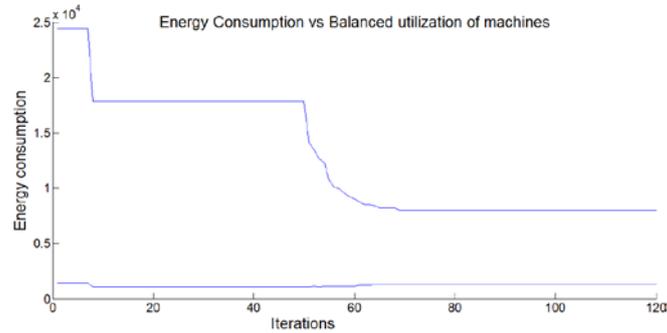Fig. 17. Convergence curve for Case 3 under energy consumption.

Fig 18. The comparisons of the five algorisms for energy consumption.

(a)   Energy consumption vs Makespan

(b)   Energy consumption vs Balanced utilization of machines

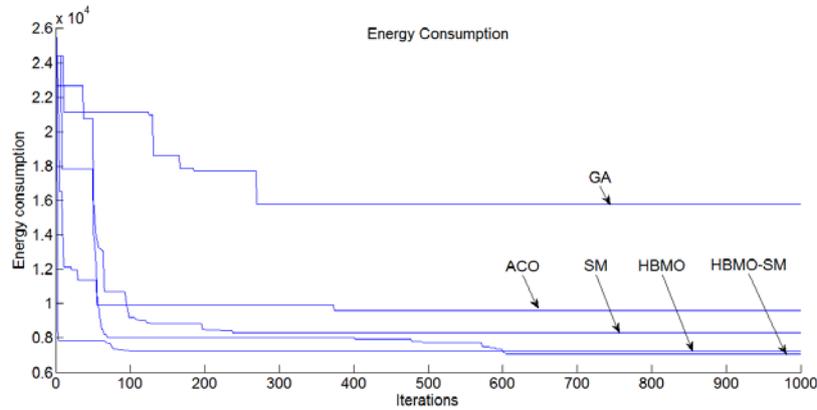Fig 19. The comparison of two criteria for Case 3 under the same condition.

Fig 20. The comparisons of the five algorisms for Case 3 under energy consumption.

6. Conclusions

Sustainable process planning and scheduling are critical to reduce its energy consumption and achieve sustainable development of machining processes. In this paper, sustainable process planning and scheduling are explored and presented in a hybrid optimization approach. In summary, the contributions of the presented approach are from the following aspects:

- Systematic models and strategies for dynamic process planning and scheduling in terms of energy consumption and other important performance criteria are established. On the basis of the models and strategies, the energy consumption of machining processes is effectively considered to achieve sustainability.
- Compared with some other optimization algorithms, the developed HBMO-SA approach can achieve better optimized results. Various cases are used to verify and demonstrate the effectiveness of the approach. The experimental benchmarking demonstrates that the approach is promising and outperforms GA, HBMO and SA. The

approach can be further used to solve other complex combinatorial optimization problems.

Future research is intended to be focused on two aspects. The energy consumption model will be applied in more complex environments involving machine breakdown and existing jobs cancellation. A further test and discussion about hybridization will be done to verify the performance of the presented algorithm.

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