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A multi-objective genetic algorithm for optimisation of energy consumption and shop floor production performance

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ABSTRACT

Increasing energy price and requirements to reduce emission are new challenges faced by manufacturing enterprises. A considerable amount of energy is wasted by machines due to their underutilisation. Consequently, energy saving can be achieved by turning off the machines when they lay idle for a comparatively long period. Otherwise, turning the machine off and back on will consume more energy than leave it stay idle. Thus, an effective way to reduce energy consumption at the system level is by employing intelligent scheduling techniques which are capable of integrating fragmented short idle periods on the machines into large ones. Such scheduling will create opportunities for switching off underutilised resources while at the same time maintaining the production performance. This paper introduces a model for the bi-objective optimisation problem that minimises the total non-processing electricity consumption and total weighted tardiness in a job shop. The Turn off/Turn on is applied as one of the electricity saving approaches. A novel multi-objective genetic algorithm based on NSGA-II is developed. Two new steps are introduced for the purpose of expanding the solution pool and then selecting the elite solutions. The research presented in this paper is focused on the classical job shop environment, which is widely used in the manufacturing industry and provides considerable opportunities for energy saving. The algorithm is validated on job shop problem instances to show its effectiveness.

1. Introduction

The increasing price of energy and the current trend of sustainability have exerted new pressure on manufacturing enterprises (Kilian, 2008). Thus, the aim of many modern manufacturing companies is to reduce the energy consumption both to save cost and to become more environmentally friendly (Mouzon et al., 2007). Based on the previous research (Fang et al., 2011; Mouzon and Yildirim, 2008), the operational methods have been proved to be feasible and effective to reduce the energy consumption of manufacturing companies. This especially applies to the mass production environment where more than 85% of energy is consumed by functions that are not directly related to the production of components (Gutowski et al., 2005).

Our research has been focused on the multi-objective scheduling approaches to a typical job shop because they have not been well investigated from the perspective of energy consumption reduction. In addition, from the practical perspective, a large majority of companies have characteristics of the job shop production environment. In the authors' previous research, a job shop scheduling problem that considered minimisation of the total weighted tardiness (TWT) and total non-processing electricity consumption (Electricity Consumption and Tardiness-ECT) has been introduced (Liu et al., 2014). At that stage, the non-processing electricity consumption (NPE) only included the electricity consumption of machine tools when they stay idle. The multi-objective optimisation algorithm NSGA-II has been proved to be effective in reducing NPE by searching for the optimal processing sequence of jobs on each machine. However, the ECT problem can be better solved if the Turn off/Turn on is also applied (Mouzon, 2008). Then, the electricity consumed by switching the machine off and on should also be included in the NPE. This required a development of a new multi-objective optimisation algorithm and its corresponding scheduling techniques to optimally use both the Turn off/Turn on and Scheduling methods. In this paper, the electricity consumption model of the ECT problem is extended to integrate the electricity consumed by Turn off/Turn on. A new Multi-objective **G**enetic *A*lgorithm for *E*lectricity Saving in *J*ob Shop *P*roduction (GAEJP) is proposed. This algorithm is designed based on the NSGA-II algorithm which we extended with two new steps that are devised for solving the new ECT problem. The goal of the new step in the algorithm entitled "1 to *n* scheduling building" is

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twofold. First it creates idle periods which are long enough to justify machine turning off, thereby creating the opportunities for switching off underutilised resources. Second it expands the pool of feasible solutions by producing multi scheduling plans for each individual in the population. A semi-active schedule building procedure is developed and used as the decoding tool together with rules to improve the generated schedules. The additional new step entitled "Family creation and individual rejection" is designed to reserve the elitist solutions within the enlarged pool of feasible schedules. The optimisation framework proposed in this paper outperforms NSGA-II in reducing electricity consumption and at the same time it keeps good values of classical scheduling objectives.

In the remaining of the paper, background and motivation for the presented research given in Section 2 are followed by the description of the research problem and the model in Section 3. In Section 4, the GAEJP developed to solve the aforementioned bi-objective scheduling problem is described. Experiment results which demonstrate the effectiveness of the algorithm are described in Section 5. Section 6 presents conclusions and discussion about the future research work.

2. Background and motivation

Mouzon et al. (2007) indicated that in many manufacturing companies, the non-bottleneck machines are always left running idle. The authors collected the time and electricity consumption data of a four CNC machines workshop of an aircraft supplier of small parts. Based on the data, on average, the machine stays idle 16% of the time during an eight hours shift. This part of electricity belongs to the non-processing electricity consumption, and it can be reduced by adjustment of the scheduling plan. Based on an industrial case of energy bill saving of foundry, Artigues et al. (2013) generalised a parallel machines model considering energy and its cost saving. Scheduling which used a branching scheme via tree search has been used as the energy saving approach. Tang et al. (2000) and Tang and Wang (2008) investigated scheduling, production planning and batching approaches to improve the energy and cost efficiency in the iron and steel production. However, the amount of research on scheduling with environmentally-oriented objectives is still in its infancy, but shows an increasing trend. For example, Fang et al. (2011) considered reducing peak power load in a flow shop. Bruzzone et al. (2012) developed a method to modify the schedule of jobs in flexible flow shops in order to adjust to the maximum peak power constraint. Du et al. (2011) developed a preference vector ant colony system to minimise the make-span and energy consumption in a hybrid flow shop. Another work focused on the flow shop was developed by Mansouri et al. (2016). The authors modelled a sequence dependent two machine permutation flow shop with energy saving concern. A constructive heuristic was proposed to trade-off the makespan and energy consumption. Dai et al. (2014) proposed a new solution which combines genetic algorithm and simulated annealing algorithm to improve the energy efficiency within a job shop. Subaï et al. (2006) considered energy and waste reduction in the hoist scheduling problem of the surface treatment processes without changing the original productivity. Zhang et al. (2012) developed a goal programming mathematical model for the dynamic scheduling in the flexible manufacturing system, which considered the reduction of energy consumption and improvement of scheduling efficiency simultaneously. Wang et al. (2011) proposed an optimal scheduling procedure to select appropriate batch and sequence policies to improve the paint quality and decrease repaints, thereby reducing energy and material consumption in an automotive paint shop. Zanoni et al. (2014) modelled and investigated a system composed of two machines in series and three stocks. Optimal batch sizes were derived for different scenarios which resulted in the minimisation of the producing, storing and energy cost of the system. Luo et al. (2013) and Liu et al. (2015) proposed new meta-heuristics to reduce the electricity cost with the presence of time-of-use electricity prices in the hybrid flow shop and job shop environment, respectively. A comprehensive review on the development of the energy-efficient scheduling has been recently provided by Gahm et al. (2016).

Kordonowy (2003) developed an approach to break the total electricity use of machining processes. Following this work and research by Mouzon (2008) and He et al. (2012), we divided the electricity consumption for a machine tool into two components: the non-processing electricity consumption (NPE) and processing electricity consumption (PE) (Liu et al., 2014). NPE is associated with the machine start-up, shut-down and idling. It can also be identified from previous works that on the system level, typical electricity saving methods include: Scheduling, Turn off/Turn on and Process Route Selection. By changing the order of jobs on machines, Scheduling method can reduce the total idle electricity consumption in a manufacturing system. The Turn off/Turn on (Mouzon, 2008) allows a machine tool to be turned off when it becomes idle for electricity saving purpose. The Scheduling and Turn off/Turn on can be applied to any type of manufacturing system to reduce the NPE. However, the Process Route Selection has a limitation that it is not applicable to workshops without alternative routes, or to workshops which have identical alternative routes for jobs. Optimisation approaches are required to enable the aforementioned three methods to be optimally used to achieve electricity consumption reduction. Dispatching rules, a genetic algorithm and a greedy randomised adaptive search procedure have been proposed by Mouzon et al. (2007) and Mouzon (2008) to optimally use the three methods to reduce both total NPE and PE for single machine and parallel machine environments. He et al. (2012) used PRS to decrease both total PE and total NPE for a flexible job shop environment.

Reading the relevant literature one can conclude that employing operational research methods to reduce the total energy consumption in a typical job shop environment which do not have parallel machines has not been explored very well yet. A general model of the job shop scheduling problem that considered minimisation of TWT and the total idle electricity consumption was proposed by the authors (Liu et al., 2014). This previous work proved that in a basic job shop, the total NPE can be reduced by adjusting scheduling plans, and NSGA-II was effective in achieving this aim. However, by observing the solutions delivered by NSGA-II, it can be found that the NPE can be further reduced if the Scheduling and Turn off/Turn on are applied together in an optimal way. This led to a substantial modification of NSGA-II whose description will follow the new mathematical model for the ECT problem presented in the next section.

3. Notation and problem statement

The notation used in the problem statement, algorithm description and throughout the paper is as follows:

Job shop problem

i, k, l	indices for jobs, machines and operations of jobs, respectively
J	a finite set of n jobs, $J = \{J_i\}_{i=1}^{n}$
M	a finite set of m machines, $M = \{M_k\}_{k=1}^{m}$
O_i	a finite list of u_i ordered operations of J_i, $O_i = \left[O_{ik}^{l}\right]_{l=1}^{u_i}$
O_{ik}^{l}	the l-th operation of job J_i processed on machine M_k
p_{ik}^{l}	processing time of operation O_{ik}^{l}
r_i	release time of job J_i into the system
d_i	due date of job J_i
w_i	weight i.e. importance of job J_i

s	a feasible schedule
$C_i(s)$	completion time of job J_i in schedule s (i.e. the completion time of the last operation of J_i, $O_i^{u_i}$)
$T_i(s)$	tardiness of job J_i, defined as $T_i(s) = max\{0, C_i(s) - d_i\}$
γ_{ik}^l	a decision variable that denotes the predefined allocation of operations on machines; γ_{ik}^l=1 if the l-th operation of job J_i is processed on M_k, 0 otherwise
M_k'	a finite list of operations processed on machine M_k, $M_k' = \left[m_k^r\right]_{r=1}^{\sum_{i=1}^n \sum_{l=1}^{u_i} \gamma_{ik}^l}$
m_k^r	r-th operation processed on machine M_k in a feasible schedule s
S_k^r	starting time of operation m_k^r on machine M_k
C_k^r	completion time of operation m_k^r on machine M_k
Energy consumption	
t	time
$P_k(t)$	input power of machine M_k
P_k^{idle}	idle power of machine M_k
t_k^{OFF}	time required to turn off machine M_k and turn it on again
E_k^{turn}	electricity consumed to turn off machine M_k and turn it on again
B_k	break-even time period on machine M_k for which Turn off/Turn on is economically justifiable instead of running the machine idle
Z_k^r	a decision variable Z_k^r=1 if a Turn off/Turn on is applied to the idle period between m_k^r and m_k^{r+1}, 0 otherwise
Genetic algorithm	
N	population size
I_{pt}	individual p in generation t
S_{pt}	a finite set of solutions assigned to individual I_{pt}, $S_{pt} = \left\{s_{pt}^v\right\}_{v=1}^{h_{pt}}$
h_{pt}	number of solutions assigned to I_{pt} after 1 to n decoding
s_{pt}^v	v-th feasible solution of individual I_{pt} which corresponds to I_{pt}^v $v = 1, \ldots, h_{pt}$
u_{pt}	number of members in family I_{pt}, $I_{pt} = \left\{I_{pt}^v\right\}_{v=1}^{u_{pt}}$
I_{pt}^v	v-th family member in I_{pt}
N'	population size after creation of families, $N' = \sum_{p=1}^N u_{pt}$
N''	population size after applying 'Individual rejection based on non-dominated sorting' to N' individuals in population P_t
$BS_{F_i}^{min}$	boundary solution in Pareto front F_i with the minimum value in the selected objective function
$BS_{F_i}^{max}$	boundary solution in Pareto front F_i with the maximum value in the selected objective function
$N_{s_{pt}^v}^1$, $N_{s_{pt}^v}^2$	first and second group of neighbours for s_{pt}^v, respectively

The bi-objective ECT problem has been formally defined by Liu et al. (2014). However, in that research, NPE included only the electricity consumption of machines when they stay idle. In the research presented in this paper, the Turn off/Turn on is applied for electricity saving and the electricity consumed by it is included in the calculation of NPE. The first part of the model describes the classical job shop scheduling problem where a finite set of n jobs $J=\left\{J_i\right\}_{i=1}^n$ are to be processed on a finite set of m machines $M=\left\{M_k\right\}_{k=1}^m$ following a predefined order. Each job is defined as a finite set of u_i ordered operations $O_i = \left\{O_{ik}^l\right\}_{l=1}^{u_i}$ where O_{ik}^l is the l-th operation of job J_i processed on machine M_k and requires a processing time p_{ik}^l. Each job J_i has a release time into the system r_i and a due date d_i by which it has to be processed. Different jobs can be prioritised using the importance factor w_i. Given a feasible schedule s, let $C_i(s)$ denote the completion time of job J_i in schedule s. The tardiness of job J_i is defined as $T_i(s)=max\{0, C_i(s) - d_i\}$. The first optimisation objective is to minimise the total weighted tardiness of all jobs:

$$minimise\left(\sum_{i=1}^{n} w_i \times T_i(s)\right) \tag{1}$$

The reader can refer to Pinedo (2012) for more details about the job shop model.

The second part of the ECT model describes the electricity consumption. It includes the electricity consumed by the Turn off/Turn on. A power input model for a machine M_k when it processes operation O_{ik}^l assumes that each machine has three constant levels of power consumption: during idle time, when switched into run-time mode and when carrying out the actual cutting operation (Kordonowy, 2003). The input power, $P_k(t)$, which a machine requires over time is defined as a stepped function represented by the red line in Fig. 1. The idle power level of a machine is defined by P_k^{idle}. The overall processing time p_{ik}^l is defined as the time interval between coolant switching on and off. The objective to reduce the total electricity consumption in the ECT problem can be realised by reducing the total non-processing electricity consumption (NPE). Hence, the objective to minimise the total NPE in a job shop to carry out a given schedule can be expressed as:

$$minimise\left(\sum_{k=1}^{m} TEM_k^{np}(s)\right) \tag{2}$$

where $TEM_k^{np}(s)$ is the NPE of machine M_k for schedule s. The NPE is a function of the scheduling plan which needs to be expressed by the sequence of different operations which have been scheduled to be processed on a machine. Let $M_k' = \{m_k^r\}_{r=1}^{\sum_{i=1}^n \sum_{l=1}^{u_i} \gamma_{ik}^l}$ denotes the finite set of operations to be processed on M_k; γ_{ik}^l is a decision variable such that γ_{ik}^l=1 if the l-th operation of job J_i is processed on M_k, 0 otherwise; S_k^r and C_k^r indicate the start and completion time of operation m_k^r on M_k in schedule s,respectively. In addition to our previous model, here the Turn off/Turn on is applied to idle periods which are long enough. The idle electricity consumption by these periods are replaced by the electricity consumed by turning the machine off and then turning it back on. E_k^{turn} is the electricity consumed by Turn off/Turn on; t_k^{OFF} is the time required to turn off machine M_k and turn it back on; B_k is the break-even time period of machine M_k for which Turn off/Turn on is economically justifiable instead of running the machine idle, $B_k = \max(E_k^{turn}/P_k^{idle}, t_k^{OFF})$ (Mouzon and Yildirim, 2008; Mouzon, 2008). Z_k^r is a decision variable such that Z_k^r=1 if a Turn off/Turn on is applied to the idle period following C_k^r, 0 otherwise. Consequently, the calculation of the NPE of machine M_k can be expressed as:

$$TEM_k^{np}(s) = P_k^{idle} \times \left[max\left(C_k^r\right) - min\left(S_k^r\right) - \sum_r \left(C_k^r - S_k^r\right) - \sum_r \left(S_k^{r+1} - C_k^r\right) \times Z_k^r\right] + E_k^{turn} \times \sum_r Z_k^r \tag{3}$$

An example of the calculation of NPE of M_k is presented in

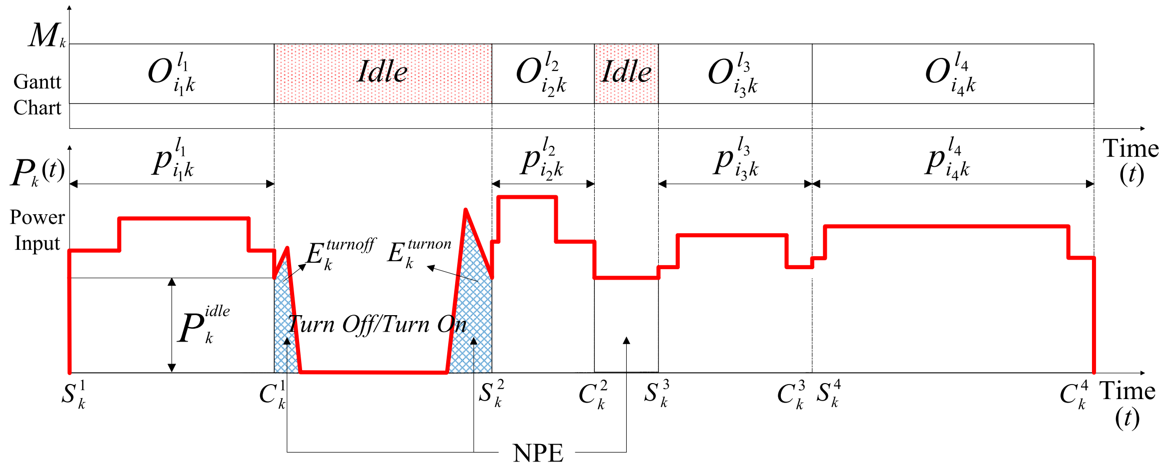

Fig. 1. An example of the Gantt chart for a schedule for machine M_k and its corresponding power profile. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

Fig. 1. Let us assume that $O_{i_1k}^{l_1}$, $O_{i_2k}^{l_2}$, $O_{i_3k}^{l_3}$, and $O_{i_4k}^{l_4}$ are processed on machine M_k. Expression (3) is used to calculate NPE of machine M_k, which is represented by the blue grid area. Firstly the total idle time of M_k is calculated, which equals $\left(C_k^4 - S_k^1\right) - \sum_{r=1}^{4}\left(C_k^r - S_k^r\right)$. Suppose that $S_k^2 - C_k^1 > max\left(B_k, t_k^{OFF}\right)$, which means it is justifiable to execute a Turn off/Turn on during the idle period between $O_{i_1k}^{l_1}$ and $O_{i_2k}^{l_2}$, then Z_k^1=1. Thus, this part of idle time should be subtracted from the total idle time, which implies $\left(C_k^4 - S_k^1\right) - \sum_{r=1}^{4}\left(C_k^r - S_k^r\right) - \left(S_k^2 - C_k^1\right)$. Then, the aforementioned value is multiplied by the idle power level of machine M_k to obtain the total idle electricity consumption. Finally, the electricity consumed by the Turn off/Turn on should be summed with the idle electricity consumption to get the value of NPE. In this case, the machine has only been turned off then started again once, so the NPE is calculated as $P_k^{idle} \times \left[\left(C_k^4 - S_k^1\right) - \sum_{r=1}^{4}\left(C_k^r - S_k^r\right) - \left(S_k^2 - C_k^1\right)\right] + E_k^{turn}$.

In summary, the multi-objective optimisation problem considers minimisation of both TWT ($f_1(s)$) and NPE ($f_2(s)$) which is expressed by Expression (4):

$$minimiseF(s) = \left(f_1(s), f_2(s)\right) s \in S \tag{4}$$

4. A novel multi-objective genetic algorithm for optimisation of energy consumption

The goal of developed GAEJP is to create more opportunities for switching off underutilised resources while maintaining the production performance. The method for reducing the total non-processing electricity consumption is to integrate fragmented short idle periods into longer idle periods in the operation sequence on each machine, since this can create opportunities to execute the Turn off/Turn on. The schedule builder used at the first step is the semi-active one. The reason for building a semi-active schedule at the initial stage instead of the active one is that in a semi-active schedule normally some operations can be shifted to the left without delaying other operations (Pinedo, 2009; Yamada, 2003). This can create some idle periods which are long enough for executing Turn off/Turn on. The encoding schema and decoding procedure of the semi-active schedule builder is explained in the next sub-section.

4.1. Encoding schema and semi-active schedule builder

We adopt the operation-based encoding schema, which is known as "permutation with repetition" (Dahal et al., 2007). Each job's index number is repeated u_i times (u_i is the number of operations of J_i). By scanning the permutation from left to right, the l-th occurrence of a job's index number refers to the l-th operation in the technological sequence of this job. As an illustration, let us follow an example of 3×3 job shop problem provided by Liu and Wu (2008), whose data are given in Table 1. For example, job J_1 requires processing on machines M_1, M_2 and M_3 and it takes 2, 2, and 3 time units, respectively.

One of the feasible individuals is [222333111]. Decoded by the active schedule builder (Dahal et al., 2007), the individual is transformed into a feasible schedule as depicted in Fig. 2(a). Comparatively, by employing the semi-active schedule builder (Yamada, 2003), the individual is transformed into a feasible schedule as depicted in Fig. 2(b). Normally, the initial semi-active schedule has larger TWT than the active one, but it provides more opportunity for improving the objective values. Fig. 2 shows how the improved semi-active schedule outperforms the active one in terms of TWT and the total NPE. The bottom schedule (Fig. 2(c)) is generated based on the middle schedule (Fig. 2(b), semi-active) in the following way: O_{11}^1 is shifted to the left of O_{21}^3; then O_{12}^2 is moved left to follow O_{32}^1; finally O_{13}^3 is shifted to the left of O_{33}^3. Let us assume that the due date for every job is the 10th time unit, and that it is justifiable to execute Turn off/Turn on for each machine when the idle period is longer than 3 time units. Thus, it can be seen that the bottom schedule outperforms the other two schedules in both the total NPE and TWT. Therefore, the proposed optimisation strategy is to build a semi-active schedule at the initial stage, then to improve the schedule by performing left shift and left moving of appropriate operations. The algorithm is described in detail in the following sub-section.

Table 1
An example of a 3×3 job shop problem.

J_1	O_{ik}^l					
	O_{ik}^1	O_{ik}^2	O_{ik}^3	r_i	d_i (time unit)	w_i
J_1	$M_1(2)$	$M_2(2)$	$M_3(3)$	0	10	3
J_2	$M_3(3)$	$M_2(1)$	$M_1(4)$	0	10	2
J_3	$M_2(1)$	$M_1(3)$	$M_3(2)$	0	10	1

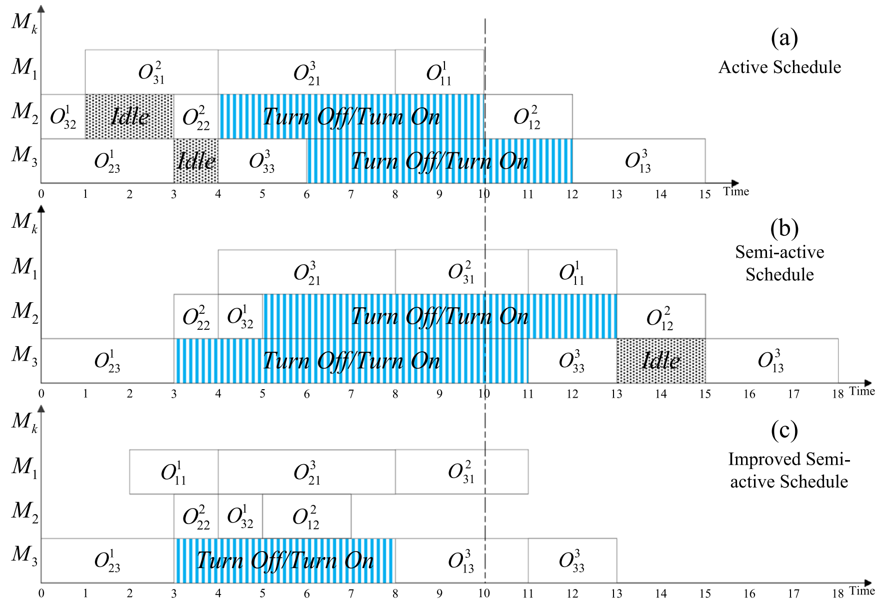

Fig. 2. Examples of active and semi-active schedules for the ECT problem.

4.2. Components of GAEJP

The flowchart of the developed GAEJP is shown in Fig. 3. The structure of the NSGA-II, our algorithm is based on is described by Deb et al. (2002). Two new steps are introduced to address the presented ECT problem which integrates Scheduling and Turn off/Turn on. The first one is labelled "1 to n schedule building". In this step, each individual in the coding space is decoded into several feasible scheduling plans (solutions) in the solution space, which have different idle periods to create opportunities for applying Turn off/Turn on. This expands the solutions pool of a chromosome. The goal of the second step "Family creation and individual rejection" is to select non-dominated solutions from the solutions pool of each individual chromosome and then to further select an elitist solution among them. The operation-based order crossover operator and swap mutation operator are adopted from Liu (2013). The two new steps are explained in detail in the following sub-sections.

4.2.1. One to n schedule building

The 1 to n schedule building firstly transforms an individual into a semi-active schedule. All the idle periods within the schedule are evaluated to find those which are sufficiently long to allow a machine to be turned off and switched back on. Then, the shutdown action is applied to those idle periods, and this generates the first feasible solution corresponding to the individual. To improve the schedule's performance on the TWT objective, two changes to the schedule are introduced: left shift of an operation to the earliest valid time period left to its current position and left move from its current position in the schedule. First, all the operations which are allowed to be shifted left in the schedule are ranked according to defined rules. The operation with the highest rank is shifted left to the earliest idle period available for it. After the left shifting, it might be found that some operations can be moved left to further improve the performance on the TWT objective. Then all these permissible left move operations are

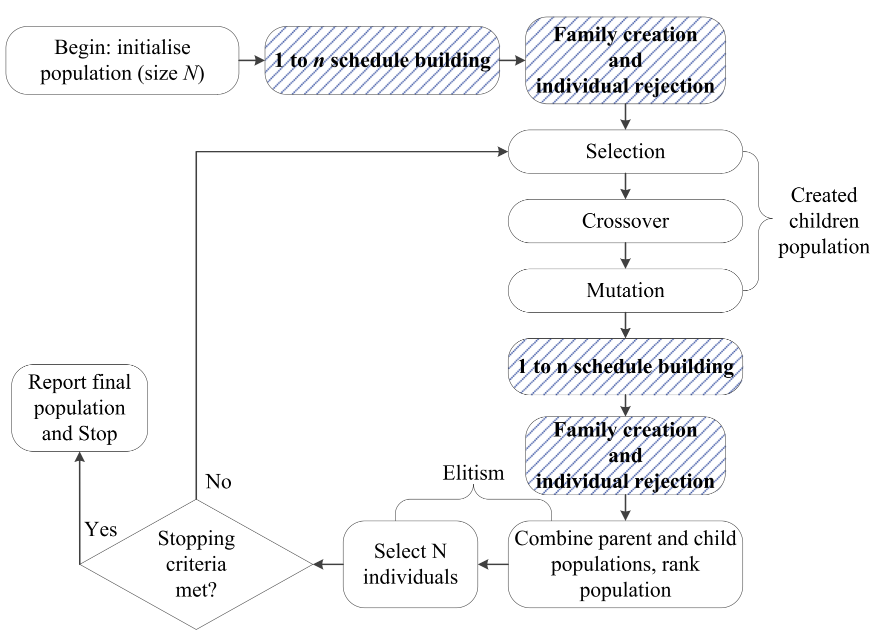

Fig. 3. Flowchart for GAEJP.

selected and ranked. The operation with the highest rank is moved left to its earliest possible starting time. After completing all the aforementioned steps, the algorithm performs iteratively the steps for collecting permissible left move operations, ranking, and left moving until there are no further operations which can be moved left. Then all the idle periods in the generated schedule are evaluated to find out those which are justifiable for the Turn off/Turn on. The values of the objective functions are calculated after the Turn off/Turn on is applied. In this way, the second feasible solution corresponding to the considered individual is obtained. The algorithm performs the described steps iteratively until there is no permissible left shift operation in the schedule. The flowchart of 1 to n schedule building step is given in Fig. 4, while the details of each step of the algorithm are given in the remainder of the sub-section.

Initial schedule building Employ the semi-active schedule builder to decode the individual I_{pt} to a semi-active schedule.

Idle periods evaluation Evaluate all the idle periods within the produced schedule to find out those for which it is justifiable to apply the Turn off/Turn on and apply it to all of them. After the Turn off/Turn on, the first feasible solution which corresponds to individual I_{pt} is obtained, denoted by s_{pt}^{1}.

Objective functions calculation Calculate the values of the objective functions of schedule s_{pt}^{1}.

Permissible left shift operations (PLSO) selection collect all the operations which are allowed to be shifted left within s_{pt}^{1}. Operation O_{ik}^{l} can be defined as a PLSO if there exists at least one idle period before it on machine M_k, and the length of the idle period is longer than the required processing time of O_{ik}^{l}.

Permissible left shift operations ranking Rank the selected PLSOs within schedule s_{pt}^{1}. The ranking rules, when applied to operations from different jobs, prioritise the one with a higher ratio of its importance to its due date (w_i/d_i). If the values of w_i/d_i for the two operations are the same, the one with larger weight is prioritised. If w_i and d_i of the two operations are the same, the ranking order is random. For operations from the same job, the one positioned earlier in the technology path is prioritised.

Left shifting The operation O_{ik}^{l} which is ranked first among all permissible left shift operations is selected and is shifted to the earliest left-shifting idle period available for it. After the left shift, a new schedule for I_{pt} is obtained, denoted by s_{pt}^{1LS}.

Permissible left move operations selection After the left shifting step has been performed, some operations can be moved left. OperationO_{ik}^{l} can be defined as permissible left move operation if there is an idle period just left to it and the completion time of O_{ik}^{l}'s preceding operation is before the starting time of O_{ik}^{l}. All the operations which are allowed to be moved left within schedule $s_{pt}^{1LS}$are selected.

Permissible left move operations (LMO) ranking All the permissible left move operations collected in schedule s_{pt}^{1LS} are ranked. The ranking rules are the same as the rules described in permissible left shift operations ranking step.

Left moving Operation O_{ik}^{l} which is ranked first is moved left on machine M_k to its earliest possible starting time. After the left move, a new schedule for I_{pt} is obtained, denoted by s_{pt}^{1LM} .

The algorithm goes back to the permissible left move operation selection step and iterates until there is no permissible left moving operation. Once the schedule without any permissible left moving operation has been generated, the idle periods within it are evaluated to find out those for which it is justifiable to apply the Turn off/Turn on. Thus, the second feasible solution corresponding to individual I_{pt} is obtained, denoted by s_{pt}^{2}. Then the algorithm performs iteratively the steps described above on schedule s_{pt}^{2} until

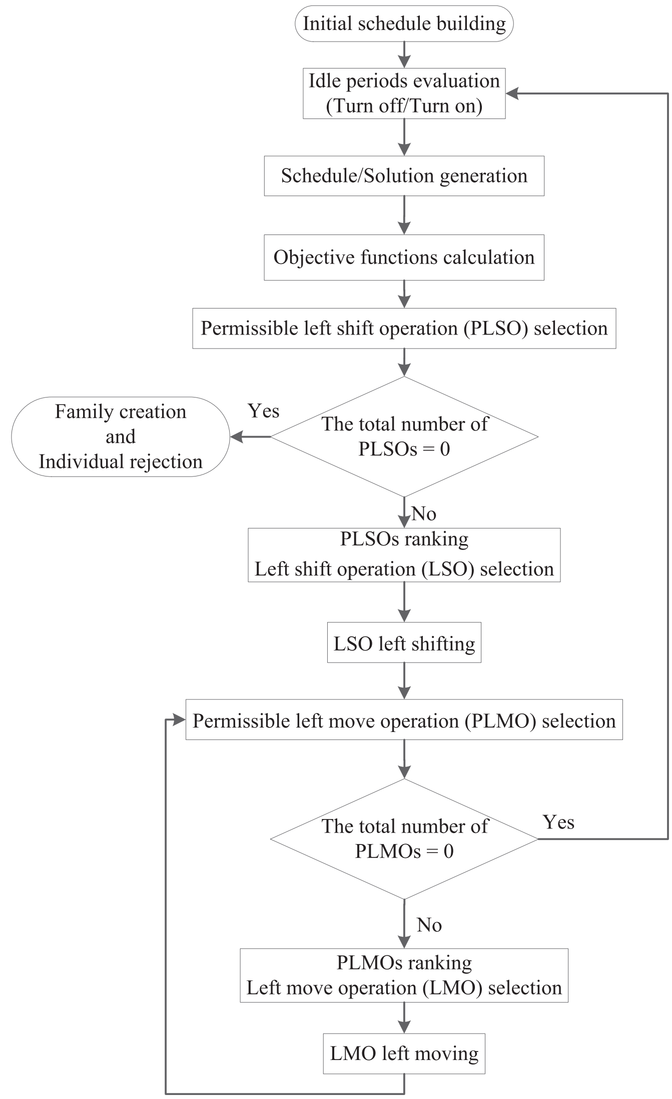

Fig. 4. The flowchart of 1 to n schedule building step.

there is no permissible left shift operation in the schedule. Let us assume that in total h_{pt} feasible solutions (schedules) which correspond to individual I_{pt} are obtained. The solutions assigned to individual I_{pt} are denoted by $S_{pt} = \left\{ s_{pt}^{v} \right\}_{v=1}^{h_{pt}}$.

A previously introduced example of 3×3 job shop is used to demonstrate the 1 to n schedule building procedure. Suppose the idle power of all machines is 1 power unit and it is justifiable to turn off then turn on a machine if the idle period is longer than 5 time units. To simplify the calculation, supposeE_k^{turn}=0, E_k^{turn} is the electricity consumed by Turn Off/Turn On.

Let us consider the individual I_{pt}=[222333111]. Initially, I_{pt} is decoded by the semi-active schedule builder to the schedule shown in Fig. 5(a). After the Turn Off/Turn On has been applied, the resulting Gantt chart of s_{pt}^{1} is shown in Fig. 5(b).

The values of objective functions of s_{pt}^{1} are $(27,2)$; the total weighted tardiness is 27 time units, while the non-processing electricity consumption is 2 energy units. There are two permissible left shift operations in s_{pt}^{1}, O_{11}^{1} and O_{32}^{1}. We select O_{11}^{1} as the left shift operation since J_1 has larger ratio w_1/d_1 $(3/10)$ than J_3 $(1/10)$. The next step is to perform left shifting step on O_{11}^{1} to obtain s_{pt}^{1LS}; the resulting Gantt chart is shown in Fig. 5(c). There is only one

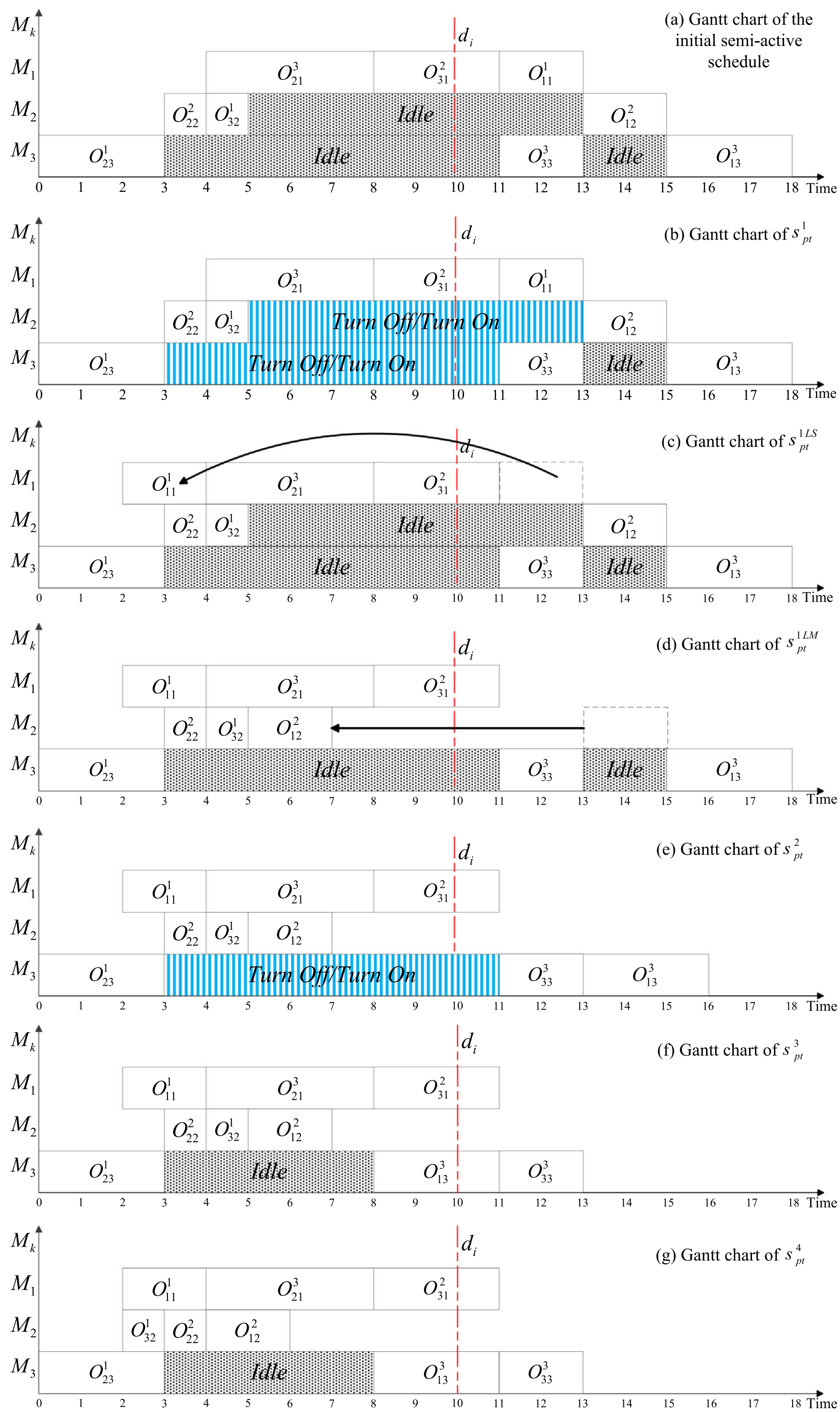

Fig. 5. The 1 to n schedule building procedure of chromosome [222333111].

permissible left move operation in schedule s_{pt}^{1LS} and that is O_{12}^{2}. Left move of O_{12}^{2} to its earliest possible starting time results in schedule s_{pt}^{1LM}. The corresponding Gantt chart is shown in Fig. 5(d).

There is just one permissible left move operation in schedule s_{pt}^{1LM}, which is O_{13}^{3}. It is moved left to its earliest possible starting time. After this move, there is no more available permissible left move operation within the schedule. Since the idle time on machine M_3 between O_{13}^{3} and O_{13}^{3} is longer than 5 time units, the Turn Off/Turn On is applied to get the schedule presented in Fig. 5(e). This is the second feasible solution for the considered individual, denoted by s_{pt}^{2}. The values of objective functions of s_{pt}^{2} are $(21,0)$.

Next, the left shift and move continue until no available permissible left shift operation can be identified. Thus, the 1 to n schedule building process for the given 3×3 job shop is completed. Following the above process, I_{pt}=[222333111] is assigned four feasible solutions. The Gantt chart of s_{pt}^{3} and s_{pt}^{4} are shown in Fig. 5(f) and (g), respectively. The values of the four solutions' objective functions are $(27,2)$, $(21,0)$, $(6,5)$ and $(6,5)$. Although s_{pt}^{3} and s_{pt}^{4} have the same values of objective functions, they have different schedules.

4.2.2. Family creation and individuals rejection

On the completion of the 1 to n schedule building step, each individual is assigned h_{pt} solutions, $h_{pt} \geq 1$. The aim of the step Family creation and individual rejection is first to select the non-dominated ones among the h_{pt} solutions corresponding to each individual, and then to preserve one elitist among the selected non-dominated ones. The two steps are described in more details below. The relationship between the coding and solutions space is shown in Fig. 6.

4.2.2.1. Family creation. In this step, all solutions in the set S_{pt} in the solution space associated with individual I_{pt} in the coding space are compared with each other by using the non-dominated sorting method (Deb et al., 2002), which sorts the solutions into different dominance levels. Only those solutions located in the best level are preserved. The number of solutions corresponding to I_{pt} is reduced from h_{pt} to u_{pt}, $S_{pt} = \left\{ s_{pt}^{v} \right\}_{v=1}^{u_{pt}}$.

Each I_{pt} is copied $u_{pt}-1$ times in the population, creating a new set denoted by $I_{pt} = \left\{ I_{pt}^{v} \right\}_{v=1}^{u_{pt}}$. I_{pt}^{v} is decoded into schedule s_{pt}^{v}. Hence, I_{pt} represents not a single individual, but a set of individuals, called family. All of the u_{pt} individuals in family I_{pt} are referred to as "family members". The members in a family have the same genotype, i.e. coding but correspond to different phenotype, i.e. schedules, and they do non-dominate each other. Before the family creation, there are N individuals in the population P_t and $\sum_{p=1}^{N} h_{pt}$ solutions associated with all individuals, $N \leq \sum_{p=1}^{N} h_{pt}$.

4.2.2.2. Individual rejections. After the family creation, the population size increases from N to N', where $N' = \sum_{p=1}^{N} u_{pt}$. Thus, the aim of the individuals rejection is to preserve the elitist in each family, keep the diversity of the population, and reduce the population size from N' back to N. Two types of individual rejections are defined to decide on which family members to keep for the next generation: individual rejections based on non-dominated sorting of the whole population which is followed by individual rejections in a family based on crowding distance.

Individuals rejection in the population based on non-dominated sorting. The non-dominated sorting is performed on all N' solutions in population P_t. As a result, the solutions which correspond to family members are sorted into different levels. Thus, within a family I_{pt}, only members whose corresponding solutions are located in the lowest level are preserved, others are abandoned. For example, let us assume that there are three members in the family I_{pt}, I_{pt}^{1}, I_{pt}^{2} and I_{pt}^{3}, and that their corresponding solutions (schedules) are s_{pt}^{1}, s_{pt}^{2} and s_{pt}^{3}. Let us further assume that based on the non-dominated sorting, s_{pt}^{1} is located in level 2, s_{pt}^{2} in level 3 and s_{pt}^{3} in level 4. In that case, only I_{pt}^{1} is preserved, while both I_{pt}^{2} and I_{pt}^{3} are abandoned. By completing this process, all the solutions of the members in a specific family are located in the same level, and the population size of P_t is now equal to N'', $N' \geq N'' \geq N$. Some members still need to be rejected from each family to reduce the population size back to N.

Individuals rejection in a family based on crowding distance. According to Deb et al. (2002), the crowding distance is an important indicator which evaluates the ability of an individual to contribute to the diversity of the population. In this step, the preserved family members whose corresponding solutions are located in the same non-dominated front are ranked by their crowding distance value. The one with the largest crowding distance is made elitist.Hence, the boundary solutions of each non-dominated front are kept since they have an infinite value of crowding distance (Deb et al., 2002). In order to address the presence of families in our algorithm we propose a modified definition of boundary solutions and a modified neighbours search to choose solutions to be used in the crowding distance calculation.

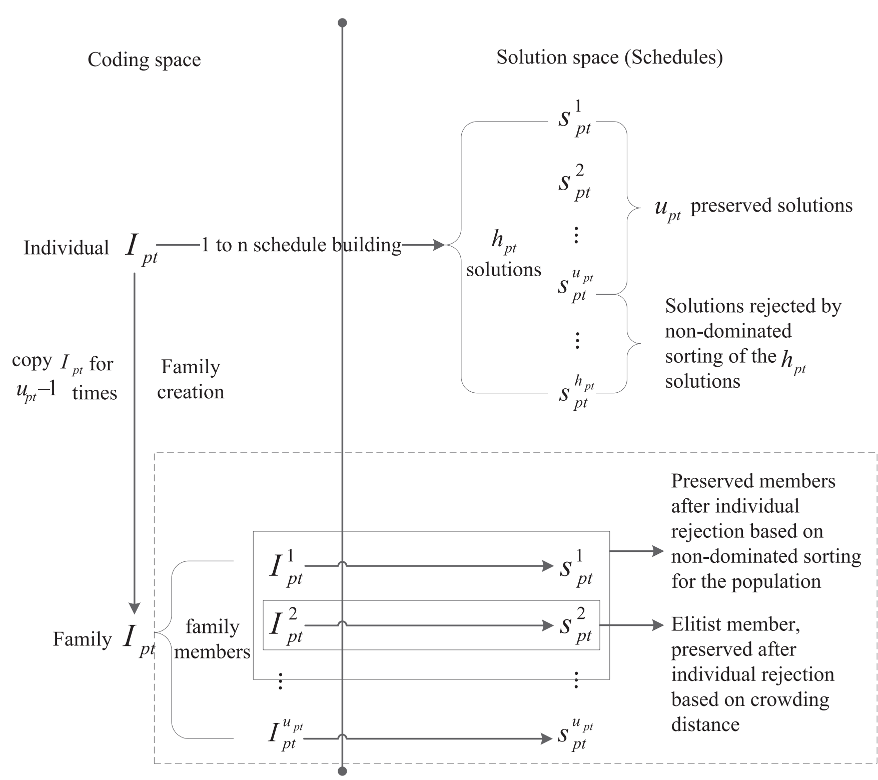

Fig. 6. The relationship between individuals, solutions (schedules) and family in the coding space and solution space.

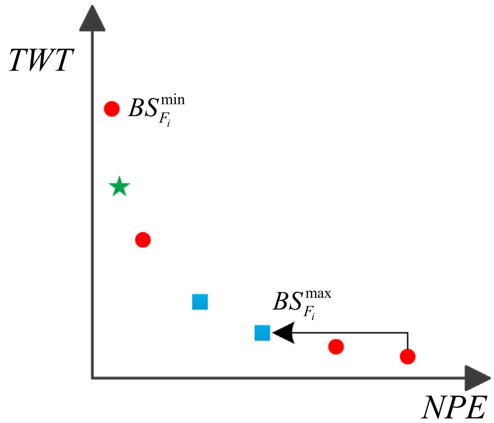

Fig. 7. An example of boundary solutions.

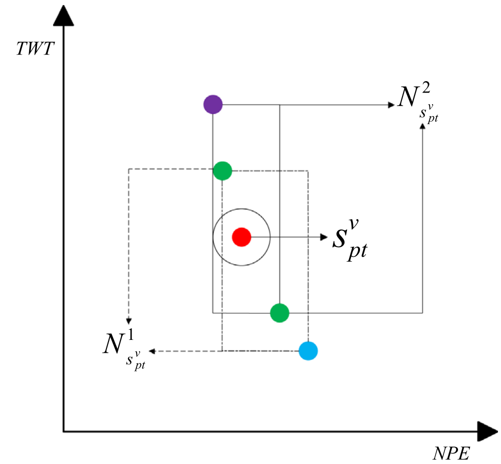

Fig. 8. An example of neighbours search.

The boundary solutions have to belong to different families. They are defined in the following way. In each front F_i, two boundary solutions are found with minimum and maximum value of each objective (see Fig. 7, where different shapes represent solutions from different families, the *x*-axis represents *NPE*, while *y*-axis represents *TWT)*. The solutions with minimum and maximum value of *NPE* are boundary solutions which are denoted by $BS_{F_i}^{min}$ and $BS_{F_i}^{max}$, respectively. There are two possible relationships between two boundary solutions, which determine which one among two of them will be kept.

(1) The individuals that correspond to $BS_{F_i}^{min}$ and $BS_{F_i}^{max}$ belong to different families. Then both of them are preserved.
(2) The individuals which correspond to $BS_{F_i}^{min}$ and $BS_{F_i}^{max}$ belong to the same family. Then one of them is randomly chosen and preserved. Thus, another boundary solution needs to be found such that the individual corresponding to it belongs to a family different from the preserved one. Let us suppose that $BS_{F_i}^{min}$ is preserved, then the new $BS_{F_i}^{max}$ needs to be found. The first solution in the list sorted by NPE in descending order whose corresponding individual belongs to a different family than $BS_{F_i}^{min}$ one is defined as the new $BS_{F_i}^{max}$. An example of the search process is depicted in Fig. 7. Analogue procedure applies if $BS_{F_i}^{max}$ is preserved and new $BS_{F_i}^{min}$ has to be found.

The solutions to be used in the calculation of crowding distance of each solution are chosen in the following way. The neighbours of solution s_{pt}^{v} are the "closest" solutions in terms of the values of TWT or NPE whose corresponding individuals belong to different families. Their families have also to be different from the family of the corresponding individual I_{pt}^{v}. Normally, there are two groups of neighbours for each solution. The first group, denoted by $N^1_{s^v_{pt}}$ is obtained by taking first the left and then the right neighbour of s_{pt}^{v}, which satisfy the family conditions, while the second group, denoted by $N^2_{s^v_{pt}}$ is obtained taking first the right neighbour and then the left. This is illustrated in Fig. 8. The crowding distance of a solution is the maximum between the crowding distance calculated by using $N^1_{s^v_{pt}}$ and $N^2_{s^v_{pt}}$. Each solution has at least one group of neighbours due to the existence of the preserved boundary solutions.

Based on above, the two individuals from different families corresponding to the boundary solutions are preserved. In each of the remaining families, the individual with the largest crowding distance is preserved, while others are rejected. Completing this step, the population size is decreased to N.

A simplified example with the population size of 2 ($N = 2$) is shown in Fig. 9 to show the family creation and individual rejection process.

5. Experimental results

The effectiveness of the developed GAEJP is validated based on comparison experiments. The solutions of GAEJP are compared with the solutions obtained by the traditional single objective scheduling methods and NSGA-II. Three job shop instances based on the F&T 10×10 (Fisher and Thompson, 1963), Lawrence 15×10 and 20×10 (Lawrence, 1984) instances are modified to incorporate electrical consumption profiles for the machine tools. The due date for each job is defined by the TWK due date assignment method (Sabuncuoglu and Bayiz, 1999), $d_i = f \times \sum_{k=1}^{m} \sum_{l=1}^{u_i} p_{ik}^{l}$, i=1, 2, ⋯,n where f is the tardiness factor. The following values of f are set: 1.5, 1.6, 1.7, 1.8 and 1.9. These values have the trend of less tight due date. For instance, $f = 1.5$, represents a tight due date case which corresponds to 50% of tardy jobs. The weight of each job is randomly allocated. The time unit is a minute. Assuming that all the machine tools are automated ones, the idle power level and electricity consumed by Turn off/Turn on of each machine are generated based on the research works focused on the characterisation of machine tools' electricity consumption, such as Dahmus (2007), Drake et al. (2006), and Lv et al. (2016). They provided us with reasonably defined ranges within which required values are generated randomly. A complete list of electrical characteristics data of machines used in the experiments can be found in Appendix I in Liu (2013).

To demonstrate the effectiveness of GAEJP in solving the ECT problem, the following comparison experiment is carried out. The classical job shop scheduling problem with the single objective to minimise TWT serves as the benchmark to represent the traditional approach to machine scheduling without the electricity saving consideration. Shifting Bottleneck Heuristic (SBH) and Local Search Heuristic (LSH) provided by the software LEKIN (Pinedo, 2009) are used to produce solutions. The solutions with minimum TWT are adopted. In each generated schedule, the total NPE value is calculated without using it as the objective function. Performance of SBH and LSH under different due date conditions are shown in Tables 2–4. In the next experiments, the goal is to prove superiority of GAEJP to NSGA-II in solving the ECT problem.

The parameter values used in the GAEJP obtained by tuning, are as follows: population size $N = 150$; crossover probability p_c=1.0; mutation probability p_m=0.4; generation $t = 8000$. The algorithm is

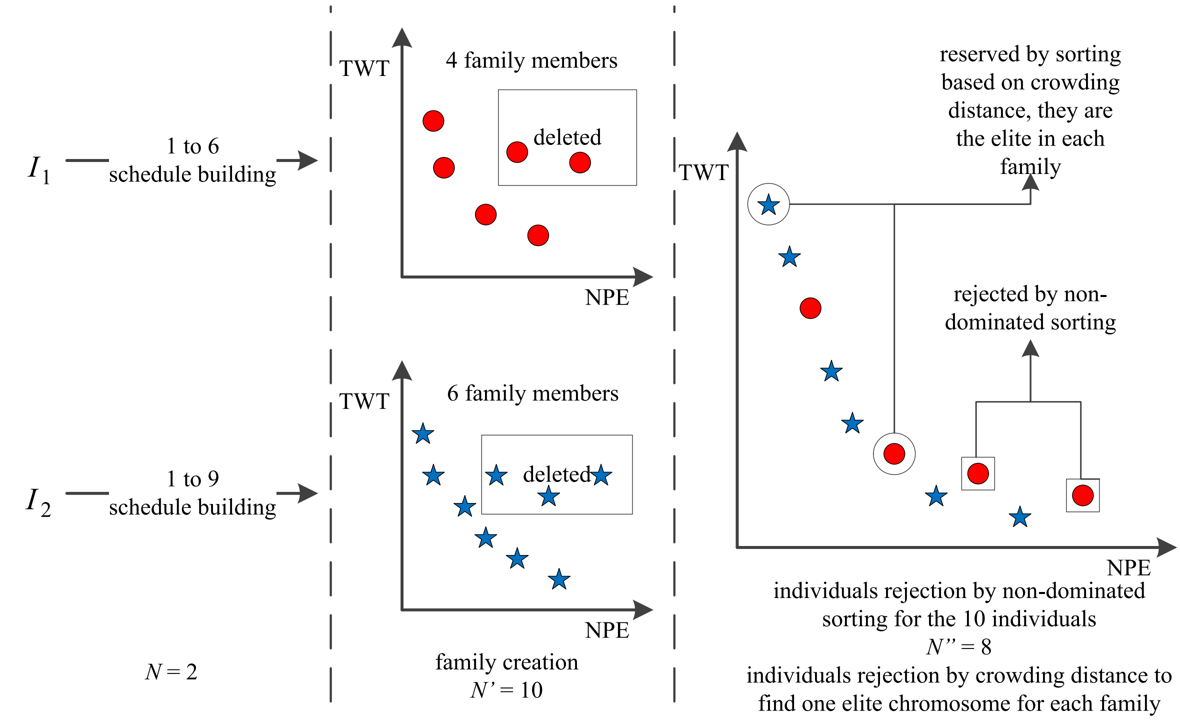

Fig 9. An example of the family creation and individuals rejection.

Table 2
The performance of SBH and LSH on the F&T 10 × 10 job shop by LEKIN.

Tardiness factor (f)	TWT (weighted min)	Total NPE (kW h)	Heuristic
1.5	309	181	SBH
1.6	127	181	SBH
1.7	25	169.7	LSH
1.8	0	169.7	LSH

Table 3
The performance of SBH and LSH on the Lawrence 15 × 10 job shop by LEKIN.

Tardiness factor (f)	TWT (weighted min)	Total NPE (kW h)	Heuristic
1.5	1321	212.8	LSH
1.6	694	207.7	LSH
1.7	293	230.7	LSH
1.8	53	169.3	LSH
1.9	0	200.0	LSH

Table 4
The performance of SBH and LSH on the Lawrence 20 × 10 job shop by LEKIN.

Tardiness factor (f)	TWT (weighted min)	Total NPE (kW h)	Heuristic
1.5	5099	153.5	LSH
1.6	4032	111.2	LSH
1.7	2805	122.1	LSH
1.8	2066	137.0	LSH
1.9	1352	126.7	LSH

run 5 times. Considering the possibility of accelerating machine wear by frequent turn off and turn on actions, they are applied only when the idle time on the machine is longer than 30 minutes. Part of the comparison among solutions of GAEJP, NSGA-II and LEKIN are shown in Figs. 10–12. The trend of results for remaining values of f is similar.

In Figs. 10–12, the hollow points represent the solutions obtained by LEKIN which had been shown in Tables 2–4, the solid points and the points with a pattern are produced by NSGA-II, and GAEJP, respectively. GAEJP achieves a considerable total NPE reduction. The NPE improvements are shown in Tables 5 and 6. Take the F&T 10 × 10 job shop as an example, when $f = 1.5$ and the machines are turned off when the idle time is longer than 30 min, the minimum and maximum values of total NPE obtained by GAEJP are 3.5 kWh and 6.0 kWh respectively, which means that it achieved from 96.7% to 98.1% improvement in the total NPE consumption compared to the values obtained by LEKIN. With the same f value, the improvement in the total NPE compared to NSGA-II is from 90.3% to 98.0%. The TWT deterioration of GAEJP results (compared to the LEKIN results) in weighted minute for each job shop instance under different tardiness conditions are shown in Tables 7 and 8. By considering the performance in both the total NPE and TWT objectives, it can be noticed that scheduling plans delivered by GAEJP always have much smaller NPE consumption than scheduling plans delivered by NSGA-II if they have similar values of TWT. For instance, in the F&T 10 × 10 job shop instance, when $f = 1.6$, one of the boundary solutions delivered by GAEJP is (1118minutes,12.2kWh); comparatively, the solution obtained by NSGA-II with the closest value of TWT is (1136minutes,170kWh), which means the most of the solutions generated by NSGA-II are dominated by solutions delivered by GAEJP. This can also be observed in the given figures.

Additional experiments have been carried out to investigate the effectiveness of GAEJP in reducing the NPE when different values of the minimum idle period allowing machine to be turn off are applied, namely using 20, 40, 50 and 60 min. We present the minimum improvement in NPE achieved across all runs of the algorithm (Tables 5 and 6). These solutions belonging to Pareto fronts, have the minimum compromise in TWT, i.e. they achieve at the same time minimum increase in TWT (Tables 7 and 8). Based on the experiment results, it can be concluded that GAEJP is effective in reducing the NPE at different levels of idle times on the machines allowing them to be turned off. Although in many cases smaller values of the minimum idle period allowing a machine to be turned off lead to larger improvements in NPE, one cannot

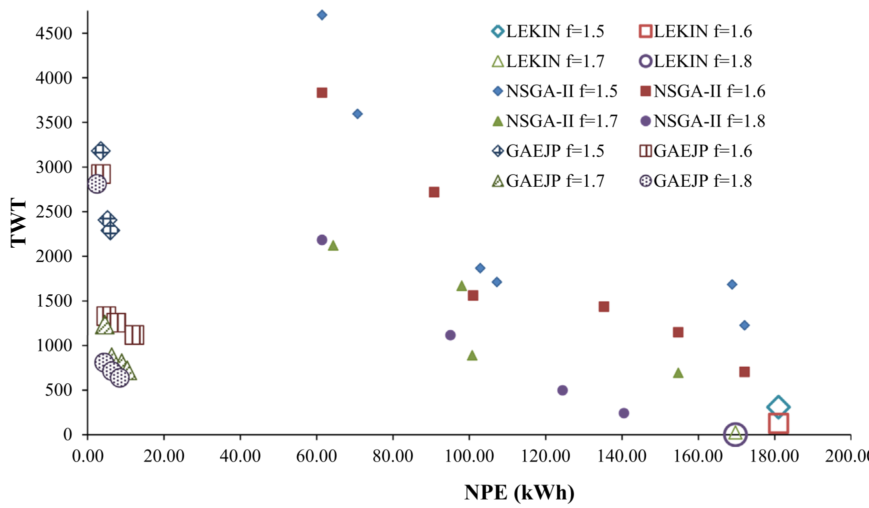

Fig. 10. Performance comparison of GAEJP, NSGA-II and LEKIN (F&T 10 × 10 job shop).

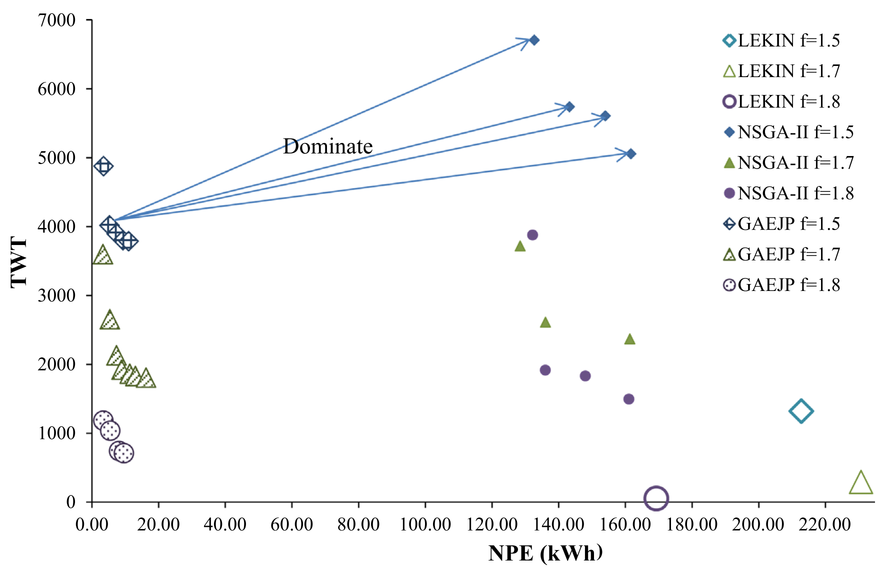

Fig. 11. Performance comparison of GAEJP, NSGA-II and LEKIN (Lawrence 15 × 10 job shop).

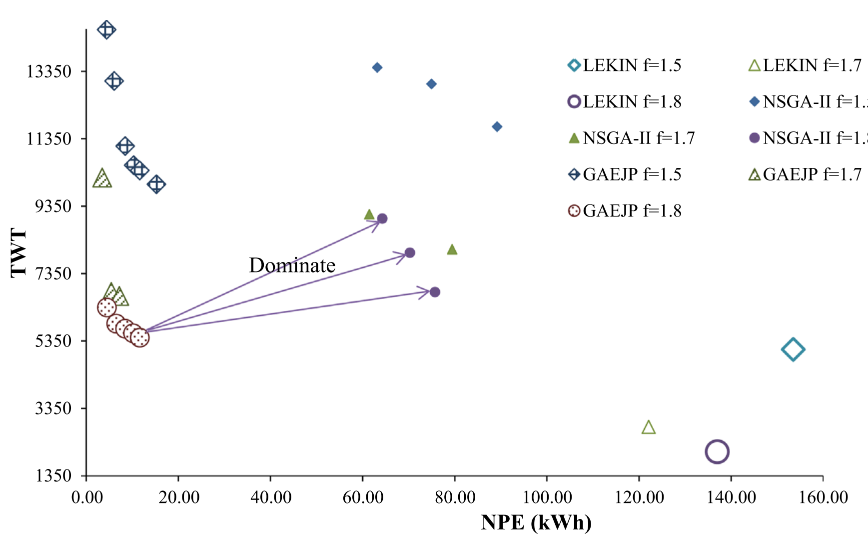

Fig. 12. Performance comparison of GAEJP, NSGA-II and LEKIN (Lawrence 20 × 10 job shop).

Table 5
The total NPE improvement in percentage for F&T 10 × 10 and Lawrence 15 × 10 instance.

Comparison of GAEJP and LEKIN		E-F&T 10 × 10				E-Lawrence 15 × 10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
NPE Improvement 20	min	95.6%	96.8%	97.2%	96.9%	96.1%	88.9%	97.3%	95.7%	96.3%
NPE Improvement 30	min	96.7%	93.2%	93.9%	95.0%	94.8%	94.5%	93.0%	94.3%	96.0%
	max	98.1%	98.1%	97.4%	98.6%	98.4%	98.0%	98.6%	98.0%	98.3%
NPE Improvement 40	min	93.5%	92.1%	96.3%	90.7%	91.9%	93.1%	92.5%	92.3%	95.1%
NPE Improvement 50	min	94.9%	91.1%	90.8%	89.9%	94.1%	88.2%	94.5%	91.7%	96.3%
NPE Improvement 60	min	89.2%	94.5%	88.3%	91.9%	89.2%	88.4%	91.7%	82.8%	90.3%
Comparison of GAEJP and NSGA-II		E-F&T 10 × 10				E-Lawrence 15 × 10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
NPE Improvement 20	min	87.2%	90.4%	92.6%	91.4%	93.7%	80.7%	95.2%	94.5%	94.1%
NPE Improvement 30	min	90.3%	80.1%	83.9%	86.3%	91.7%	90.4%	87.4%	92.8%	93.7%
	max	98.0%	98.0%	97.1%	98.3%	97.8%	97.4%	97.9%	97.9%	98.1%
NPE Improvement 40	min	80.9%	76.7%	90.3%	74.4%	87.0%	88.0%	86.6%	90.2%	92.3%
NPE Improvement 50	min	85.0%	73.8%	75.7%	72.2%	90.5%	79.4%	90.1%	89.4%	94.2%
NPE Improvement 60	min	68.2%	83.8%	69.1%	77.6%	82.7%	79.8%	85.2%	77.9%	84.8%

Table 6
The total NPE improvement in percentage for Lawrence 20 × 10 instance.

Comparison of GAEJP and LEKIN		E-Lawrence 20 × 10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
NPE Improvement 20	min	92.4%	86.5%	93.8%	94.5%	94.0%
NPE Improvement 30	min	90.1%	93.3%	94.1%	91.5%	90.1%
	max	97.1%	96.9%	97.1%	96.7%	96.5%
NPE Improvement 40	min	87.3%	81.5%	90.3%	85.8%	87.2%
NPE Improvement 50	min	80.3%	69.0%	77.4%	87.7%	81.8%
NPE Improvement 60	min	77.8%	76.8%	79.9%	75.7%	81.7%
Comparison of GAEJP and NSGA-II		E-Lawrence 20 × 10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
NPE Improvement 20	min	81.5%	74.0%	87.6%	88.2%	88.5%
NPE Improvement 30	min	75.9%	87.0%	88.3%	81.9%	81.1%
	max	95.0%	95.9%	95.6%	94.1%	95.5%
NPE Improvement 40	min	69.1%	64.3%	80.7%	69.8%	75.5%
NPE Improvement 50	min	52.1%	40.2%	55.2%	73.9%	65.0%
NPE Improvement 60	min	46.2%	55.4%	60.1%	48.2%	64.9%

conclude that it holds all the time. For instance, the largest minimum NPE improvement compared to the LEKIN results for E-Lawrence 20 × 10, f=1. 7, was achieved when the minimum idle period for turning of the machine was 30 min. On the other hand, the compromise of TWT varies considerably when different values of the minimum idle period allowing machine to be turned off are applied. For instance, in the E-Lawrence 15 × 10 job shop, f=1. 9, the increase in TWT is only 10 when 40 min is used as the lower boundary to turn off the machines, compared to the LEKIN result, while the improvement in NPE is 75.5%. This is the best value of TWT across all five evaluated lower boundaries of idle periods. Thus, it can be concluded that for a specific job shop, it is worthy

Table 8
The TWT increase in weighted minutes for Lawrence 20 × 10.

Comparison of GAEJP and LEKIN		E-Lawrence 20 × 10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
TWT Increase 20	min	5010	4565	4420	3857	2288
TWT Increase 30	min	4898	3860	3880	3386	2738
	max	9480	9008	7391	4281	5139
TWT Increase 40	min	5074	3988	4443	3808	2948
TWT Increase 50	min	4765	5358	3973	3738	2775
TWT Increase 60	min	5966	4222	4306	3205	3575

investigating which value of the minimum idle period allowing the machines to be turned off will result in the good trade-off between TWT and NPE. From the application perspective, this can provide more options for the decision maker. For example, for the E-Lawrence 15 × 10 job shop, f=1. 9, when 40 min is used to apply the turn off, the solution with 75.5% improvement in NPE and only 10 increase in TWT might be more preferable than the solution with 98.3% improvement in NPE and 647 increase in TWT (obtained by using 30 min idle period to apply the turn off).

It can be observed that GAEJP combined with Turn off/Turn on is more effective in reducing the total NPE than NSGA-II, without compromising TWT too much. For Lawrence 15 × 10 and 20 × 10 job shop, all solutions obtained by NSGA-II are dominated by at least one solution obtained by GAEJP, as shown in Figs. 11 and 12. For the F&T 10 × 10 instance, some of the NSGA-II solutions are not dominated by any GAEJP solutions. For this instance, Pareto fronts generated by two algorithms are combined together to form new Pareto fronts, and only non-dominated solutions are preserved. It can be noticed from Fig. 10 that solutions obtained by the GAEJP take a larger proportion of the total number of solutions in

Table 7
The TWT increase in weighted minutes for F&T 10 × 10 and Lawrence 15 × 10.

Comparison of GAEJP and LEKIN		E-F&T 10 × 10				E-Lawrence 15 × 10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
TWT Increase 20	min	1957	1881	1185	493	2963	2931	1162	350	130
TWT Increase 30	min	1979	991	695	638	2465	2094	1515	659	78
	max	2870	2794	1209	2811	3555	3165	3306	1131	647
TWT Increase 40	min	861	811	565	95	2385	2413	826	795	10
TWT Increase 50	min	1933	1664	1107	145	3420	1843	901	1120	31
TWT Increase 60	min	1206	744	156	232	2304	1947	1195	438	80

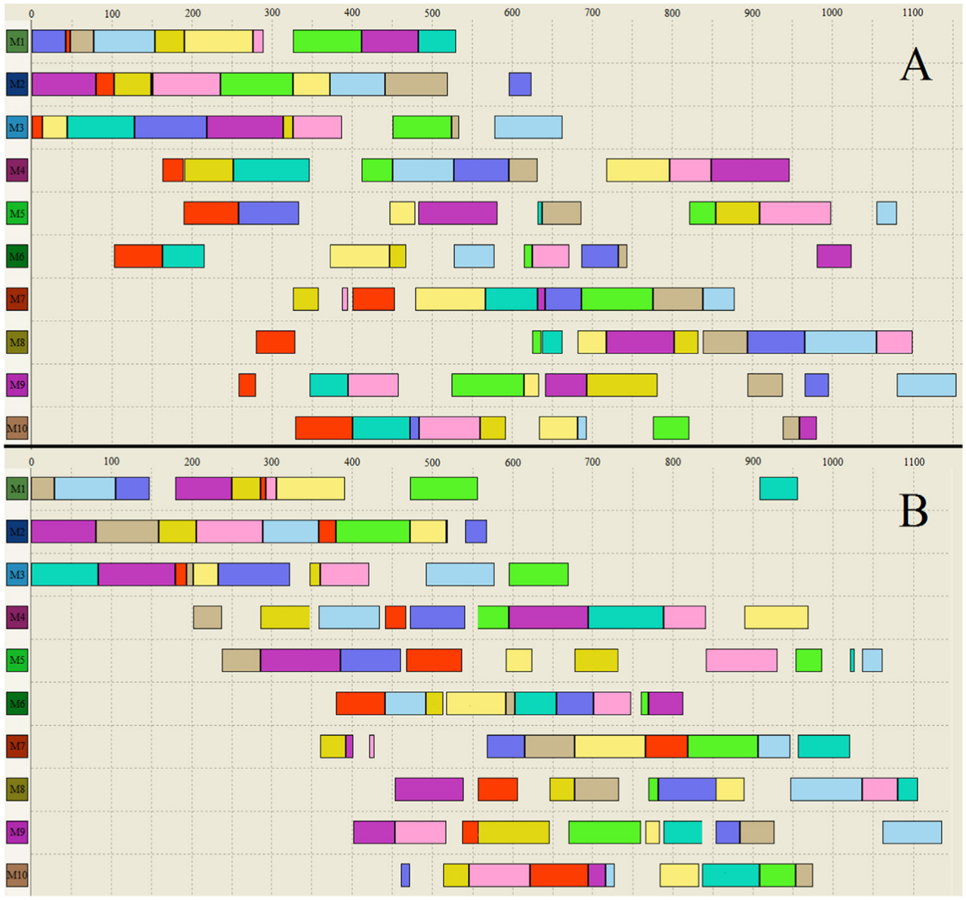

Fig. 13. The Gantt chart of optimal schedule produced by GAEJP (A) and by NSGA-II (B) when $\boldsymbol{f} = 1.5$ (F&T 10 × 10 job shop instance).

the new Pareto fronts, which means GAEJP can provide more options to the production manager.

The upper part A and bottom part B of Fig. 13 show the Gantt charts of optimal schedules produced by GAEJP and NSGA-II respectively for E-F&T 10 × 10 job shop instance when $f = 1.5$. It can be observed that the schedule produced by GAEJP has a smaller total amount of idle periods on all machines (31 idles periods on the GAEJP schedule versus 37 idle periods on the NSGA-II schedule), and in general the lengths of those idle periods are longer. This means when the varieties of jobs' components and their amounts are increasing, it is easier to place the new operations in the existing idle periods in scheduling plans produced by GAEJP. From above, the scheduling plans produced by GAEJP might be more preferable for managers when considering the real life job shop manufacturing system. An interesting question is whether the Turn off/Turn on applied to the optimisation result of NSGA-II may lead to a better result than that produced by GAEJP. However, in the case presented in Fig. 13, the original objective function values of scheduling plans produced by GAEJP and NSGA-II are $\left(2288\ \text{min}, 6.0\ \text{kW h}\right)$ and $\left(3595\ \text{min}, 170\ \text{kW h}\right)$, respectively. When the Turn off/Turn on is applied to the bottom scheduling plan, the objective function values become $\left(3595\ \text{min}, 14.5\ \text{kW h}\right)$. Therefore, the solution delivered by GAEJP is still preferable for the production manager. A more thorough investigation of the effects of applying Turn off/Turn on to the optimisation results of NSGA-II will be investigated in the future research work.

6. Conclusions and future work

Reducing electricity consumption as well as keeping good performance in classical scheduling objectives gains more and more importance in modern manufacturing. The model for the Multi-objective Total Non-processing Electricity Consumption (NPE) and Total Weighted Tardiness (TWT) job shop problem which integrates Scheduling with the Turn off/Turn on of machines has been introduced. For solving this problem, the multi-objective optimisation algorithm based on NSGA-II, GAEJP, with two new steps has been developed. The performance of the algorithm has been tested on three extended versions of job shop instances which incorporate electrical consumption profiles for the machine tools. In addition, comparison experiments have been applied to demonstrate the effectiveness of GAEJP in solving the ECT problem. Firstly, the Shifting Bottleneck Heuristic and the Local Search Heuristic have been used as the single objective heuristic optimisation methods to deliver the baseline scenarios of the aforementioned job shops. The result of the comparison indicates that by applying GAEJP the total non-processing electricity consumption is decreased considerably, with an acceptable level of deterioration of the total weighted tardiness. The Pareto fronts produced by GAEJP have also been compared with those obtained by NSGA-II, which involved only the optimal schedules of jobs without applying Turn off/Turn on. It can be observed that GAEJP is more effective in reducing the total NPE than NSGA-II, without compromising its performance on TWT. Thus, the superiority of the GAEJP in solving the ECT problem has been demonstrated. In future work, the algorithm should be tested on a wider set of job shop instances to validate its general applicability. The developed GAEJP has the potential to solve other multi-objective optimisation problems. This will be explored in our future research work. More investigation into comparison of GAEJP and NSGA-II when they are used as the optimisation approach for both Scheduling and Turn off/Turn on methods will be conducted. Also, it will be investigated how to set a favourable value of the minimum idle period allowing the machines to be turned off for a specific job shop.

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