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An investigation into minimising total energy consumption and total weighted tardiness in job shops☆

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ABSTRACT

Manufacturing enterprises nowadays face the challenge of increasing energy prices and requirements to reduce their emissions. Most reported work on reducing manufacturing energy consumption today focuses on the need to improve the efficiency of resources (machines) largely ignoring the potential for energy reducing on the system-level where the operational method can be employed as the energy saving approach. The advantage is clearly that the scheduling and planning approach can also be applied across existing legacy systems and does not require large investment. Therefore, a multi-objective scheduling method is developed in this paper with reducing energy consumption as one of the objectives. This research focuses on classical job shop environment which is widely used in the manufacturing industry. A model for the bi-objectives problem that minimises total electricity consumption and total weighted tardiness is developed and the Non-dominant Sorting Genetic Algorithm is employed as the solution to obtain the Pareto front. A case study based on a modified 10 × 10 job shop is presented to show the effectiveness of the algorithm and to prove the feasibility of the model.

1. Introduction

Energy is one of the most vital resources for manufacturing. In the last 50 years the consumption of energy by the industrial sector has more than double and industry currently consumes about half of the world's energy (Mouzon et al., 2007). Energy consumption is a very important cost element for manufacturing enterprises. The price of energy is growing higher as a result of the increasing crude oil prices (Kilian, 2008). For example, in 2006, energy costs for U.S. manufacturers were $100 billion annually, which today is even higher (Mouzon et al., 2007). Additionally, energy consumption is one of the most significant factors that lead manufacturing enterprises to become environmental unfriendly. In the U.S., the manufacturing sector consumes about one-third of the energy used and contributes to about 28% of greenhouse gas emissions (Mouzon, 2008). One of the most important forms of energy for manufacturing is electricity which is highly polluting during its production processes. Every year in China, manufacturing consumes around 50% of the entire electricity produced (Tang et al., 2006), and generates at least 26% of the total carbon dioxide emission. Thus, the increasing price of energy and the current trend of sustainability have exerted new pressure on manufacturing enterprises. They therefore have to reduce energy consumption both to save cost and to become more environmentally friendly.

Most existing research on reducing manufacturing energy consumption has focused so far on developing more energy (particularly electrical energy) efficient machines or machining processes (Duflou et al., 2012; Fang et al., 2011). However, compared to the background energy consumed by the manufacturing equipment operations, the energy requirements for the active removal of material can be quite small (Dahmus and Gutowski, 2004), especially in the mass production environment, it takes no more than 15% of the total energy usage. The majority of energy is consumed by functions that are not directly related to the production of components (Gutowski et al., 2005). This implies that efficiency improving efforts focussing solely on the machines or processes may miss a significant energy saving opportunity. In fact, there is a larger energy reducing margin on the system-level where the operational method can be employed as the energy saving approach. Additionally, compared to machine or process redesign, implementation of optimised shop floor scheduling and plant

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operation strategies only require a modest capital investment and can easily be applied to existing systems (Fang et al., 2011).

As a result, employing operational methods can be a feasible and effective approach for manufacturing enterprises to reduce the energy consumption (Mouzon and Yildirim, 2008). The job shop type of manufacturing system is selected as the research object for the following reasons: from the academic perspective, it fills the research gaps that the multi-objective scheduling approaches for a typical job shop type of manufacturing system have not been well investigated from the perspective of energy consumption reduction. Most of the current energy-conscious scheduling researches are single machine and flow shop oriented. On the other hand, from the practical perspective, large majority of companies operate job shop model, especially for the small and medium enterprises (SMEs). For instance, the original equipment manufacturers (OEMs) in the aerospace industry usually employ the job shop manufacturing system for their capability to satisfy the increasingly diversified customer demands (Harrison et al., 2004). A general model of the job shop scheduling problem that considers minimising total weighted tardiness (TWT) and total energy consumption is proposed in this paper. Based on the review developed by Marler and Arora (2004) for the engineering multi-objective optimisation techniques, the evolutionary scheduling approaches (Dahal et al., 2007) and the proof of the effectiveness of Genetic Algorithm in improving the energy efficiency of production plans (Quilligan and Upton, 2012), the Non-dominant Sorting Genetic Algorithm (NSGA-II) (Deb et al., 2002) has been adopted for achieving the bi-objective optimisation. The optimisation framework proposed in this paper can be applied to discrete event machining production system and may save significant amounts of energy and reduce the cost as well as keep a good performance of classical scheduling objectives. The term “machining” in this paper will refer to processes such as milling, turning, drilling, and sawing (Dahmus and Gutowski, 2004).

In the remaining of the paper, the research problem will be more formally defined after the background research and research motivation; then the model will be presented, followed by an introduction to the NSGA-II and how it has been applied to optimised the bi-objective scheduling problem; finally, a case study is presented to demonstrate the effectiveness of the feasibility of the model and the effectiveness of the algorithm for the research problem.

2. Background and motivation

A considerable amount of research has been conducted in the area of sustainable machining. Duflou et al. (2012) and Fysikopoulos et al. (2013) provide the state-of-the-art reviews in energy and resource efficiency increasing methods and techniques in the area of discrete part manufacturing. A detailed process model that can be used to determine the environmental impacts resulting from the machining of a particular part have been presented by Munoz and Sheng (1995). Based on experiments on an automated milling machine, Diaz et al. (2009) conclude that high-speed cutting would reduce the energy consumption per volume of material processed for machine tools which demands high constant power. Method of estimating machining energy consumption according to numerical control (NC) code has been proposed by He et al. (2012b). This kind of method provides a potential faster way to estimate energy consumption of machining processes. Avram and Xirouchakis (2011) have developed a methodology to estimate the energy requirements during use phase of spindle and feed axis according to automatic programming tool (ATP) file. This method considers the entire machine tool system by taking into account steady-state and transient regimes. Dahmus and Gutowski (2004) and Kordonowy (2003) developed a system level research which not only includes energy requirement for material removal process itself, but also associated processes such as axis feed. The approach which breaks the total energy use of machining processes has been employed as the bases for modelling power input of machine tools on the workshop level. According to this approach, the electricity consumption for a machine tool in a feasible schedule can be divided to two types: the non-processing electricity consumption (NPE) and processing electricity consumption (PE). NPE is associated with machine start-up, shut-down and idling. The electricity consumed when a job is processed on a specific machine can be defined as job related processing electricity consumption (JPE), including the basic power consumption of machine tools, i.e. idle power, the runtime operations and the actual cutting consumption. Thus, PE is the sum of all the JPE on a specific machine. Each JPE has been defined as a constant value by both Mouzon (2008) and He et al. (2012a) in their models, since on the workshop level, what we mainly concern about is how scheduling plans affect the total electricity consumption of the manufacturing system. Therefore, the JPE can be seen as a black box for scheduling problems. This modelling approach will be adopted for this research.

The typical electricity saving method (ESMs) on the system level include: Sequencing, Turn Off/Turn On and Process Route Selection (PRS). The sequencing method has been adopted by Mouzon (2008) to reduce the total NPE in single machine environment and parallel machine environment. Since the order of jobs which are processed on the same machine will affect the total amount of the idle time and the length of each idle period of that machine. Drake et al. (2006) realised that in manufacturing environment, large quantities of energy are consumed by non-bottleneck machines as they lie idle, and that whenever a machine or is turn on or turn off, there are significant amounts of start-up or shut-down energy consumption. Based on this fact, Mouzon (2008) proposed a Turn Off/Turn On method, which means a machine tool could be turned off when it becomes idle for electricity saving purpose. In some factories, it is not feasible to switch machines off when they become idle. Thus, Aughney and O’Donnell (2012) define a “powersave” mode for machines where one can save energy without turning the machine off. According to above, both of the Sequencing and Turn Off/Turn On methods can be applied to any type of manufacturing system for the electricity saving purpose by reducing the NPE of the machines.

Mouzon (2008) employed the PRS to reduce both total PE and total NPE for parallel machine environment. He et al. (2012a) used the same method to decrease both total PE and total NPE for a flexible job shop environment. The limitation for PRS is that it is only effective in systems which have alternative routes with different energy characteristics for the same job, i.e. PRS is not applicable to workshops without alternative routes, or having identical alternative routes for jobs, for instance, the job shop environment.

Optimisation techniques are required to be developed to enable the above ESMs to be optimally applied to the manufacturing systems, thereby, reducing the energy consumption. Methods including dispatching rules, a genetic algorithm and a greedy randomised adaptive search procedure have been proposed by Mouzon et al. (2007) and Mouzon (2008) to achieve this aim. However, according to the classification method for manufacturing models by Pinedo (2012), the above research works focus on the single machine environment and the parallel machine environment limits the applicability of their methods for wider range of production systems. The amount of research on scheduling with environmentally-oriented objectives is currently small but increasing. For example, Fang et al. (2011) considered reducing peak power load in a flow shop. Bruzzonea et al. (2012) developed a method to modify the schedule of the jobs in flexible flow shops in order to adjust to the maximum peak power constraint. Subaï et al. (2006) considered energy and waste reduction in hoist scheduling problem of the surface treatment processes without changing the original productivity. 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.

Based the discussion above, the motivation for this research from an academic aspect is employing operational methods to reduce the total energy consumption in a typical job shop environment without machines in parallel still has not been explored very well. The objective of reducing the total energy consumption can be converted to the reduction of the total NPE since there is no alternative route in the system and hence the total PE remains constant. The lack of a more fundamental energy saving oriented job-shop model and its related scheduling techniques are significant gaps in the current research which needs to be addressed. Based on the fundamental model and scheduling method, more complex models, for instance, the flexible job shop with recirculation and more sophisticate optimisation techniques can be developed.

For this research, the NPE only includes the idle power consumption of machine tools. Adopting the TWT as the performance indicator, the underlying objective for this paper is defined as: Multi-objective Total NPE and TWT Job Shop Scheduling (Electricity Consumption and Tardiness-ECT). The modelling method for this problem will be presented below.

3. Problem definition and notations

Job shops are prevalent in industry. Normally, there are several jobs and each job visit a number of machines following a predetermined route. As shown in Fig. 1, component A and B are processed in a job shop with four machines, the processing routine for them are Machine 1–3–2–4 and Machine 3–1–4–2 respectively. The job shop model used in this research is the deterministic (static) one which means the number of jobs is a fixed value and all of them are ready to be processed at time 0. The recirculation circumstance is not considered in this model which means a job only visit any given machine at most once. The aim of this research is to reduce both TWT and NPE in an aforementioned static job shop. The formal mathematical definition of the problem will be described in detail in the following sections.

3.1. Notations

The notations used in the problem statement and throughout the paper are as follows:

C_{ik}^{l} completion time of O_{ik}^{l} on M_k
$C_i(s)$ completion time of J_i in schedule s (i.e. the completion time of the last operation of J_i, $O_i^{u_i}$)
C_k^{r} completion time of m_k^{r} on M_k
d_i due date of J_i

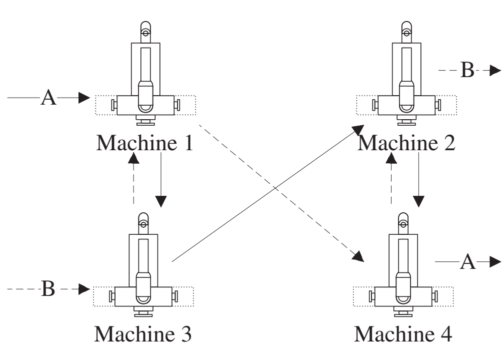

Fig. 1. A typical job shop.

$E_{ik}^{l\text{cutting}}$ electricity consumption of M_k when it actually executes cutting for O_{ik}^{l}
$E_{ik}^{l\text{runtime}}$ electricity consumption of M_k when it executes the runtime operations for processing O_{ik}^{l}
$E_{ik}^{l\text{basic}}$ electricity consumed by M_k with the idle power level during p_{ik}^{l}
E_{ik}^{l} JPE of O_{ik}^{l} on M_k
J a finite set of n jobs, $J = \{J_i\}_{i=1}^{n}$
M a finite set of m machines, $M = \{M_k\}_{k=1}^{m}$
$M_k^{'}$ a finite set of operations processed on M_k, $M_k^{'} = \{m_k^{r}\}_{r=1}^{\sum_{i=1}^{n}\sum_{l=1}^{u_i}\gamma_{ik}^{l}}$
m_k^{r} r-th operation processed on M_k within a feasible schedule s
O_i a finite set of u_i ordered operations of J_i, $O_i = \{O_{ik}^{l}\}_{l=1}^{u_i}$
O_{ik}^{l} l-th operation of J_i processed on M_k
p_{ik}^{l} processing time of O_{ik}^{l}
P_k input power of M_k
P_k^{idle} idle power of M_k
$P_{ik}^{l\text{runtime}}$ power level of M_k when it executes the runtime operations for processing O_{ik}^{l}
$P_{ik}^{l\text{cutting}}$ power level of M_k when it actually executes cutting for O_{ik}^{l}
r_i release time of J_i into the system
S_{ik}^{l} starting time of O_{ik}^{l} on M_k
S_k^{r} starting time of m_k^{r} on M_k
s a feasible schedule plan
S a finite set of all feasible schedule plans, $s \varepsilon S$
$T_i(s)$ tardiness of J_i, defined as $T_i(s) = \max\{0, C_i(s) - d_i\}$
$t_{ik}^{l\text{cutting}}$ cutting time
w_i weighted importance of J_i
$Y_{ii'k}^{ll'}$ $Y_{ii'k}^{ll'} = 1$ if O_{ik}^{l} precedes $O_{i'k}^{l'}$ on M_k, 0 otherwise
γ_{ik}^{l} $\gamma_{ik}^{l} = 1$ if the l-th operation of J_i processed on M_k, 0 otherwise

3.2. Job shop model

The job shop scheduling problem outlined above is formally defined following the work of Özgüven et al. (2010), Jain and Meeran (1998) and Vázquez-Rodríguez and Petrovic (2010). In a job shop, a finite set of n jobs $J = \{J_i\}_{i=1}^{n}$ are to be processed on a finite set of m machines $M = \{M_k\}_{k=1}^{m}$ following a predefined order. Each job is defined as a finite set of u_i ordered operations $O_i = \{O_{ik}^{l}\}_{l=1}^{u_i}$ where O_{ik}^{l} is the l-th operation of job J_i processed on machine M_k and requiring a processing time denoted by p_{ik}^{l}. The start time S_{ik}^{l} when an operation O_{ik}^{l} begins to be processed on machine M_k will be determined based on the defined production

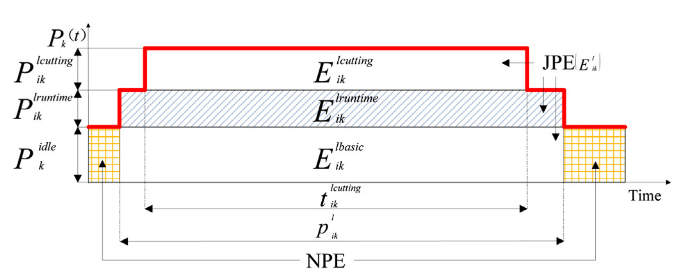

Fig. 2. The simplified power input of a machine tool when it is working on one operation.

schedule, while C_{ik}^{l} is the corresponding completion time of that operation. The order of any two operations on a machine M_k is expressed by a decision variable $Y_{ii'k}^{ll'}$ which is $Y_{ii'k}^{ll'} = 1$ if operation O_{ik}^{l} precedes $O_{i'k}^{l'}$ and 0 otherwise. Each job J_i has a release time into the system r_i and a due date d_i. Different jobs can be prioritised using the weighted importance factor w_i for each job J_i as a number between 0 and 1.

The model is subject to the following constraints to ensure its integrity during the schedule optimisation:

$$S_{ik}^{l} \geq r_i, \ \forall J_i \in J, \ \forall O_{ik}^{l} \in O_i, \ \forall M_k \in M \tag{1}$$

$$\begin{aligned} &C_{ik}^{l+1} - C_{ik'}^{l} \geq p_{ik}^{l+1}, \ 1 \leq l < l+1 \leq u_i, \ k \neq k', \\ &\forall J_i \in J, \ \forall O_{ik}^{l+1}, \ O_{ik'}^{l} \in O_i, \ \forall M_k, \ M_{k'} \in M \end{aligned} \tag{2}$$

$$\begin{aligned} &S_{ik}^{l+1} - C_{ik'}^{l} \geq 0, \ 1 \leq l < l+1 \leq u_i, \ k \neq k', \\ &\forall J_i \in J, \ \forall O_{ik}^{l+1}, \ O_{ik'}^{l} \in O_i, \ \forall M_k, \ M_{k'} \in M \end{aligned} \tag{3}$$

$$\begin{aligned} &C_{i'k}^{l'} - C_{ik}^{l} \geq p_{i'k}^{l'}, \ Y_{ii'}^{ll'} = 1, \ i \neq i', \\ &\forall J_i, \ J_{i'} \in J, \ \forall O_{ik}^{l} \in O_i, \ \forall O_{i'k}^{l'} \in O_{i'}, \ \forall M_k \in M \end{aligned} \tag{4}$$

where

$$Y_{ii'k}^{ll'} \in \{0,1\} \ i \neq i', \ \forall J_i, \ J_{i'} \in J, \ \forall O_{ik}^{l} \in O_i, \ \forall O_{i'k}^{l'} \in O_{i'}, \ \forall M_k \in M$$

$$S_{ik}^{l} \geq 0, \ C_{ik}^{l} \geq 0 \ \forall J_i \in J, \ \forall O_{ik}^{l} \in O_i, \ \forall M_k \in M$$

$$C_{ik'}^{l} \geq 0 \ \forall J_i \in J, \ \forall O_{ik'}^{l} \in O_i, \ \forall M_{k'} \in M$$

Constraint (1) ensures that the starting times S_{ik}^{l} for all operations O_{ik}^{l} must be greater or equal to the release times r_i of the job J_i they belong to. Constraint (2) and (3) ensures that the precedence relationships between the operations of a job are not violated. I.e. the operation O_{ik}^{l+1} cannot start before the previous operation $O_{ik'}^{l}$ has been completed and no job can be processed by more than one machine at a time. Constraint (4) takes care of the requirement that no machine can process more than one operation at a time.

A schedule s that complies with constraints (1)–(4) is said to be a feasible schedule. S is a finite set of all feasible schedules s such that $s \varepsilon S$. Furthermore, given a feasible schedule s, let $C_i(s)$ indicate the completion time of job J_i in schedule s. The tardiness of job J_i can then be denoted as $T_i(s) = \max\{0, C_i(s) - d_i\}$ and the first optimisation objective to minimise the total weighted tardiness of all jobs can be expressed as:

$$\text{minimise}\left(\sum_{i=1}^{n} w_i \times T_i(s)\right) \tag{5}$$

3.3. Electricity consumption model

The electricity consumption model is based on existing research work on environmental analysis of machining (Avram, 2010; Diaz et al., 2010; Dietmair and Verl, 2009; Kordonowy, 2003). A simplified power input model for each machine M_k when it is working on operation O_{ik}^{l} has been developed as shown in Fig. 2. The model assumes that each machine M_k has three constant levels of power consumption: during idle time, when switched into runtime mode and when carrying out the actual operation; here presented as cutting operation.

The input power $P_k(t)$ a machine M_k requires over time is defined as a stepped function represented by the red line in Fig. 2. The idle power level of a machine M_k is defined by P_k^{idle}, the increase in power during runtime is defined by $P_{ik}^{l\text{runtime}}$, and the further additional power requirement for cutting is given by $P_{ik}^{l\text{cutting}}$. The overall processing time p_{ik}^{l} is defined as the time interval between coolant switching on and off. The cutting time $t_{ik}^{l\text{cutting}}$ for an operation O_{ik}^{l} is often a slightly shorter time interval during which the highest power level is required; $P_k^{\max} = P_k^{\text{idle}} + P_{ik}^{l\text{runtime}} + P_{ik}^{l\text{cutting}}$.

Assuming that the power levels remain constant during an operation, the basic energy consumption of a machine M_k during the runtime for operation O_{ik}^{l} can be defined as $E_{ik}^{l\text{basic}} = P_k^{\text{idle}} \times p_{ik}^{l}$ and the additional energy required to put the machine into runtime mode is $E_{ik}^{l\text{runtime}} = P_k^{l\text{runtime}} \times p_{ik}^{l}$. The extra energy required for the cutting process during operation O_{ik}^{l} can be defined as $E_{ik}^{l\text{cutting}} = P_{ik}^{l\text{cutting}} \times t_{ik}^{l\text{cutting}}$. Hence, the job related processing electricity consumption (JPE) required to carry out operation O_{ik}^{l} on machine M_k is $E_{ik}^{l} = E_{ik}^{\text{idle}} + E_{ik}^{l\text{runtime}} + E_{ik}^{l\text{cutting}}$.

According to the above definitions, E_{ik}^{l} can be treated as a constant for each operationO_{ik}^{l}, since both the power level and the process duration for each operation are fixed values. Therefore, it is easy to conclude that the processing electricity consumption (PE) required for all operations processed on a machine M_k expressed as $\sum E_{ik}^{l}$ is also a constant which will not be affected by different scheduling plans. Thus, the objective to reduce the total electricity consumption of a job shop can be converted to reduce the total non-processing energy (NPE). Hence, the objective function can be set as the sum of all the NPE consumed by all the machines in a job shop to carry out a given job schedule:

$$\text{minimise}\left(\sum_{k=1}^{m} \text{TEM}_k^{\text{np}}(s)\right) \tag{6}$$

where $\text{TEM}_k^{\text{np}}(s)$ is the NPE of machine M_k for schedule s. Unlike the PE, the NPE is a function of the scheduling plan. Hence, $\text{TEM}_k^{\text{np}}(s)$ needs to be expressed based on the specific order the different operations O_{ik}^{l} have been scheduled to run on a machine M_k. $M_k' = \{m_k^r\}_{r=1}^{\sum_{i=1}^{n}\sum_{l=1}^{u_i}\gamma_{ik}^{l}}$ is the finite set of operations processed on M_k. γ_{ik}^{l} is a decision variable that $\gamma_{ik}^{l} = 1$ if the l-th operation of job J_i processed on M_k, 0 otherwise. With S_k^r and C_k^r respectively indicate the start and completion time of operation m_k^r on M_k for a schedule s, this schedule can be graphically expressed as a Gantt chart as shown in Fig. 3. Consequently, the calculation of the NPE of machine M_k can be expressed based on start and completion times defined for a schedule s :

$$\text{TEM}_k^{\text{np}}(s) = P_k^{\text{idle}} \times \left[\max(C_k^r) - \min(S_k^r) - \sum_r (C_k^r - S_k^r)\right] \tag{7}$$

Fig. 3 is an example for the calculation of the NPE of M_k. $O_{i_1k}^{l_1}$, $O_{i_2k}^{l_2}$, $O_{i_3k}^{l_3}$, and $O_{i_4k}^{l_4}$ are processed by M_k. Based on Equation (7), to get the value of NPE which is represented by the blue grid area, firstly the total idle time of machine M_k in above schedule needs to be calculated, which is $(C_k^4 - S_k^1) - \sum_{r=1}^{4}(C_k^r - S_k^r)$. Then, the aforementioned value is multiplied by the idle power level of machine M_k to obtain the NPE for a schedule.

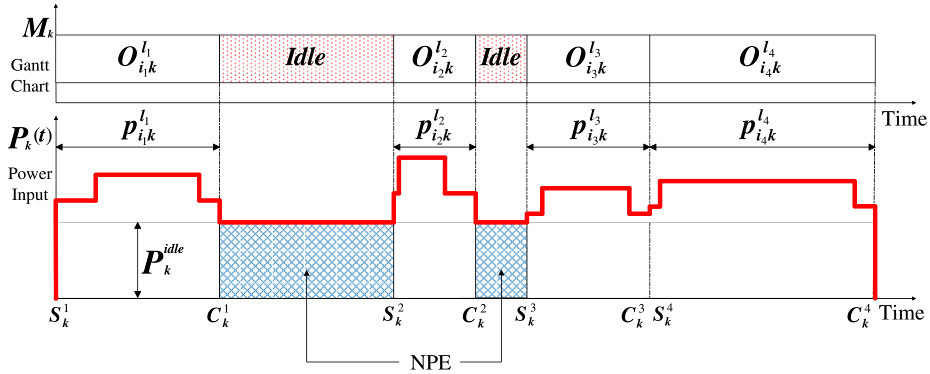

Fig. 3. Gantt chart of M_k and its corresponding power profile.

In summary, the two objective function for the optimisation of both TWT and NPE can be expressed based on (Vázquez-Rodríguez and Petrovic, 2010) using Equations (5) and (6) as:

$$\text{minimise } F(s) = (f_1(s), f_2(s)) \; s \in S \tag{8}$$

$$f_1(s) = \sum_{i=1}^{n} w_i \times T_i(s); \; f_2(s) = \sum_{k=1}^{m} TEM_k^{np}(s) \tag{9}$$

4. NSGA-II and its related operators

The NSGA-II has two main operators: the non-dominated sorting procedure and crowding distance sorting procedure. Non-dominated sorting procedure ranks the solutions in different Pareto fronts. The crowded distance sorting procedure calculates dispersion of solutions in each front and preserves the diversification of the algorithm. In each generation of this algorithm, these two functions form the Pareto fronts (Rabiee et al., 2012). Vilcot and Billaut (2008) provides a summary for the working procedure of NSGA-II, as in following. For more information refer to Deb et al. (2002).

4.1. Non-dominant sorting procedure

All the solutions of a certain population (denoted by P_t) are evaluated according to the non-dominated sorting method as shown in Fig. 4. Level 1 contains all the dominant individuals within the population. If individuals in the first level are not considered, the second set of dominant individuals constitutes level 2. The process iterates until each individual is classified to one of the levels. The level (rank) where an individual locates is the most important factor of its fitness that the individual with lower rank is preferable.

4.2. Crowding distance sorting procedure

The crowding distance of a solution is defined by Deb et al. (2002) as: "an estimate of the perimeter of the cuboid formed by using the nearest neighbours as the vertices". The diversity of the population is guaranteed by using the crowding distance sorting procedure. For an individual, the crowding distance is the sum of the normalised distance between the right and left neighbours for each objective function. The extreme solutions have a crowding distance equal to infinity (see Fig. 5).

4.3. NSGA-II algorithm

In the beginning of the algorithm, an initial population P_0 with the size of N is randomly generated. All the individuals of P_0 are sorted using the above two procedures. Then, the algorithm employs selection, crossover and mutation operators to create the first offspring set Q_0 ($|Q_0| = N$). The selection operator is a binary tournament: between two individuals, the selected individual is the one with the lower rank. If two individuals are on the same level, the winner is the one with the larger value in the crowding distance. At a given generation t, R_t is defined as the union of the parents P_t and their offspring Q_t. Thus, $|R_t| = 2N$. Individuals of R_t. are sorted following the aforementioned two procedures. Frontier F_f is defined as the set of non-dominated solutions of level f. The individuals in P_{t+1} are the solutions of frontiers F_1 to F_λ with λ such that $\sum_{i=1}^{\lambda} |.F_i|. \le N$ and $\sum_{i=1}^{\lambda+1} |.F_i|. > N$ plus the $N - \sum_{i=1}^{\lambda} |.F_i|.$ first solutions of $F_{\lambda+1}$ according to their descending value in crowding

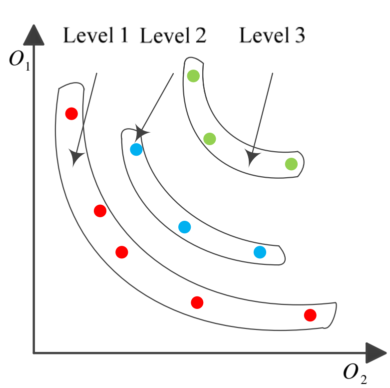

Fig. 4. Non-dominated levels (Deb et al., 2002).

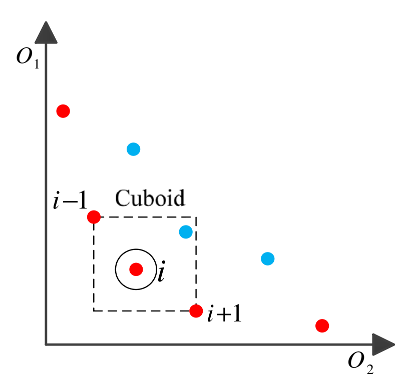

Fig. 5. Computation of the crowding distance (Deb et al., 2002).

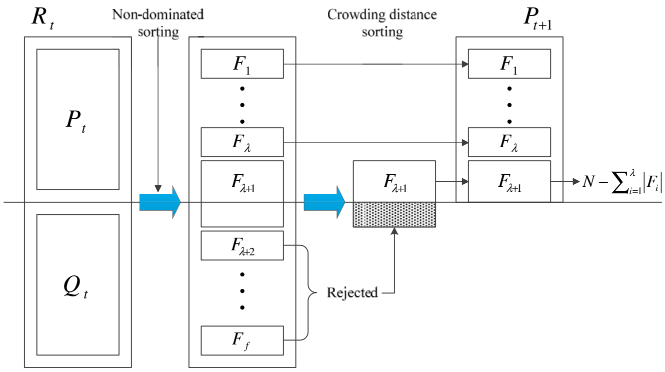

Fig. 6. Construction of population P_{t+1}.

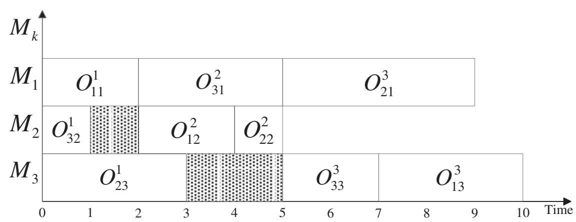

Fig. 7. Gantt chart of chromosome [321123321], transformed by the active schedule builder (Liu and Wu, 2008).

distance. The remaining solutions are rejected. Solutions from P_{t+1} are used to make the new offspring population Q_{t+1}. Fig. 6 illustrates the generation of population P_{t+1}

4.4. Encoding schema and schedule builder

The operation-based encoding schema (OBES) is adopted for this research which is mathematically known as "permutation with repetition" (Dahal et al., 2007), where 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. According to an example provided by Liu and Wu (2008), [321123321] is a feasible chromosome for a 3 × 3 job shop, 3 on the first gene position stands for O_{32}^1 ; 3 on the sixth gene position stands for O_{31}^2 ; 3 on the seventh gene position stands for O_{33}^3. Thus, the chromosome can be translated to a list of ordered operations as $[O_{32}^1 O_{23}^1 O_{11}^1 O_{12}^2 O_{22}^2 O_{31}^2 O_{33}^3 O_{21}^3 O_{13}^3]$. Decoded by the active schedule builder, the chromosome can be transformed into a feasible schedule as depicted in Fig. 7. For more information about the decoding procedure of the active schedule builder refer to Dahal et al. (2007). The advantage of such a scheme is that all the generated schedules are legal and active (Dahal et al., 2007; Wang et al., 2009).

4.5. Crossover and mutation operators

Referring to Liu and Wu (2008), Cheng et al. (1999) and Ono et al. (1996), the crossover and mutation operators in this research are defined as below:

4.5.1. Crossover operator

The operation-based order crossover (OOX) which is developed based on the job-based order crossover (JOX) is adopted as the crossover operator. The advantage of OOX is that it can avoid producing illegal chromosome in offspring. Given parent 1-A_1 and parent 2-A_2, OOX generates child 1-A_1' and child 2-A_2' by the following procedure:

1. Randomly, choose the same operations from both of the parents A_1 and A_2. The loci of the selected operations are preserved.
2. Copy the operations chosen at step 1 from A_1 to A_1', A_2 to A_2', the loci of them are preserved in the offspring A_1' and A_2'.
3. Copy the operations, which are not copied at step 2, from A_2 to A_1', A_1 to A_2', the order of them are preserved in the offspring.

For example, in a 3 × 3 job shop, [321123321] and [222333111] are feasible parent chromosomes. The loci of operations, which are O_{32}^1, O_{22}^2 and O_{13}^3 in the boxes are preserved.

$$A_1 = [\boxed{3}211\boxed{2}332\boxed{1}]$$

$$A_2 = [2\boxed{2}2\boxed{3}3311\boxed{1}]$$

A_1' and A_2' are feasible child chromosomes as shown below:

$$A_1' = [\boxed{3}223\boxed{2}311\boxed{1}]$$

$$A_2' = [2\boxed{2}1\boxed{3}1332\boxed{1}]$$

4.5.2. Mutation operator

The swap mutation operator is employed in this research which means two difference arbitrary genes of the parent chromosome are chosen and swap the values. Following the above example, A_1'' is the final child chromosome of A_1 after applying mutation on A_1'.

Table 1
The parameters of the 10 × 10 job shop.

$M_k\,(p_{ik}^l)$	O_{ik}^1	O_{ik}^2	O_{ik}^3	O_{ik}^4	O_{ik}^5	O_{ik}^6	O_{ik}^7	O_{ik}^8	O_{ik}^9	O_{ik}^{10}	r_i	d_i	w_i
J_1	M_1 (29)	M_2 (78)	M_3 (9)	M_4 (36)	M_5 (49)	M_6 (11)	M_7 (62)	M_8 (56)	M_9 (44)	M_{10} (21)	0	592	1
J_2	M_1 (43)	M_3 (90)	M_5 (75)	M_{10} (11)	M_4 (69)	M_2 (28)	M_7 (46)	M_6 (46)	M_8 (72)	M_9 (30)	0	769	2
J_3	M_2 (91)	M_1 (85)	M_4 (39)	M_3 (74)	M_9 (90)	M_6 (10)	M_8 (12)	M_7 (89)	M_{10} (45)	M_5 (33)	0	852	3
J_4	M_2 (81)	M_3 (95)	M_1 (71)	M_5 (99)	M_7 (9)	M_9 (52)	M_8 (85)	M_4 (98)	M_{10}. (22)	M_6. (43)	0	982	1
J_5	M_3 (14)	M_1 (6)	M_2 (22)	M_6. (61)	M_4 (26)	M_5 (69)	M_9 (21)	M_8 (49)	M_{10} (72)	M_7 (53)	0	589	3
J_6	M_3 (84)	M_2 (2)	M_6 (52)	M_4 (95)	M_9 (48)	M_{10} (72)	M_1 (47)	M_7. (65)	M_5 (6)	M_8 (25)	0	744	2
J_7	M_2 (46)	M_1 (37)	M_4 (61)	M_3 (13)	M_7 (32)	M_6 (21)	M_{10} (32)	M_9 (89)	M_8 (30)	M_5 (55)	0	624	3
J_8	M_3 (31)	M_1 (86)	M_2 (46)	M_6 (74)	M_5 (32)	M_7 (88)	M_9 (19)	M_{10} (48)	M_8 (36)	M_4 (79)	0	808	2
J_9	M_1 (76)	M_2 (69)	M_4 (76)	M_6 (51)	M_3 (85)	M_{10} (11)	M_7 (40)	M_8 (89)	M_5 (26)	M_9 (74)	0	895	1
J_{10}	M_2 (85)	M_1 (13)	M_3 (61)	M_7 (7)	M_9 (64)				M_5 (90)	M_8 (45)	0	810	1

Table 2
The idle power (P_k^{idle}) of M_k.

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
P_k^{idle}	2400 W	3360 W	2000 W	1770 W	2200 W	7500 W	2000 W	1770 W	2200 W	7500 W

Table 3
The optimisation result of SBH and LSH of the 10 × 10 job shop by LEKIN.

Tardiness factor (k)	TWT (twt_{s1}^k) in weighted min	Total NPE (npe_{s1}^k) in kWh	Heuristic
1.5	309	181	SBH
1.6	127	181	SBH
1.7	25	169.7	LSH
1.8	0	169.7	LSH

Table 4
The parameters settings for the NSGA-II.

Tardiness factor k	Population size N	Crossover probability p_c	Mutation probability p_m	Generation t	Pareto front P_k
1.5	1000	1.0	0.6	40,000	$P_{1.5}$
1.6	1000	1.0	0.6	40,000	$P_{1.6}$
1.7	800	1.0	0.6	30,000	$P_{1.7}$
1.8	800	1.0	0.6	25,000	$P_{1.8}$

$$A_1' = [32\boxed{2}3231\boxed{1}1]$$

$$A_1'' = [32\boxed{1}3231\boxed{2}1]$$

5. Case study

A modified job shop instance incorporates electrical consumption profiles for the machine tools: E-F&T 10 × 10 is developed based on the Fisher and Thompson 10 × 10 instance (F&T 10 × 10) (Fisher and Thompson, 1963) as the case study. To satisfy the requirements of this research, the due date and weight for each job and the processing time units of the jobs time need to be defined. According to the TWK due date assignment method (Sabuncuoglu and Bayiz, 1999; Shi et al., 2007), $d_i = k \times \sum_{i=1}^{m} p_{ik}^l,\ i = 1, 2, \cdots, n$ where k is the tardiness factor. The value of k will be set as 1.5, 1.6, 1.7, 1.8 which corresponds to the trend of less tight due dates in this research. The weight of each J_i is randomly allocated. The time unit is defined as minute. The parameters of the 10 × 10 job shop are given in Table 1, where, for instance, $k = 1.5$, this value of k represents a tight due date case (corresponds to 50% tardy jobs).

According to the objective of minimising the total NPE, the idle power level of each machine needs to be defined. Suppose that all the machine tools in this research are automated ones, the individual value of the idle power level of each machine in the 10 × 10 job shop can be abstracted from research works developed by Avram and Xirouchakis (2011), Baniszewski (2005), Dahmus (2007), Diaz et al. (2010), Drake et al. (2006), Kalla et al. (2009), Li et al. (2011) and Rajemi (2010), are shown in Table 2.

5.1. Comparison experiment

To demonstrate the effectiveness of NSGA-II in solving the ECT problem, the following comparison experiment has been carried out. Scenario 1 (S1) represents a scheduling plan created following a well-established traditional scheduling approach of a manufacturing company without considering reducing total NPE as an objective. Being set as the control group and baseline, S1 corresponds to the job shop scheduling problem with the single objective to minimise the TWT. The Shifting Bottleneck Heuristic (SBH) and Local Search Heuristic (LSH) approaches provided by the software LEKIN (Pinedo, 2009) have been used as the optimisation techniques in this scenario. For the E-F&T 10 × 10 job shop, the TWT value has been given after each run of the optimisation technique. The total NPE value has been calculated based on each optimised scheduling plan under different due date conditions, as shown in Table 3. The parameters settings of the NSGA-II were obtained after the initial tuning process, as shown in Table 4.

For the NSGA-II, the values of the two objective functions under different due date conditions can be denoted as two sets: $twt_{GA}^k = \{twt_{GA}^{kq}\}_{q=1}^p$ and $npe_{GA}^k = \{npe_{GA}^{kq}\}_{q=1}^p$, where k is the tardiness factor and p is the total number of solutions in P_k. The algorithm had been developed based on the Jmetal framework (Nebro and Durillo, 2011). The comparison between the solutions in S1 (a single objective job shop scheduling problem) and the solutions in P_k is shown in Fig. 8.

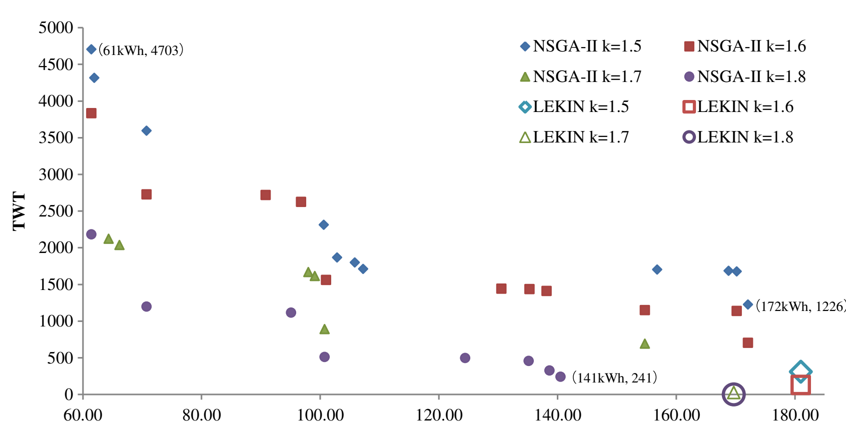

Fig. 8. The solution comparison between NSGA-II and the baseline scenario.

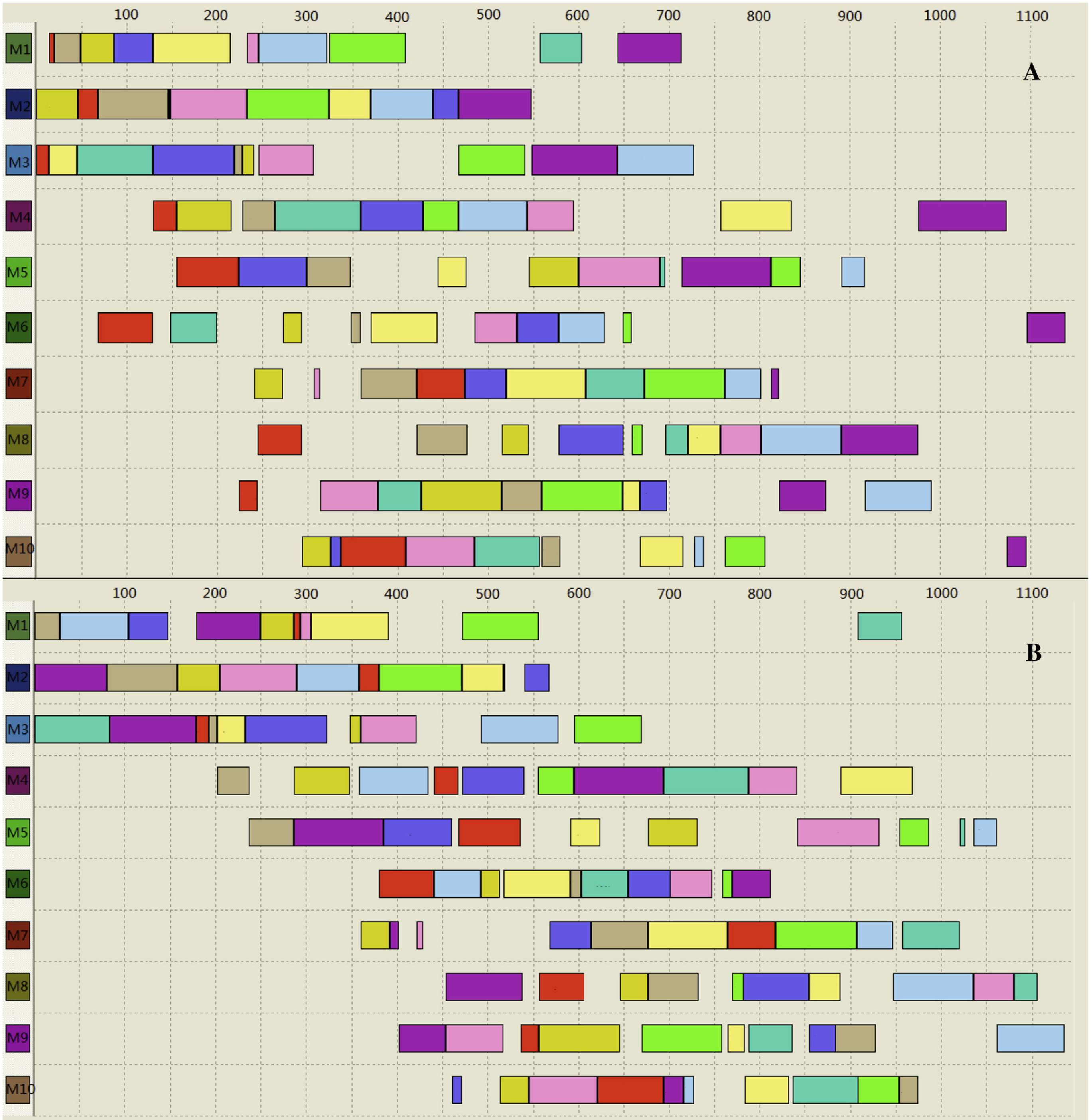

Fig. 9. Gantt chart of optimised schedule of SBH produced by LEKIN (A) and Gantt chart of optimised schedule of NSGA-II (B) while $k = 1.5$.

When $k = 1.5$, a considerable total NPE reduction can be observed when employing NSGA-II as the bi-objective optimisation approach, compared to the single objective optimisation result of SBH. The minimum and maximum value in $npe_{GA}^{1.5}$ are 61 kWh and 172 kWh respectively, which means a 4.9–66.1% improvement in the total NPE consumption compare to the values in LEKIN, i.e. 0.9 kWh/Job to 12 kWh/Job reduction in electricity consumption per job can be achieved. There is an increase in TWT, the minimum value in $twt_{GA}^{1.5}$ is 1226 weighted min, while $twt_{s1}^{1.5} = 309$ weighted min (the blue hollow point). However, when the due date become less tight, the difference between twt_{GA}^{k} and twt_{s1}^{k} is much smaller. For instance, when $k = 1.8$, $\min\{twt_{GA}^{1.8}\} - twt_{s1}^{1.8} = 241$ weighted min, at the same time, the total NPE reduction is 16.9% compared to the value in LEKIN.

5.2. Discussion

Based on the above, it can be observed that NSGA-II is effective in reducing the total NPE in a scheduling plan while sacrificing its performance with restrict to TWT, especially when a very tight due date is presented. However, it can be expected that this sacrifice can be neglected when there are more jobs to be produced in the work

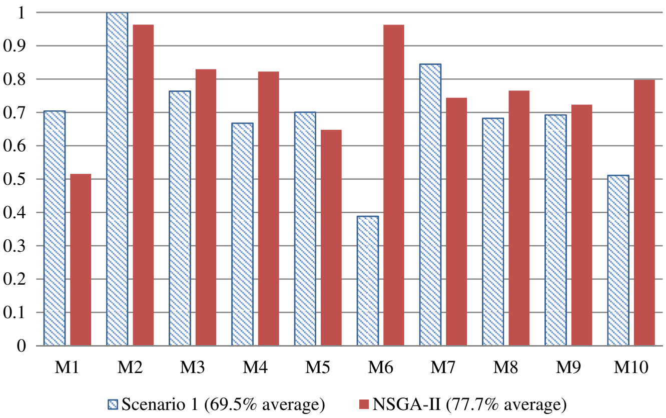

Fig. 10. Comparison in Productive time/Total up-time for machines.

shop. For instance, when combining 100 such 10 × 10 job shop, the difference between twt_{GA}^{k} and twt_{s1}^{k} only takes a very small portion of the total weighted production time. Nevertheless, the decrease in the total NPE will become a more and more considerable along with the increasing number of jobs. The upper (part A) and bottom (part B) of Fig. 9 represent the Gantt charts of optimised schedules of SBH and NSGA-II respectively when $k = 1.5$. It is easy to observe that the schedule produced by NSGA-II has a higher ratio of Production Time compared to the Total Up-Time of the machines (PT/TUP) for most of the machines, as shown in Fig. 10. In this case, the average values of PT/TUP for all machines in S1 and the NSGA-II optimisation scenario are 69.5% and 77.7% respectively. From above, the scheduling plans produced by NSGA-II are more preferable for managers when considering the real life job shop type manufacturing system, since the varieties and amounts of components in the real manufacturing circumstance will largely increase compared to the simple 10 × 10 job shop, and the PT/TUP is a very important indicator for the shop floor management. On the other hand, from the experimental perspective, the algorithm will potentially reduce the total NPE without sacrificing its performance on minimising the TWT for some job shop instances other than the E-F&T 10 × 10. Thus, more job shop instances should be applied to investigate the performance of NSGA-II on the ECT problem in future work. In addition, it can be observed from Fig. 8 that the less tight the due date, the less deterioration in minimising TWT objective, i.e. the more non-bottleneck machines in the manufacturing system, the larger opportunity to reduce the total NPE.

6. Conclusions and future work

Reducing electricity consumption as well as keeping good performance in classical scheduling objectives in job shops is a difficult problem that can take a large amount of time to optimally solve. The model for the Multi-objective Total Non-processing Electricity Consumption (NPE) and Total Weighted Tardiness (TWT) Job Shop Scheduling problem has been developed in this paper. For solving this problem, the multi-objective optimisation algorithm NSGA-II is applied. The performance of the algorithm has been tested on an extended version of Fisher and Thompson 10 × 10 job shop scenario which incorporates electrical consumption profiles for the machine tools. In addition, a comparison experiment has been applied where the Shifting Bottleneck Heuristic and the Local Search Heuristic had been adopted as the single objective optimisation techniques to deliver the baseline scenario of the E-Fisher and Thompson 10 × 10 job shop. The result of the comparison indicates that by applying NSGA-II, the total non-processing electricity consumption in the job shop is decreasing significantly, but at the sacrifice of its performance on the total weighted tardiness objective up to a certain level. However, it can be expected that this sacrifice can be neglected if the number of successive jobs is increasing. This makes the optimisation method developed in this paper effective to reduce the electricity consumption in a real manufacturing circumstance. Since in a real job shop, the amount of jobs is much larger than that of the simple 10 × 10 case and is scheduled over longer periods of time. In addition, the deterioration in the TWT objective will be less if bottlenecks in the job shop can be reduced, i.e. by relaxing the due dates of the jobs.

In future work, the algorithm should be tested on wider set of job shop scenarios to validate its more general applicability. This paper only focused on how to reduce the total NPE in a basic job shop by changing the processing sequence of jobs on each machine. However, the Turn off/Turn on method developed by Mouzon et al. (2007) is another very effective approach in achieving this objective. Therefore, developing new algorithms which enable both of the sequencing and Turn Off/Turn On approaches to be optimally applied in solving the Electricity Consumption and Tardiness problem is worthy to be investigating. Finally, reducing the electricity consumption in a dynamic job shop should be studied in the future. Existing dynamic scheduling algorithms should be extended to reduce the electricity consumption and improve productivity for job shops where the components are arriving at the production system at randomly distributed times. This will extend the applicable range of the developed multi-objective optimisation methodology to include stochastic manufacturing systems which are widely used in the real manufacturing world.

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