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Mathematical modeling and multi-attribute rule mining for energy efficient job-shop scheduling

Liping Zhang [a], Zhixiong Li [b, c] *, Grzegorz Królczyk [d], Dazhong Wu [e], Qiuhua Tang [a]

[a] Key Laboratory of Metallurgical Equipment and Control Technology & Hubei Key Laboratory of Mechanical Transmission and Manufacturing Engineering, Wuhan University of Science and Technology, Wuhan, 430081, China
[b] School of Engineering, Ocean University of China, Tsingdao, 266100, China
[c] State Key Laboratory of Hydraulic Engineering Simulation and Safety, Tianjin University, Tianjin, 300350, China
[d] Department of Manufacturing Engineering and Automation Products, Opole University of Technology, Opole, 45758, Poland
[e] Department of Mechanical and Aerospace Engineering, Department of Industrial Engineering and Management Systems, University of Central Florida, Orlando, FL, 32816, USA

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A B S T R A C T

Manufacturing industry accounts for about one-third of the world's total energy consumption (TEC). This study aims to develop a novel mixed-integer mathematical model to represent the direct energy consumption of machines and indirect energy consumption on a shop floor. In comparison with traditional modeling methods, this paper proposes an effective gene expression programming-based rule mining (GEP-RM) algorithm to generate dispatching rules automatically. This method consists of three attributes that have significant impacts on the TEC of a manufacturing process. In addition, diversified rule mining operators with self-learning are designed to ensure population diversity and convergence. Moreover, a perturbation trigger mechanism for reconstructing rules is introduced to avoid being trapped into a local optimum. An unsupervised learning algorithm is achieved by setting the evolution direction with global best and current worst in order to mine the value of the substantial historical data. Experimental results have shown that the proposed multi-attribute rule mining approach outperforms other dispatching rules in terms of energy saving and production efficiency.

1. Introduction

Job-shop scheduling is one of the most critical issues in planning and managing manufacturing processes (Ren and Wang, 2012). Moreover, over the past few decades, global energy consumption grows significantly. Particularly, the energy consumption in the manufacturing sector, which accounts for nearly one-half of the global energy consumption, has almost doubled over the last 60 years (Abdelaziz et al., 2011). For the manufacturing enterprises, energy consumption constitutes a major portion of the total production cost (Wang et al., 2011), and hence, energy saving production becomes a key factor for their economic competitiveness and the energy efficient Job-shop scheduling problem (EEJSP) has attracted considerable attentions.

Previous research related to reducing energy consumption has primarily focused on developing more energy efficient machines and processes (Fang et al., 2011a; Haapala et al., 2009; Diarra et al., 2010). However, the energy required for machining operations is often a relatively small part of TEC in a job shop. In this regard, Gutowski et al. (2005) demonstrated that energy was consumed even when the machine was idle since 85.2% of the consumed energy was used in non-machining operations at Toyota. This observation is also supported by Drake et al. (2006) who reported that the consumed energy for removing materials from a part was 19% of the total consumed energy by the milling machine. Draganescu et al. (2003) carried out statistical experiments concerning machine tool efficiency and specific consumed energy. Garg et al. (2015) investigated the relationship between energy consumption and input process parameters, including cutting speed, surface roughness, and tool wear rate. This study has shown that the energy consumption partially depends on the machining parameters such as cutting speed, feed rate and depth of cut.

* Corresponding author. School of Engineering, Ocean University of China, Tsingdao, 266100, China.
E-mail addresses: zhangliping@wust.edu.cn (L. Zhang), zhixiong.li@knights.ucf.edu (Z. Li), g.krolczyk@po.opole.pl (G. Królczyk), Dazhong.Wu@ucf.edu (D. Wu), tangqiuhua@wust.edu.cn (Q. Tang).

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Mouzon et al. (Mouzon and Yildirim, 2008; Mouzon et al., 2007) utilized a greedy randomized multi-objective adaptive search meta-heuristic to minimize TEC and total tardiness on a single machine. Dietmair and Verl (2009) optimized a complex manufacturing system from four aspects, including time, quality, cost and energy consumed. Fang et al. (2011b) presented a mathematical programming model for the flow shop scheduling that considered peak power load, energy consumption, and associated carbon footprint, and its effectiveness was validated by using a simple case study. Diaz and Dornfeld (2012) studied a manufacturing system from the aspects of cost and energy reduction. Dai et al. (2013) proposed an energy-efficient model for flexible flow shop scheduling and used an improved genetic-simulated annealing algorithm to obtain Pareto solutions. Christian et al. (2016) developed a research framework for energy-efficient scheduling to reduce energy consumption. Zhang and Chiong (2016) introduced the objective of minimizing energy consumption into a typical production scheduling model. They pointed out that energy consumption of machine systems can also be reduced by scheduling jobs on different machines without additional costs.

EEJSP has been investigated by a great number of researchers via exact methods, dispatching rules or meta-heuristic algorithms (He et al., 2015; He, Liu, Cao, Li, 2005). The exact methods including branch and bound, can guarantee global convergence (Liu et al., 2013). However, as the size of the problem increases, its computational time increases exponentially and the lower bound may not be obtained during polynomial time. Hence, dispatching rules and meta-heuristic algorithms attract growing attention from researchers. The meta-heuristic algorithms, including genetic algorithms (Gokan et al., 2015), teaching-learning-based optimization algorithms (Lin et al., 2015), constructive heuristics (Mansouri et al., 2016) and particle swarm optimization (Tang et al., 2015) have been proven effective and efficient in searching high-quality solutions during reasonable time (Ren and Wang, 2012), but they have not been applied directly into real manufacturing for the lack of convenience and instantaneity.

Dispatching rules, also called heuristic approaches, are generally used to select the jobs with high priority from a set of waiting jobs to be processed. They have many advantages such as strong implementability, satisfactory performance, low computational requirement, and flexibility to incorporate domain knowledge and expertise, and hence they are being commonly used in production scheduling in industry. Most literatures have presented mathematical programming models in the flow shop scheduling problem or job-shop scheduling problem that considers energy consumption (Liu et al., 2014), and have utilized the exact methods and meta heuristic algorithms (Yi et al., 2012; Lei and Guo, 2015) to solve the model. However, Huang and Suer (2015) have demonstrated that the dispatching rules are not very effective due to the lack of flexibility. Since there are n! selections for n waiting jobs, it is difficult to develop effective dispatching rules. In addition, little research has been reported on the dispatching rules for energy efficient scheduling problems.

To make manufacturing processes more environmentally sustainable, effective and efficient dispatching rules for energy efficient production scheduling are required. To address this issue, we propose a Gene Expression Programming-based rule mining (GEP-RM) algorithm that combines both artificial intelligence and swarm intelligence to find the energy-efficient rules that achieve satisfactory scheduling schemes of the energy efficient job-shops. The main contribution of this work is as follows: multi-attributes related to TEC are extracted from historical data and utilized in the subsequent evolutions of GEP-RM algorithm. After a series of rule mining with self-study and unsupervised learning on the ground of substantial data, new multi-attribute rules are created using the GEP-RM algorithm.

The remainder of the paper is organized as follows. Section 2 details two motivating examples. Section 3 describes the EEJSP problem and formulates a new mix-integer mathematical model. Section 4 presents the methodology of mining multi-attribute rules via GEP-RM algorithm. Section 5 reports and analyses the corresponding results. In section 6, a general conclusion is drawn.

2. Motivating examples

In this section, we will present two motivating examples. In real-world job shops, production managers often make scheduling decisions based on their experience or empirical knowledge. This research aims to explore a novel approach to supporting production managers to make optimal decisions.

Makespan is a regular measure of the time-related performance evaluation of scheduling decisions. It is worth noticing that the TEC may present different states under the same makespan. For example, four operations from two jobs, each of which have two operations, are assigned to two machines. The parameters of the operations are listed as follows: (1, 1, 2, 1, 3.5), (1, 2, 1, 3, 4), (2, 1, 1, 8, 4), and (2, 2, 2, 5, 6). The numbers in the brackets from left to right represent job index, operation index, predefined machine index, processing time and cutting power. The unload power of machines 1 and 2 are 1kw and 2kw respectively, and the coefficients of Stute power and indirect energy consumption are 1.2 and 1.

As shown in Fig. 1, both scheduling schemes have the same makespan. However, machine 2 in Fig. 1(a) relaxes between the finishing time of job 1's first operation and the bnning time of the job 2's second operation, resulting in large unload energy consumption. And machine 2 in Fig. 1(b) starts to work only when both operations can be performed continuously. The TEC contains two parts: direct energy consumption and indirect energy consumption. The direct energy consumptions of these two scheduling schemes are 52.5kwh and 38.5kwh respectively. The indirect

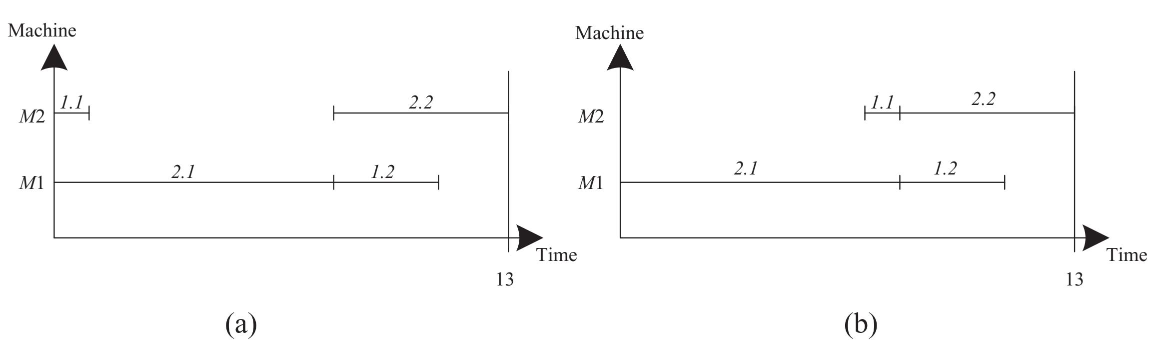


Fig. 1. Two different scheduling schemes under the same makespan.

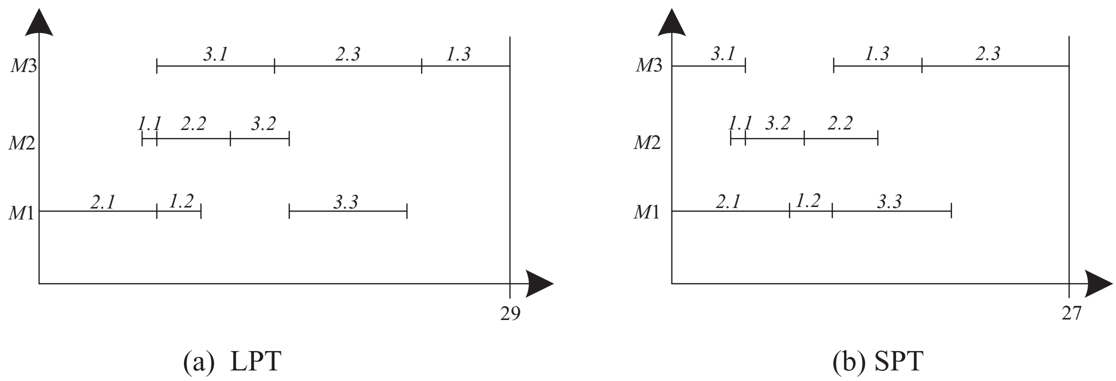


Fig. 2. Two different scheduling schemes under different makespans.

energy consumption of these two scheduling schemes is 13kwh for the same makespan. Thus the TEC of them is 65.5kwh and 51.5kwh respectively. Obviously, the TEC in Fig. 1(a) is much greater than that in Fig. 1(b). This means that reasonable scheduling schemes can reduce the TEC. Under the circumstance of great unload energy consumption, the idle time are expected to be reduced so as to minimize the TEC.

Though the existing dispatching rules are simple and easy to utilize, and have been used with increasing frequency in the process of real production, their performance may show disagreement and be not satisfactory for the target of saving energy in enterprises. Taking three jobs with each job having three operations as an example, the parameters of each operation are listed as follows: (1, 1, 2, 1, 3.5), (1, 2, 1, 3, 4), (1, 3, 3, 6, 5), (2, 1, 1, 8, 4), (2, 2, 2, 5, 6), (2, 3, 3, 10, 3.5), (3, 1, 3, 5, 5), (3, 2, 2, 4, 4), (3, 3, 1, 8, 6) and (3, 3, 1, 8, 6). And the unload power of machines 1, 2, 3 are 1kw, 2kw and 4kw respectively. The scheduling scheme adopted in Fig. 2(a) is the LPT rule which selects the operation with the longest processing time first, while that in Fig. 2(b) is the SPT rule which chooses the operation with the shortest processing time first.

Apparently, the makespan in Fig. 2(a) is 2 h longer than that in Fig. 2(b), and machine 1 in Fig. 2(a) and machine 3 in Fig. 2(b) work continually while others operate continuously. Since the unload power of machine 3 is four times that of machine 1, the TEC in Fig. 2(a) is greater than that in Fig. 2(b). The direct energy consumption (DEC) of these two scheduling schemes is 175.3kwh and 193.3kwh, respectively. The indirect energy consumption (IEC) of them is respectively 29kwh and 27kwh. Thus, the TEC of them is 204.3kwh and 220.3kwh, respectively. This means dispatching rules have a great effect on the TEC. There may exist certain suitable dispatching rules reflecting the attributes of energy saving to be explored. Subsequently, the GEP-RM algorithm was developed in this study to find suitable dispatching rules to reduce the TEC.

3. Problem formulation

EEJSP is concerned with the assignment of operations of a job to machines, which is subject to technological and capacity constraints (Branke et al., 2015), so as to achieve certain evaluation criteria in terms of energy consumption. Technological constraints define that each operation can be executed only after the complement of its precedent operations. Capacity constraints define that a machine can perform the next operation unless it finishes the earlier one. Thus, this problem can be described in details as follows.

Assume a set of n jobs $\{i = 1, 2, \ldots, n\}$ with each job having a set of $|J_i|$ operations $\{j = 1, 2, \ldots, |J_i|\}$ on a set of m machines $\{k = 1, 2, \ldots, m\}$. Each job should pass through each machine once and only once. Each machine can perform only one job at one time without interruption (Sha and Lin, 2010). Thus, the total number L of the sequenced operations can be calculated with $L = \sum|J_i|$. Solving the EEJSP requires to seek for an optimal or near-optimal sequence of these L operations to satisfy the TEC criterion. Therefore, this problem is described by a triplet $Jm|PC, PU|E_{\min}$.

Objective function: the objective function is to minimize the TEC. The TEC falls into two categories: DEC and IEC. The DEC is mainly used in the manufacturing process to execute the jobs directly, such as the cutting process, while the IEC includes the lighting and temperature maintaining. Let us assume that the IEC is proportional to the running time of the shop floor (Yang et al., 2014). Thus, the IEC can be described in Eq. (1).

$$IEC = \beta C_{\max} \tag{1}$$

where, β is equal to 1.

DEC is measured by the total unload energy consumption of all the machines (Zhang et al., 2013). The total unload energy consumption of machine k, EU_k, can be calculated by Eq. (2). Let us further assume that the calculation of the total unload energy consumption of machine k bns at the start of the first job and ends at complement of the last job.

$$EU_k = (\alpha - 1)\sum_{i=1}^{n}\sum_{j=1}^{|J_i|}\left(PC_{ij} \cdot p_{ij}\right) + PU_k\sum_{i=1}^{n}\sum_{j=1}^{|J_i|}p_{ij} + PU_k \cdot It_k \tag{2}$$

where, α is equal to 1.2.

TEC is the sum of the total unload energy consumption of all the machines and the indirect consumption, as shown in Eq. (3).

$$TEC = DEC + IEC = \sum_{k=1}^{m} EU_k + IEC \tag{3}$$

Therefore, the objective function is derived in Eq. (4).

$$\min TEC = \sum_{k=1}^{m}\left((\alpha - 1)\sum_{i=1}^{n}\sum_{j=1}^{|J_i|}\left(PC_{ij} \cdot p_{ij}\right) + PU_k\sum_{i=1}^{n}\sum_{j=1}^{|J_i|}p_{ij} + PU_k \cdot It_k\right) + \beta \cdot C_{\max} \tag{4}$$

The objective function can be achieved if and only if the following constraints are fully satisfied.

Assignment constraints: Each operation O_{ij} should be performed exactly once and there exists only one task in each position of the sequence which holds L operations.

$$\sum_{t=1}^{T} Y_{ijt} = 1, \forall O_{ij} \tag{5}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{j=|J_i|} Y_{ijt} = 1, \forall t \in T \tag{6}$$

Precedence constraints: Due to the precedence relations between two operations in any job, each operation can be executed unless its precedent operations are finished.

$$\sum_{t=1}^{T} tY_{ijt} < \sum_{t=1}^{T} tY_{i,j+1,t}, \forall O_{ij}, O_{i,j+1}, j < \left| J_i \right| \tag{7}$$

Machine constraints: For any two operations assigned to the same machine, one operation can be started after the earlier one is completely finished.

$$CO_{ij} \le CO_{i'j'} - p_{i'j'} + M \cdot (2 - Y_{ijt} - Y_{i'j't'}), \forall O_{ij}, O_{i'j'}, t < t', m_{ij} = m_{i'j'} \tag{8}$$

Time sequence constraints: All L operations are considered to be sequenced in an ascending order. Thus, the immediate following operation in the sequence can start only after its preceding operation.

$$CO_{ij} - p_{ij} \le CO_{i'j'} - p_{i'j'} + M \cdot (2 - Y_{ijt} - Y_{i'j',t+1}), \forall O_{ij}, O_{i'j'}, t < L \tag{9}$$

Start time constraints: If an operation is assigned to one machine at sequence t, the start/completion time of this operation is also regarded as the start/completion time of the machine that performs the operation. If no operation is assigned to a machine at sequence t, we assume that there is a virtual operation and the completion time of this virtual operation is equal to the start time.

$$SM_{kt} \le CO_{ij} - p_{ij} + M \cdot (1 - Y_{ijt}), \quad \forall O_{ij}, M_{ij} = k \tag{10}$$

$$SM_{kt} \ge CO_{ij} - p_{ij} - M \cdot (1 - Y_{ijt}), \quad \forall O_{ij}, M_{ij} = k \tag{11}$$

$$CM_{kt} \le CO_{ij} + M \cdot (1 - Y_{ijt}), \quad \forall O_{ij}, M_{ij} = k \tag{12}$$

$$CM_{kt} \ge CO_{ij} - M \cdot (1 - Y_{ijt}), \quad \forall O_{ij}, M_{ij} = k \tag{13}$$

$$CM_{kt} \le SM_{kt} + M \cdot (1 - Y_{ijt}), \quad \forall O_{ij}, M_{ij} \ne k \tag{14}$$

$$CM_{kt} \ge SM_{kt} - M \cdot (1 - Y_{ijt}), \quad \forall O_{ij}, M_{ij} \ne k \tag{15}$$

$$SM_{k,t+1} \ge CM_{kt}, \quad \forall k, t < L \tag{16}$$

Idle time constraints: The idle time of a machine can be calculated by Eq. (17).

$$It_{kt} = \begin{cases} SM_{k,t+1} - CM_{kt}, & if \quad CM_{kt} > 0 \\ 0, & if \quad CM_{kt} = 0 \end{cases} \quad \forall k, t < L \tag{17}$$

Maximum completion time constraint: The maximum completion time means the completion time of the last operation.

$$C_{\max} = \max_{\forall O_{ij}} CO_{ij} \tag{18}$$

Thus, EEJSP is precisely defined with objective function in Eq. (4) and the constraints in Eqs. 5–18.

4. GEP-based multi-attribute rule mining algorithm

Gene expression programming is an evolutionary artificial intelligence technique developed by Ferreira (2002), and has been used to address symbolic regression, time series prediction, classification, and optimization (Yang et al., 2016). Based on the genetic process of biological organisms, the proposed GEP-RM algorithm works with the population in which each individual is denoted as a dispatching rule (Ferreira, 2001). This rule is represented as an algebraic expression. Taking SPT as an example, its algebraic expression is noted as min *pt*, in which *pt* means the processing time. This expression schedules the next job with the minimum *pt* from a set of waiting jobs.

In this study three attributes are extracted and embedded in the form of terminal symbols into each rule. The population evolves via rule mining operators including selection, mutation, transposition and recombination. It should emphasize that the performance of a rule is evaluated by the performance function (Goncalves et al., 2005). Moreover, unsupervised learning of the rule performance evaluation is achieved by setting evolution direction with global best and current worst rules, so as to avoid the empirical combination of simple dispatching rules and overcome the shortcomings of lacking response variables.

4.1. Computational framework

The flowchart of the GEP-RM algorithm is shown in Fig. 3. A set of encoded solutions to the problem, called population, evolves via rule mining operators. GEP-RM bns with the random generation of the initial population. Then, each rule is evaluated to obtain its performance value. The offspring are generated with the selection mechanism that randomly chooses rules from the population with probability. It is worth noting that the better rules have greater chance to be selected. Subsequently, the offspring evolves via mutation, transposition and recombination. The new population will be evaluated again. The whole process is repeated until the stopping criterion is reached.

4.2. Multi-attribute representation

The rule in GEP-RM consists of a linearly symbolic string with fixed length composed of one or more genes (Ferreira, 2001). Here, the character string is called the genotype of the rule, and the mathematical formula represents the phenotype of the rule. The genotype and phenotype are mutually dependent and can be directly transformed into each other (Yang et al., 2016).

In Eq. (4) the TEC is closely related to the idle time of machines (It_k) and makespan (*Cmax*). As well known, the idle time are determined by the task assignment, while makespan is decided to a large extent by predefined parameters called systematical attributes. These attributes can be classified into two categories: the job-related and machine-related. The job-related attributes often include the processing time of an operation (*pt*), the number of remaining unscheduled operations of a job (*nr*), and the sum of remaining processing time (*sr*). The machine-related attributes include the cutting power of each operation (PC_{ij}) and the unload power of the machine (PU_k). Because all these attributes are related to energy consumption, it would be better to integrate them to discover the dispatching rule.

Usually, dispatching rules produce scheduling schemes by utilizing the known information. Considering that the job-related attributes are known in this study while the machine-related parameters are varying, only the job-related attributes are taken

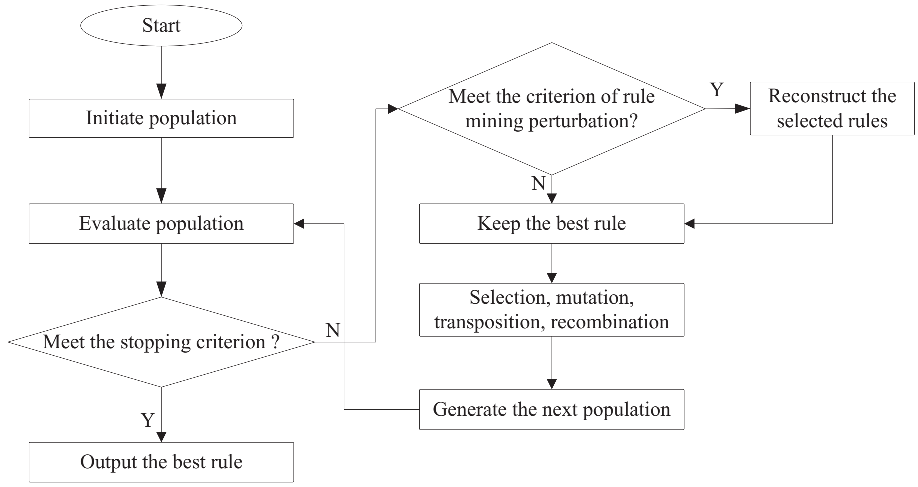


Fig. 3. Flowchart of GEP-RM algorithm.

into account to discover the multi-attribute rules.

These attributes are combined into the GEP-RM algorithm through the representation of symbols. There are two types of symbol sets in gene representation: function symbol (FS) and terminal symbol (TS) sets. FS and TS have a significant effect on the learning ability of the GEP-RM algorithm (Nie et al., 2013). In this study three job-related attributes $\{pt,\ \ nr,\ \ sr\}$ are defined as TSs and five basic arithmetic operators $\{+,-,*,/,\}$ as FSs.

Suppose the character string of a rule is represented as $[+\ -\ pt\ \ *\ \ pt\ \ nr\ sr\ \ nr\ \ pt\ ]$. The character string of the rule in Fig. 4(a) can be converted to an equivalent expression tree (ET) as shown in Fig. 4(b) using depth-first search mode. This ET form can be expressed as a mathematical formula in Fig. 4(c).

A completed ET is the sufficient condition of formulating mathematical expressions. To obtain a valid ET, the character string of the rule is comprised of two parts, namely Head and Tail. Each element in Head may be FS or TS while each element in Tail only contains a TS. The lengths of both Head (h) and Tail (l) are fixed, which can be calculated by Eq. (19) (Zhong et al., 2016).

$$l = h(\lambda - 1) + 1 \tag{19}$$

Where λ is the maximum argument in the functions. Equation (19) ensures the number of terminal symbols in Tail can satisfy the requirement by Head in the worst case where all the symbols in Head are function symbols. Thus, the validity of the generated ET is obtained. As shown in Fig. 4, the maximum argument $\lambda = 2$, the lengths of Head $h = 4$, and the lengths of Tail $l = 5$.

4.3. Scheduling scheme

A matrix ϑ is selected to represent the scheduling job set. The scheduling job set matrix is defined in Eq. (20) based on a scheduling problem which has 3 jobs and each job has 3 operations.

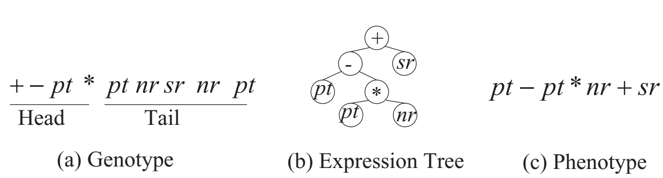


Fig. 4. Transformation from genotype to phenotype.

$$\vartheta = \begin{pmatrix} O_{11}(3,1) & O_{12}(2,2) & O_{13}(4,3) \\ O_{21}(3,2) & O_{22}(5,3) & O_{23}(3,1) \\ O_{31}(3,3) & O_{32}(2,1) & O_{33}(3,2) \end{pmatrix} \tag{20}$$

Where $O_{ij}(a,b)$ denotes that the processing time of operation O_{ij} is a and the candidate machine number is b. The rule decides the priority value of each candidate operations. Thus, the operation sequence and machine selection are known in advance. However, the starting and finishing time of each operation is undetermined. The active schedule method is considered to generate the feasible scheduling scheme. For example, a character string $\{pt + pt - sr\ pt\ sr\ nr\ nr\}$ is given. Then the rule is denoted as pt. In order to minimize the rule pt, the job sequence is $\{O_{11}\ \ O_{12}\ \ O_{21}\ \ O_{31}\ \ O_{32}\ \ O_{33}\ \ O_{13}\ \ O_{22}\ \ O_{23}\}$. Thus, the starting and finishing time of each operation can be obtained via active schedule method.

4.4. Rule mining

4.4.1. Selection

Popular selection techniques include roulette wheel selection, rank-based selection, seed selection, tournament selection and so on. These techniques can guarantee the survival and colonize the best rules to produce a new generation. Tournament selection is adopted in this study because it endows good rules with more survival opportunity and balances the influence of super rules and inferior rules (Gao et al., 2011). The rules are randomly chosen for performance evaluation and the best rule is directly selected for the next generation. Inferior rules are allowed into the next generation. This step is repeated until the population size is met.

4.4.2. Mutation

Mutation tends to produce perturbations on current rules in order to enrich the manifestation of rule population. Two types of mutation (i.e., one-point mutation and flip mutation) are adopted in this study. The mutation type is randomly chosen at each iteration in the evolution. Different measures are designed for each mutation to ensure the feasibility of mutated rules.

One-point mutation replaces the symbol of one random position by other symbols. A suitable criterion is required to ensure the validity and completeness of the new rule. If the selected position locates at the Head, its symbol can be replaced by any symbol from

FS or TS. Otherwise, if the selected position is at the Tail, its symbol can be replaced by any symbol from TS. Fig. 5(a) demonstrates the mutation procedure, in which Position 2 is randomly selected as the mutation point. As a result, symbol "-" is changed into "*nr*".

Flip mutation implements the substring between two different random head positions in reverse order. This mutation procedure is demonstrated in Fig. 5(b). Positions 2–5 are randomly selected as the mutation points. The substring between positions 2–5 is flipped to generate a new child.

4.4.3. Transposition

The transposable elements are fragments of the genome that can be activated by moving to other places (Ferreira, 2002). This operator can activate invalid codes in the rule-mining process. There are two kinds of transposition, called insertion sequence transposition and root insertion sequence transposition. Insertion sequence transposition randomly chooses a fragment with a function or terminal at the first position, and then, transposes it to the Head of the gene. As represented in Fig. 6(a), the fragment " *pt nr " is selected and inserted into the Position 2 in the Head. The last three symbols in the Head are removed.

Root insertion sequence transposition randomly chooses a fragment with a function at the first position, and then, transposes it to the start of the gene. As shown in Fig. 6(b), the fragment " *pt nr " is selected and inserted into the start of the gene. Similarly, the last three symbols in the Head are removed.

4.4.4. Recombination

Recombination permits exclusive recombination of mathematically concise blocks (Ferreira, 2001). This operator can keep the favorable fragment into next generation and mine the superior rules. There are two kinds of recombination. One is the one-point recombination and the other is the two-point recombination.

In one-point recombination, one point is randomly chosen as the recombination point. Two downstream fragments after this recombination point from two rules are exchanged afterwards, as shown in Fig. 7(a). In two-point recombination, two points are randomly chosen as the crossover points. Two middle fragments between the crossover points are exchanged, as depicted in Fig. 7(b).

4.5. Rule performance evaluation

If and only if the rule performance evaluation is correctly designed, the rule population can be evolved in the predetermined direction (Yang et al., 2016). Essentially, the classical GEP is a supervised learning method which gives a fixed set of input-output pairs and enables the evolution function to fit the known input-output pairs. The evaluation *f* measures the performance error on the training or testing set. Because the job-shop scheduling is NP-hard, it is difficult to find the optimal solution to minimize the TEC; moreover, it is difficult to provide the optimal solution to train each rule. Thus, an unsupervised learning is design to evaluate each rule in the proposed GEP-RM algorithm.

Assume that there are n training scenarios. The performance value of rule j for all the scenarios is evaluated by

$$f_j = \sum_{i=1}^{n} \frac{F_{ij} - F_{i,\min}}{F_{i,\max} - F_{i,\min}} \tag{21}$$

where F_{ij} denotes the TEC of the rule j at scenario i ($i = 1, 2, ..., n$ and $j = 1, 2, ..., popsize$), $F_{i,\max}$ means the worst rule for scenario i in the current iteration, and $F_{i,\min}$ means the best rule for scenario i through all iterations.

If the performance value of a rule is 0, this rule is near to the global optimal solution for each training scenario. We also notice that the performance value of each rule depends on the continuously changes of current worst and global best rules, which may result in different performance values for a rule with the same character string in different iterations. Nevertheless, the best rule remains the smallest performance value.

4.6. Rule mining perturbation

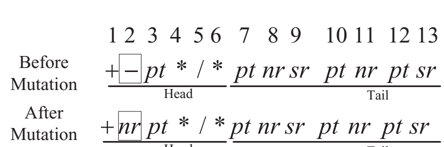
According to the rule performance evaluation in Eq. (21), the rule performance value may change continuously, but the current character string of the best rule may stay unchanged for several generations. Thus, a perturbation of rule mining mechanism is triggered if the current character string of the best rule stays unchanged and the predefined maximum number is reached. Rules are selected from the population with the given probability and are then reconstructed randomly from scratch.

5. Results and discussions

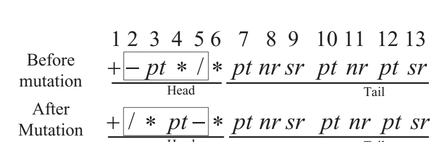
In order to evaluate the performance of the proposed method, experimental tests were implemented in C++ language on a PC with Intel Core 2 Duo CPU 2.20 GHz processor and 2.00 GB RAM memory.

5.1. Data description and parameter tuning

In this section, we choose 43 benchmarks about JSP including three Fisher and Thompson benchmarks, and 40 Lawrence benchmarks. Since the data about cutting power and unload power in these benchmarks are not available, they are randomly generated under the uniform distribution for further experiments. The values of the cutting power for each operation on any machine and the unload power of each machine are set as real number, and are limited by U [3.5–6.5] and U [0.25–3], respectively, where U represents the uniform distribution. Meanwhile, eleven scenarios are included for a given benchmark in which each scenario set with the above method has a unique value of cutting power and unload power. Hence, there are 473 scenarios in total. A training set consists of 30 scenarios and the remained scenarios are used in testing sets. Under this circumstance, the GEP-RM algorithm runs ten independent times over the given training sets and testing sets in order to evaluate the robustness of the proposed approach.

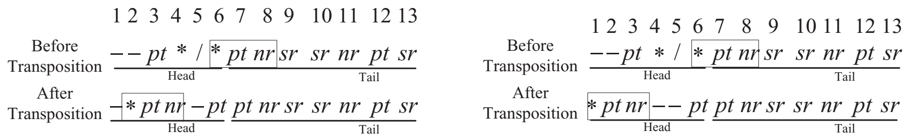


(a) One-point mutation



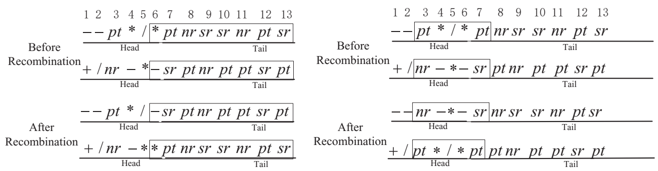
(b) Flip mutation

Fig. 5. Two types of mutation.



(a) Insertion sequence transposition (b) Root insertion sequence transposition

Fig. 6. Two types of transposition.



(a) One-point recombination (b) Two-point recombination

Fig. 7. Two types of recombination.

Note that, researchers have paid a large amount of attention to these famous benchmarks for a long time and have obtained the current best makespan or the lower bound. However, the optimal solutions or lower bound for EEJSP have not been reported so far. Thus, the rule performance evaluation with unsupervised learning as mentioned above is applied here.

Before running the proposed algorithm, some parameters should be determined in advance. After a serial of preliminary trials, these parameters are verified and shown in Table 1.

5.2. Experimental results

In this section, the computational results of GEP-RM algorithm are presented. Then, the new multi-attribute rules by GEP-RM algorithm are discussed. Next, the performance of the proposed GEP-RM algorithm is analyzed. Comparison experiments with the classical dispatching rules are designed to test the performance of the new multi-attribute rules; and, correlation analysis is also performed to depict the relationship between the TEC and makespan.

Fig. 8 reports the results of ten independent runs that contain character strings and corresponding rules. In fact, utilizing any of these discovered multi-attribute rules, all candidate operations are endowed with different priorities, and the operation with the highest priority is allocated first. This process is terminated until all operations have been allocated. In this case, the schedule scheme based on any of these rules is obtained. The TEC or other information, such as makespan, the staring time and the completion time of each operation, are also derived. These rules can be widely used in the real production for their operability.

It is noticed that rules (1, 5, 6, 7) are unique and appear different from the others. Rules (4,8) have the same mathematical formula but different character strings. Rules (2,3,9,10) show negative correlation of the priority with the number of remaining unscheduled operations of the job (*nr*), although the mathematical formula of these rules exhibit minor difference. In sum, there are six rules from ten independent runs. For convenience, we name rules 1, 5, 6 and 7 as GEPI, GEPII, GEPIII and GEPIV respectively, rules (4,8) as GEPV, and rules (2,3,9,10) as GEPVI.

On the other hand, since the processing time of each operation and remaining processing time of each job is longer than 1 h in most scenarios, six rules display that the priority of the candidate operations has positive correlation with the processing time of operation (*pt*), and has negative correlation with the number of remaining unscheduled operations of the job (*nr*). But the correlation of the priority of the candidate operations and the sum of remaining processing time of the job (*sr*) are sometimes positive and sometimes negative.

The computational results of 473 scenarios are used to investigate the performance of these new multi-attribute rules. Table 2 gives the TEC calculated by GEPV. To verify the statistical significance of the problem size in the influence of TEC, we perform a one-way analysis of variance (ANOVA) and report the results in Table 3.

As illustrated in Table 2, the TEC increases one or even two orders of magnitude with the growth of the problem scale. On the contrary, the TEC changes marginally with the same problem scale. There are slight differences in different scenarios from the same benchmark. Table 3 shows that the P value is close to 0. This is means the problem size has the statistically significant influence on the TEC. Hence, the problem size shows major impact on the TEC while the processing time, cutting power and unload power owns minor influence.

Essentially, the data sources of processing time, cutting power and unload power obey a certain distributions. Though zero idle time is the enterprises target, it is difficult to realize. This means when the number of jobs increases, the unload time of the machine grows longer and consequently the TEC continues to increase. While, in the same problem scale, the difference in processing time, cutting power and unload power causes slight difference in idle time, and thus exerts insignificant influence on cutting energy consumption and unload energy consumption.

Table 1
Parameter tuning.

Parameter	Setting	Parameter	Setting
Population size	20	One point mutation rate	0.1
Number of iterations	50	Flip mutation rate	0.1
Head size	6	One-point recombination rate	0.2
Tail size	7	Two-point recombination rate	0.2
FS	+, -, × ,/, √	Insertion sequence transposition	0.15
TS	pt, nr, sr	Root insertion sequence transposition	0.15
Rule performance function		Pre-set value for selection	3
Pre-set value for rule mining perturbation	5	Pre-set rate for rule mining perturbation	0.3
Maximum argument	2		

Index	*Character Strings*													*Rules*
(1)	$-$	sr	$-$	$-$	pt	pt	pt	nr	sr	pt	sr	pt	sr	$-\frac{sr}{pt}-nr$
(2)	$/$	$/$	$+$	pt	pt	pt	nr	pt	st	nr	pt	pt	pt	$\frac{2}{nr}$
(3)	$-$	$-$	$*$	pt	nr	$*$	pt	nr	nr	pt	sr	pt	sr	$-nr$
(4)	$\sqrt{}$	$/$	$+$	pt	sr	$*$	sr	sr	pt	nr	sr	pt	nr	$\frac{\sqrt{pt+sr}}{sr}$
(5)	$-$	pt	sr	$+$	$\sqrt{}$	pt	sr	sr	sr	sr	pt	nr	pt	$pt-sr$
(6)	$*$	$/$	nr	$/$	$-$	nr	sr	sr	sr	pt	sr	pt	nr	$\frac{nr*sr^2}{nr-sr}$
(7)	$-$	$/$	$/$	$-$	$/$	pt	pt	sr	nr	pt	nr	sr	pt	$\frac{1-sr}{pt*nr}-nr$
(8)	$/$	$\sqrt{}$	$+$	pt	sr	sr	nr	pt	sr	sr	sr	nr	pt	$\frac{\sqrt{pt+sr}}{sr}$
(9)	$/$	$\sqrt{}$	$+$	$\sqrt{}$	$*$	$*$	nr	nr	nr	nr	nr	pt	pt	$-nr$
(10)	$-$	$\sqrt{}$	$/$	$-$	$\sqrt{}$	$/$	nr	nr	nr	nr	nr	sr	sr	$-nr$

Fig. 8. Character strings and rules after ten different runs.

5.2.1. Statistical analysis of multi-attribute rules

Since the TEC differences among different scenarios are significantly large, the discovered multi-attribute rules are measured by the performance criterion of Relative Percentage Deviation (RPD). The RPD is calculated in Eq. (22).

$$RPD = \frac{\overline{H}_{l,o} - \overline{H}_{l,\min}}{\overline{H}_{l,\max} - \overline{H}_{l,\min}} \tag{22}$$

where $\overline{H}_{l,o}$ is the average value calculated by the oth rule for benchmark l, $\overline{H}_{l,\min}$ and $\overline{H}_{l,\max}$ are the minimal and maximal average values calculated by each discovered rules for benchmark l.

To investigate the statistical significance of the six new multi-attribute rules, we perform an analysis of variance (ANOVA) and report the results in Table 4. This analysis has a single factor which is the multi-attribute rule with six levels. The response variable is given by the RPD of every scenario, where *SS* is the sum of squares, *df* is the degrees of freedom and *MS* is the mean square. A 95% confidence interval is set to evaluate statistically significant differences among the rules.

Table 4 shows the *P* value is equal to 0.0096 which is much smaller than the significance level 0.05. This shows that the difference among all rules is statistically significant. To identify which rule has a more important effect, pairwise multiple comparisons are applied among group means by using the information in RPD. Fig. 9 gives the multiple comparisons of the six new rules.

The multiple comparisons display the estimations of comparison intervals. As shown in Fig. 9, the means of groups GEPIV, GEPV, GEPVI and group GEPI are significantly different. Hence, the results suggest that if the raw data of GEPI are deleted, the rest rules may be statistically insignificant. Under this circumstance, we take out GEPI and the new ANOVA results show that the *P* value is equal to 0.8525, which is far greater than the significance level of 0.05. This result demonstrates that GEPI performs worst and should be deleted.

Meanwhile, the confidence intervals of GEPII, GEPIII, GEPIV, and GEPVI are near to that of GEPV as shown in Fig. 9. The *P* value is equal to 0.8525 without GEPI. In a statistical sense, GEPII, GEPIII, GEPIV, GEPV and GEPVI are insignificant. In other words, the multi-attribute rules GEPII, GEPIII, GEPIV, GEPV and GEPVI are similar in solving these problems in the statistical sense.

From the perspective of mean RPD, the mean RPD of GEPI, GEPII, GEPIII, GEPIV, GEPV and GEPVI are 0.66, 0.49, 0.46, 0.43, 0.41 and 0.43 respectively. GEPV with smaller RPD (0.41) is slightly superior to other rules. Thus we will use GEPV as the representative rule to further discuss the performance of the proposed GEP-RM algorithm.

5.2.2. Performance evaluation

The proposed GEP-RM algorithm plays a critical role to find new multi-attribute rules. Fig. 10 shows the convergence graph of rule GEPV. The X-axis represents the number of iterations, and the Y-axis represents the performance value calculated by Eq. (21).

In Fig. 10, one can note that the optimal performance value changes irregularly as the number of iterations increases. This value does not reduce continually or keep at a certain level. In fact, the rule performance value defined in Eq. (21) is related to three parameters, the performance value of the current rule, the maximum performance value in current iteration and the global minimum performance value in the whole iterations. These parameters continue to change at each iteration. Therefore, the rule performance may vary with the iterations.

However, there is something interesting from the convergence analysis. Though the optimal performance value is varying significantly, the character string of the best rule does not refresh when the number of iterations reaches a certain number. In this case, the character string of the best rule always keeps as $/\ +\ pt\ sr\ *\ sr\ sr\ pt\ nr\ sr\ pt\ nr$ after 34 iterations. This observation demonstrates that the proposed GEP-RM algorithm has good convergence ability.

Fig. 10 also shows that the performance values are evenly distributed within the range of 30 at each iteration. Even if the proposed GEP-RM algorithm has convergent to a best rule, the performance values of all the rules are also evenly distributed in the

Table 2
Total energy consumption of GEPV.

	J	M	1	2	3	4	5	6	7	8	9	10	11
FT06	6	6	1495.9	1329.4	1359.9	1597.4	1451.1	1625.6	1602.1	1412.5	1298.9	1428.5	1307.9
FT10	10	10	43621.6	50721.8	45589	50946.7	51942.1	43619.8	44561.8	46576	50306.7	46724.9	42980.4
FT20	20	5	36823.1	34945.7	29220.6	30140.8	29930.7	29953.5	26998.7	27191.5	28379.1	33916.6	29818.2
LA01	10	5	19034.3	16463.4	18139.3	18153.6	17368.5	16493.4	16159.1	16716.1	16424.4	20133.8	19119.1
LA02	10	5	14936.8	16195.6	16524.3	14103.6	16707.8	19009.7	15995.6	15723.9	15074.6	14410.1	16437.2
LA03	10	5	13915.1	16497.9	14094.8	14220.8	14502.9	13026.5	14730.5	16562.7	17196.7	14593	15755.1
LA04	10	5	16857.6	14671.6	18941.4	15327.9	18289.1	18156.2	15907.6	15781.7	16263.5	14897.4	15669.7
LA05	10	5	14515.1	15197.9	14731.8	12229	14427.3	15552.6	14424.9	12546.5	15344.4	13020.6	14644.4
LA06	15	5	25581.8	21899.6	19615.7	23636.5	24454.4	22001.1	21283.3	27450.3	25753.8	21495.3	24019.2
LA07	15	5	20083.2	25347.9	22985.7	20522.9	22240.9	23071.6	23140.4	21848.4	23578.2	23457	20549.8
LA08	15	5	25506.3	24288.1	21276.6	23936.6	24653.6	22778.7	21574	19917.1	21800.6	22980.1	23459
LA09	15	5	26028.7	20358	23221.9	22489.1	25698.1	23224.4	22552.5	21918	21277.3	21636.8	25306.1
LA10	15	5	23498.5	28466.9	22715.1	29030.9	26109.4	27940.6	22713	28402.6	28087	27286.5	25422.9
LA11	20	5	27252.3	29545.3	26123.5	30451	28668.2	31443.7	33595.7	29264.1	30622.7	35366.1	35815.8
LA12	20	5	26803.9	30001.8	30171.7	24111.8	28895.1	29639.9	25807.1	30817.7	24368.5	23457.1	27447.3
LA13	20	5	29317.3	25243.5	26337.9	27257.6	26241.5	25189.1	25206.9	28436.7	28367.6	25197.5	26837.1
LA14	20	5	30480.8	29753.1	31686.4	27004	28254	28926.4	29478.3	28581	27840	29247	26236.1
LA15	20	5	31412.5	30499	32865.4	35293.7	33436.4	35206.9	31191.1	31505.5	32498.7	34328.5	31320.3
LA16	10	10	46860.9	45272.6	45417.6	44082.2	47933.3	46150	46249.2	41054.8	46500.5	44589.1	42995.8
LA17	10	10	39345.1	39012.2	39734.9	47036	38803.2	40630.8	41340	42421.7	38648.8	41926	38859.5
LA18	10	10	44987.6	42858.2	43324.8	41407	43696.8	42374.4	44661.8	41553.5	39936.6	44817.2	46896.5
LA19	10	10	42697.8	39864.5	41959.2	41246.4	41107.6	50347.5	43127.7	45972.4	47332.1	41634.6	39836.9
LA20	10	10	42294.3	50746.1	44376.7	46473.4	42523.3	46377.1	44356.8	49958.9	48590.1	41644.8	48272.6
LA21	15	10	57128.1	55139	56733.8	52703.6	60830.2	52364.6	55599.3	54807.4	54573.7	58360.7	56497.7
LA22	15	10	55956.1	51914.2	53198.9	50744.6	50224.9	53425	53843.9	54453.9	53661.2	58172.8	51980.9
LA23	15	10	50345.3	48857	50221.5	51407.7	50245.5	52182.6	55628.4	55213.7	51639.9	55113.3	58431.6
LA24	15	10	54282.7	60083.9	49621.6	57183.4	52108.8	59353.7	51762.1	55754.2	51286.5	52437.4	49833.2
LA25	15	10	65844.3	57383.9	48338.1	53717.9	58687.9	57749.7	51740	53706.5	60515.2	57714.6	56541.4
LA26	20	10	62304.7	67456.1	72547.7	67592.2	63975.2	66620.1	63730.5	69769.1	71259	66047.1	70362.5
LA27	20	10	65555.6	67634	68613.1	74500.3	63619.8	67573.7	64649.2	71524	71095.8	73750.6	60376.3
LA28	20	10	83688.8	68425.1	67706.8	68267.6	77769	68102.3	68678.1	66156.3	74406.3	77655.6	62724.2
LA29	20	10	64314.1	61254.6	63490	65680.1	74066.7	66426.3	66383.7	66167.2	64171.6	67558	66529.5
LA30	20	10	68963.8	72083.4	68836.3	68954.6	71942.6	76615.2	64960.2	64848.6	71607.7	75756.2	66600.7
LA31	30	10	94145.1	89520.7	81568.9	97189	100419	92565.1	96309.1	101261	90496.1	91547.7	88572.8
LA32	30	10	96634.5	104531	105691	104410	92361.8	105478	87671.1	100703	106755	98681.6	81450.2
LA33	30	10	90899.4	92741.7	88653.2	86862.6	96716.1	89441.8	87394	86502.6	89650.8	93884.6	94905.3
LA34	30	10	87458.4	101406	85609.9	97372.9	94898.2	93234.1	87649.4	90202.5	83302.9	83269.7	82922.1
LA35	30	10	97611.4	92632.2	92446.6	101713	89659.6	91352.5	90893.1	85672.5	103486	96258.1	102948
LA36	15	15	96025.6	107093	97435.9	97063.5	104080	105067	96671.4	97812	96432.2	94030.2	111668
LA37	15	15	100671	108300	110774	105867	114677	102813	101759	102192	103365	106041	101077
LA38	15	15	99628.2	96928.2	91775	94048	107513	92180.4	97270.1	97040.5	105304	93794.3	94464.9
LA39	15	15	99029	94242.5	93079.5	98567.6	96382.6	107202	105548	92323.2	99961.4	101101	94527.8
LA40	15	15	93334.4	97333.2	96396.6	96619.5	90077.4	93772.5	98362.1	93121.9	87605.4	98381.9	97443.4

Table 3
ANOVA for the problem size.

Source	*SS*	*df*	*MS*	*F*	*Prob > F*
Problem size	4.06612×10^{11}	7	5.80874×10^{10}	1792.01	0
Error	1.50728×10^{10}	465	3.24147×10^{7}		
Total	4.21684×10^{11}	472			

Table 4
ANOVA for the six new rules.

Source	*SS*	*df*	*MS*	*F*	*Prob > F*
Rule	1.8843	5	0.37686	0.004	0.0096
Error	30.5097	252	0.12107	–	–
Total	32.394	257	–	–	–

solution space. The rule performance value has a direct relationship with the current worst and global best rules, which are re-evaluated and updated with the algorithm evolution. Therefore, the rule performance value may fluctuate while the best rule keeps the same character string after 34 iterations. This exhibits that the diversity of the rule population is always kept throughout the entire evolutionary process.

5.2.3. Performance comparison with classical dispatching rules

In order to compare the performance of the new multi-attribute rules, we conduct experiments to compare the discovered GEPV with other existing dispatching rules using the 473 scenarios. A brief description of the candidate dispatching rules is given in (Nguyen et al., 2018). Eight dispatching rules are considered as the candidate rules: (1) SPT to select the operation with the shortest processing time, $\min\limits_{l \in allowed} pt_l$; (2) LPT to select the operation with the longest processing time, $\max\limits_{l \in allowed} pt_l$; (3) SSO to select the operation belonging to the job that has the shortest subsequent operation, $\min\limits_{l \in allowed} nr_l$; (4) LSO to select the operation belonging to the job that has the longest subsequent operation, $\max\limits_{l \in allowed} nr_l$; (5) SRM to select the operation belonging to the job that has the shortest remaining processing time (excluding the operation under the current consideration), $\min\limits_{l \in allowed} (sr_l - pt_l)$; (6) LRM to select the operation belonging to the job that has the longest remaining processing time (excluding the operation under the current consideration), $\max\limits_{l \in allowed} (sr_l - pt_l)$; (7) MWKR to select the operation belonging to the job that has the most remaining work, $\max\limits_{l \in allowed} sr_l$; (8) SWKR to

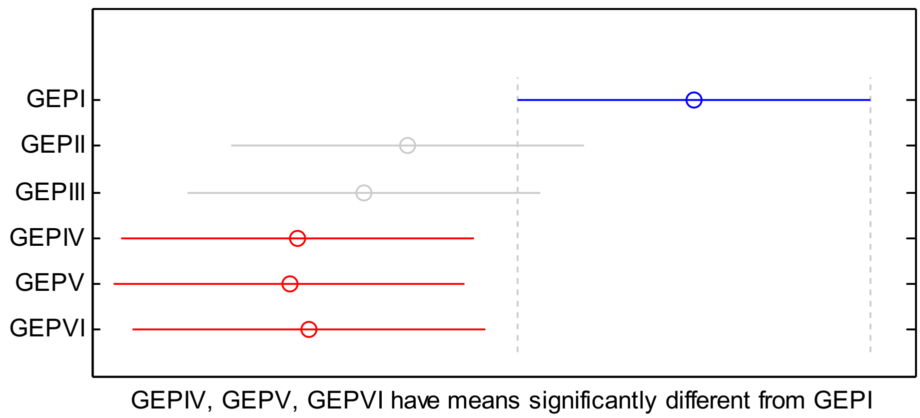


Fig. 9. Multiple comparison of the six new multi-attribute rules.

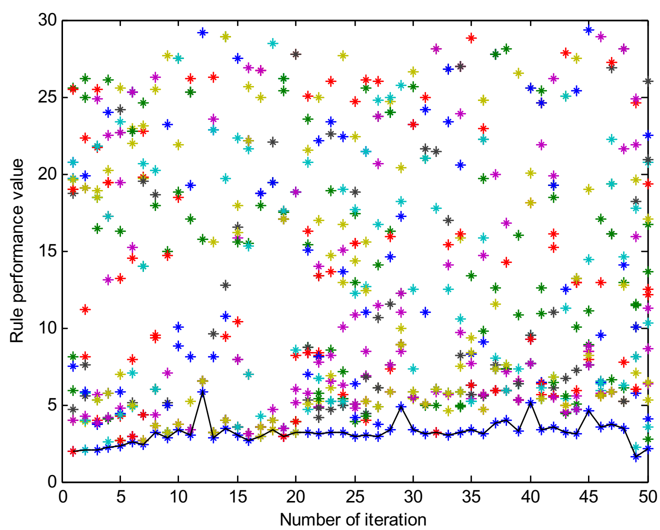


Fig. 10. Convergence graph of the GEP-RM algorithm.

select the operation belonging to the job that has the smallest work remained, $\min_{l \in allowed} sr_l$.

Table 5 reports the results of the TEC among GEPV and the classical dispatching rules under one scenario from 43 benchmarks. The deviations of TEC mean the ratio of the difference between the TEC and the minimal TEC in the range of TEC.

As illustrated in Table 5, 20 out of 43 scenarios calculated by GEPV are significantly superior to other eight dispatching rules, including SPT, LPT, SSO, LSO, SRM, LRM, MWKR, and SWKR. Meanwhile, it can be seen that LSO, LRM and MWKR produce good performance in solving the EEJSP because 12 scenarios in LSO, 6 scenarios in LRM, and 3 scenarios in MWKR are superior to others. Moreover, the deviation value of only 2 scenarios in GEPV is larger than 0.2 and the total deviation amount in GEPV is 3.004, which are the minimum values among all dispatching rules. Especially, the average deviation (0.07) of GEPV demonstrates that the TEC is close to the optimal solution.

Based on the above findings and analysis, we can conclude that GEPV produces satisfactory performance and robustness in solving the EEJSP. Methodologically, in the design process of the proposed GEP-RM algorithm, three attributes related to the TEC are highlighted and regarded as the terminal set. Four rule mining operators including selection, mutation, transposition and recombination are designed to train the rules via self-learning. Moreover, a perturbation of rule mining mechanism is presented so as to avoid the rules falling into the local optimum. As a result, the proposed method is able to consider the TEC into the rule training scenarios.

The unconventional design of rule mining based on big data in this research endows the new multi-attribute rules with superiority in the following three aspects: (1) compared with the time-related performance criteria in classical dispatching rules, minimizing the TEC is a much reasonable objective for the energy efficient scheduling problem; (2) based on the known information, the abstracted multiple attributes make the implicit and complex inherent relationship among all TEC related factors explicit and visible; (3) the discovered rules via GEP-RM are revealed with artificial intelligence including self-learning and unsupervised learning, which is not an empirical combination of dispatching rules.

5.2.4. Correlation analysis of TEC and makespan

According to Eq. (4), makespan is regard as a fraction to calculate the TEC. Thus, we list the makespan of GEPV and the classical dispatching rules in Table 5. The deviation of makespan is defined in the similar way of defining the deviation of TEC. Though the motivating examples reveal that TEC may have negative influence on makespan, a positive correlation between them is observed in Fig. 11.

The correlation coefficient r between them can be calculated by

$$r = \frac{\sum_{l=1}^{43} (E_l - \overline{E})(C_l - \overline{C})}{\sqrt{\sum_{l=1}^{43} (E_l - \overline{E})^2 \sum_{l=1}^{43} (C_l - \overline{C})^2}} = 0.851 \tag{23}$$

where E_l and C_l are the TEC and makespan for scenario l via GEPV. $\overline{E}$ and $\overline{C}$ are the average energy consumption and makespan among all scenarios via GEPV.

The TEC shows highly positive correlation with makespan because the correlation coefficient r (0.851) is near 1. Generally, machines with high unload power consume more energy than those with low unload power when the idle time is the same. It is obvious that in assigning jobs to machines, it would be better to reduce the idle times as much as possible on the machines with high unload power. This might sacrifice makespan and make the distribution of the idle times unbalanced. Meanwhile, the minimization of makepan might lead to schedules with low idle times. Thus the idle times derived by the discovered rules may be evenly distributed on each machine to enhance the machine utilization.

Table 5
Total energy consumption/deviation among GEPV and the classical dispatching rules.

	J	M	SPT	LPT	LSO	SSO	LWKR	MWKR	LRM	SRM	GEPV
FT06	6	6	1941/0.76	1967/0.81	1475/0.04	1847/0.62	2092/1.00	1668/0.34	**1449/0.00**	2092/1.00	1496/0.07
FT10	10	10	49078/0.48	55096/1.00	45770/0.19	49882/0.55	54231/0.92	44785/0.10	44348/0.06	50708/0.62	**43622/0.00**
FT20	20	5	43695/1.00	39723/0.42	37564/0.11	39558/0.40	40429/0.52	37322/0.07	37449/0.09	41225/0.64	**36823/0.00**
LA01	10	5	24001/0.60	20735/0.21	20062/0.12	25278/0.75	27309/1.00	19564/0.06	19902/0.10	24367/0.64	**19034/0.00**
LA02	10	5	18738/1.00	17452/0.66	15569/0.17	17439/0.66	18590/0.96	16075/0.30	15642/0.19	18424/0.92	**14937/0.00**
LA03	10	5	16367/0.69	14998/0.30	14659/0.21	16979/0.86	17469/1.00	14589/0.19	15102/0.33	16673/0.78	**13915/0.00**
LA04	10	5	17657/0.22	18368/0.42	17513/0.18	19469/0.73	20454/1.00	17568/0.20	17356/0.14	19042/0.61	**16858/0.00**
LA05	10	5	19460/0.92	17390/0.57	**13997/0.00**	18799/0.81	19914/1.00	14511/0.09	14674/0.11	16534/0.43	14515/0.09
LA06	15	5	35011/0.80	28528/0.26	25904/0.04	33133/0.65	37328/1.00	25582/0.01	25951/0.04	36119/0.90	**25452/0.00**
LA07	15	5	21418/0.37	21610/0.41	20083/0.09	21767/0.44	24481/1.00	20177/0.11	20304/0.14	24068/0.91	**19631/0.00**
LA08	15	5	29765/0.66	27965/0.44	**24420/0.00**	31837/0.92	32491/1.00	25884/0.18	24896/0.06	29300/0.60	25506/0.13
LA09	15	5	34404/0.85	29495/0.35	26145/0.01	31815/0.59	35844/1.00	28054/0.21	26238/0.02	35662/0.98	**26029/0.00**
LA10	15	5	28618/0.71	24316/0.25	**22047/0.00**	28642/0.72	31244/1.00	24011/0.21	23926/0.20	27137/0.55	23499/0.16
LA11	20	5	33630/0.75	31645/0.52	27252/0.01	33209/0.70	34841/0.89	27741/0.07	27462/0.04	35774/1.00	**27160/0.00**
LA12	20	5	31066/0.48	28577/0.21	26804/0.01	30264/0.39	31326/0.51	28084/0.15	27008/0.03	35764/1.00	**26710/0.00**
LA13	20	5	38599/1.00	30082/0.12	**28919/0.00**	35793/0.71	34583/0.59	29593/0.07	29932/0.10	35246/0.65	29317/0.04
LA14	20	5	39295/0.98	34234/0.45	30414/0.05	36672/0.70	37808/0.82	31058/0.12	**29901/0.00**	39509/1.00	30481/0.06
LA15	20	5	34820/0.40	33780/0.29	30976/0.01	35134/0.43	40720/1.00	31158/0.02	**30953/0.00**	37547/0.68	31413/0.05
LA16	10	10	58407/1.00	49698/0.33	46394/0.08	51190/0.45	54284/0.69	**45313/0.00**	47030/0.13	57733/0.95	46861/0.12
LA17	10	10	48576/0.87	43892/0.53	**36711/0.00**	50338/1.00	50159/0.99	41166/0.33	38695/0.15	48435/0.86	39345/0.19
LA18	10	10	53259/0.82	52645/0.77	**43750/0.00**	51503/0.67	55346/1.00	45741/0.17	45267/0.13	49847/0.53	44988/0.11
LA19	10	10	50149/0.76	44685/0.37	**39560/0.00**	47242/0.55	53543/1.00	43852/0.31	44410/0.35	51877/0.88	42698/0.22
LA20	10	10	46303/0.38	50753/0.73	44257/0.21	54158/1.00	51007/0.75	41664/0.01	41571/0.00	51685/0.80	42294/0.06
LA21	15	10	70142/0.76	66986/0.57	57470/0.02	67159/0.58	74313/1.00	58724/0.09	57901/0.04	74260/1.00	**57128/0.00**
LA22	15	10	60239/0.44	61690/0.53	54856/0.10	64969/0.73	69295/1.00	53774/0.04	**53165/0.00**	66575/0.83	55956/0.17
LA23	15	10	63506/0.60	56262/0.27	55550/0.24	72018/0.99	72345/1.00	53171/0.13	50645/0.01	65020/0.67	**50345/0.00**
LA24	15	10	69244/0.98	64303/0.70	**51868/0.00**	65106/0.75	69538/1.00	54157/0.13	53832/0.11	68584/0.95	54283/0.14
LA25	15	10	83008/0.78	74119/0.42	64097/0.02	79787/0.65	87164/0.94	66090/0.10	**63509/0.00**	88652/1.00	65844/0.09
LA26	20	10	75200/0.73	70550/0.48	63665/0.12	76667/0.80	76902/0.82	**61485/0.00**	63474/0.11	80398/1.00	62305/0.04
LA27	20	10	78803/0.65	73870/0.41	66993/0.07	80288/0.73	85849/1.00	66276/0.04	68593/0.15	79364/0.68	**65556/0.00**
LA28	20	10	101117/0.65	89363/0.31	**78633/0.00**	98675/0.58	103993/0.73	87712/0.26	83617/0.14	113239/1.00	83689/0.15
LA29	20	10	79017/0.69	73684/0.44	65162/0.05	84171/0.93	85606/1.00	64314/0.01	64314/0.01	83208/0.89	**64188/0.00**
LA30	20	10	84804/0.52	83584/0.48	72118/0.10	95947/0.89	99189/1.00	71122/0.07	69660/0.02	90787/0.72	**68964/0.00**
LA31	30	10	104867/0.40	106245/0.44	**90086/0.00**	113560/0.64	116700/0.72	95641/0.15	92811/0.07	126880/1.00	94145/0.11
LA32	30	10	123607/0.77	118453/0.62	97966/0.05	120858/0.69	131938/1.00	96702/0.01	96313/0.00	127414/0.87	96635/0.01
LA33	30	10	105212/0.83	104116/0.78	**85983/0.00**	108428/0.97	109230/1.00	90808/0.21	92029/0.26	109001/0.99	90899/0.21
LA34	30	10	104692/0.67	104892/0.67	**84535/0.00**	107194/0.75	114715/1.00	88744/0.14	87098/0.08	107638/0.77	87458/0.10
LA35	30	10	114298/0.58	110493/0.44	97749/0.01	115808/0.63	126622/1.00	100201/0.09	99374/0.06	121509/0.82	**97611/0.00**
LA36	15	15	108651/0.39	108632/0.38	96675/0.02	111581/0.48	120294/0.74	96529/0.02	96928/0.03	128771/1.00	**96026/0.00**
LA37	15	15	117836/0.74	109234/0.37	105599/0.21	116866/0.70	123724/1.00	102848/0.09	102456/0.08	120361/0.85	**100671/0.00**
LA38	15	15	111682/0.59	115392/0.71	102146/0.27	124288/1.00	120461/0.87	**93900/0.00**	94912/0.03	121226/0.90	99628/0.19
LA39	15	15	107800/0.29	117658/0.61	99029/0.01	114307/0.50	124021/0.82	100961/0.07	100905/0.07	129690/1.00	**98651/0.00**
LA40	15	15	116325/0.69	110378/0.52	93407/0.04	108516/0.47	127028/1.00	98304/0.18	**92106/0**	119588/0.79	93334/0.04

Therefore, the correlation of the TEC with makespan is positive in most circumstances.

6. Conclusions

In this paper, we introduced a novel mixed-integer mathematical model to address the energy efficient job shop scheduling problem. In addition, we developed a GEP-RM algorithm by combining three attributes related to TEC in order to discover new evolutional energy-efficient rules. The proposed GEP-RM algorithm integrated unsupervised learning and swarm intelligence to optimize population diversity and convergence. Because the proposed method is based on artificial intelligence, it is flexible to incorporate domain knowledge and expertise into the searching of dispatching rules. Therefore, the obtained energy-efficient rules would perfectly meet the requirement of minimum TEC. Moreover, this paper also designs necessary rule mining operators to guarantee the global exploration and local exploitation of the proposed algorithm. Lastly, 473 scenarios were designed to test the performance of the multi-attribute rules in this study. The main conclusions are as follows:

(1) A novel mixed-integer mathematical model was formulated, in which global event points and virtual operations are utilized to describe precisely the energy efficient job-shop scheduling.
(2) The rules generated by the rule mining algorithm have significant superiority over existing dispatching rules in terms of energy saving and production efficiency. Each of them can be applied easily and conveniently like the typical rules in real production.
(3) The TEC and makespan are highly positive correlated in most circumstances since the correlation coefficient r (0.851) is near 1.

In future work, the proposed method will be applied to field datasets acquired from practical production systems. New rules hidden in the field datasets will be explored to solve real-world job-shop scheduling problem.

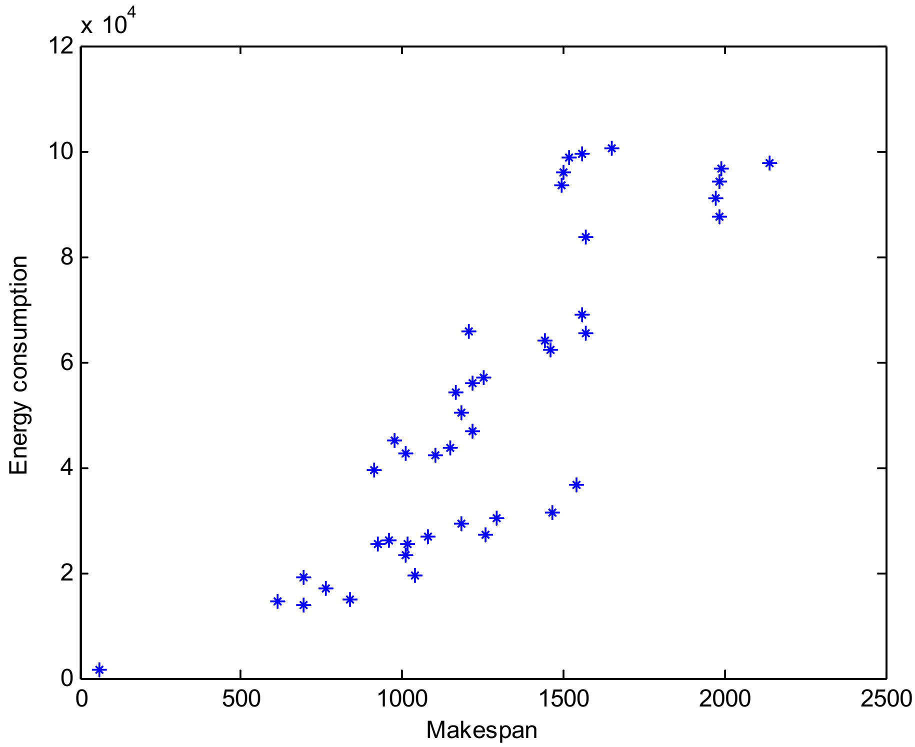


Fig. 11. Relationship between TEC and makespan.

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Appendix A

Table 4Total energy consumption/ deviation among GEPV and the classical dispatching rules

	J	M	SPT	LPT	LSO	SSO	LWKR	MWKR	LRM	SRM	GEPV
FT06	6	6	1941/0.76	1967/0.81	1475/0.04	1847/0.62	2092/1.00	1668/0.34	**1449/0.00**	2092/1.00	1496/0.07
FT10	10	10	49078/0.48	55096/1.00	45770/0.19	49882/0.55	54231/0.92	44785/0.10	44348/0.06	50708/0.62	**43622/0.00**
FT20	20	5	43695/1.00	39723/0.42	37564/0.11	39558/0.40	40429/0.52	37322/0.07	37449/0.09	41225/0.64	**36823/0.00**
LA01	10	5	24001/0.60	20735/0.21	20062/0.12	25278/0.75	27309/1.00	19564/0.06	19902/0.10	24367/0.64	**19034/0.00**
LA02	10	5	18738/1.00	17452/0.66	15569/0.17	17439/0.66	18590/0.96	16075/0.30	15642/0.19	18424/0.92	**14937/0.00**
LA03	10	5	16367/0.69	14998/0.30	14659/0.21	16979/0.86	17469/1.00	14589/0.19	15102/0.33	16673/0.78	**13915/0.00**
LA04	10	5	17657/0.22	18368/0.42	17513/0.18	19469/0.73	20454/1.00	17568/0.20	17356/0.14	19042/0.61	**16858/0.00**
LA05	10	5	19460/0.92	17390/0.57	**13997/0.00**	18799/0.81	19914/1.00	14511/0.09	14674/0.11	16534/0.43	14515/0.09
LA06	15	5	35011/0.80	28528/0.26	25904/0.04	33133/0.65	37328/1.00	25582/0.01	25951/0.04	36119/0.90	**25452/0.00**
LA07	15	5	21418/0.37	21610/0.41	20083/0.09	21767/0.44	24481/1.00	20177/0.11	20304/0.14	24068/0.91	**19631/0.00**
LA08	15	5	29765/0.66	27965/0.44	**24420/0.00**	31837/0.92	32491/1.00	25884/0.18	24896/0.06	29300/0.60	25506/0.13
LA09	15	5	34404/0.85	29495/0.35	26145/0.01	31815/0.59	35844/1.00	28054/0.21	26238/0.02	35662/0.98	**26029/0.00**
LA10	15	5	28618/0.71	24316/0.25	**22047/0.00**	28642/0.72	31244/1.00	24011/0.21	23926/0.20	27137/0.55	23499/0.16
LA11	20	5	33630/0.75	31645/0.52	27252/0.01	33209/0.70	34841/0.89	27741/0.07	27462/0.04	35774/1.00	**27160/0.00**
LA12	20	5	31066/0.48	28577/0.21	26804/0.01	30264/0.39	31326/0.51	28084/0.15	27008/0.03	35764/1.00	**26710/0.00**
LA13	20	5	38599/1.00	30082/0.12	**28919/0.00**	35793/0.71	34583/0.59	29593/0.07	29932/0.10	35246/0.65	29317/0.04
LA14	20	5	39295/0.98	34234/0.45	30414/0.05	36672/0.70	37808/0.82	31058/0.12	**29901/0.00**	39509/1.00	30481/0.06
LA15	20	5	34820/0.40	33780/0.29	30976/0.01	35134/0.43	40720/1.00	31158/0.02	**30953/0.00**	37547/0.68	31413/0.05
LA16	10	10	58407/1.00	49698/0.33	46394/0.08	51190/0.45	54284/0.69	**45313/0.00**	47030/0.13	57733/0.95	46861/0.12
LA17	10	10	48576/0.87	43892/0.53	**36711/0.00**	50338/1.00	50159/0.99	41166/0.33	38695/0.15	48435/0.86	39345/0.19
LA18	10	10	53259/0.82	52645/0.77	**43750/0.00**	51503/0.67	55346/1.00	45741/0.17	45267/0.13	49847/0.53	44988/0.11
LA19	10	10	50149/0.76	44685/0.37	**39560/0.00**	47242/0.55	53543/1.00	43852/0.31	44410/0.35	51877/0.88	42698/0.22
LA20	10	10	46303/0.38	50753/0.73	44257/0.21	54158/1.00	51007/0.75	41664/0.01	41571/0.00	51685/0.80	42294/0.06
LA21	15	10	70142/0.76	66986/0.57	57470/0.02	67159/0.58	74313/1.00	58724/0.09	57901/0.04	74260/1.00	**57128/0.00**
LA22	15	10	60239/0.44	61690/0.53	54856/0.10	64969/0.73	69295/1.00	53774/0.04	**53165/0.00**	66575/0.83	55956/0.17
LA23	15	10	63506/0.60	56262/0.27	55550/0.24	72018/0.99	72345/1.00	53171/0.13	50645/0.01	65020/0.67	**50345/0.00**
LA24	15	10	69244/0.98	64303/0.70	**51868/0.00**	65106/0.75	69538/1.00	54157/0.13	53832/0.11	68584/0.95	54283/0.14
LA25	15	10	83008/0.78	74119/0.42	64097/0.02	79787/0.65	87164/0.94	66090/0.10	**63509/0.00**	88652/1.00	65844/0.09
LA26	20	10	75200/0.73	70550/0.48	63665/0.12	76667/0.80	76902/0.82	**61485/0.00**	63474/0.11	80398/1.00	62305/0.04
LA27	20	10	78803/0.65	73870/0.41	66993/0.07	80288/0.73	85849/1.00	66276/0.04	68593/0.15	79364/0.68	**65556/0.00**

(*continued*)

	J	M	SPT	LPT	LSO	SSO	LWKR	MWKR	LRM	SRM	GEPV
LA28	20	10	101117/0.65	89363/0.31	**78633/0.00**	98675/0.58	103993/0.73	87712/0.26	83617/0.14	113239/1.00	83689/0.15
LA29	20	10	79017/0.69	73684/0.44	65162/0.05	84171/0.93	85606/1.00	64314/0.01	64314/0.01	83208/0.89	**64188/0.00**
LA30	20	10	84804/0.52	83584/0.48	72118/0.10	95947/0.89	99189/1.00	71122/0.07	69660/0.02	90787/0.72	**68964/0.00**
LA31	30	10	104867/0.40	106245/0.44	**90086/0.00**	113560/0.64	116700/0.72	95641/0.15	92811/0.07	126880/1.00	94145/0.11
LA32	30	10	123607/0.77	118453/0.62	97966/0.05	120858/0.69	131938/1.00	96702/0.01	96313/0.00	127414/0.87	96635/0.01
LA33	30	10	105212/0.83	104116/0.78	**85983/0.00**	108428/0.97	109230/1.00	90808/0.21	92029/0.26	109001/0.99	90899/0.21
LA34	30	10	104692/0.67	104892/0.67	**84535/0.00**	107194/0.75	114715/1.00	88744/0.14	87098/0.08	107638/0.77	87458/0.10
LA35	30	10	114298/0.58	110493/0.44	97749/0.01	115808/0.63	126622/1.00	100201/0.09	99374/0.06	121509/0.82	**97611/0.00**
LA36	15	15	108651/0.39	108632/0.38	96675/0.02	111581/0.48	120294/0.74	96529/0.02	96928/0.03	128771/1.00	**96026/0.00**
LA37	15	15	117836/0.74	109234/0.37	105599/0.21	116866/0.70	123724/1.00	102848/0.09	102456/0.08	120361/0.85	**100671/0.00**
LA38	15	15	111682/0.59	115392/0.71	102146/0.27	124288/1.00	120461/0.87	**93900/0.00**	94912/0.03	121226/0.90	99628/0.19
LA39	15	15	107800/0.29	117658/0.61	99029/0.01	114307/0.50	124021/0.82	100961/0.07	100905/0.07	129690/1.00	**98651/0.00**
LA40	15	15	116325/0.69	110378/0.52	93407/0.04	108516/0.47	127028/1.00	98304/0.18	**92106/0.00**	119588/0.79	93334/0.04

Appendix B

Table 5
Makespan / deviation among GEPV and the classical dispatching rules

	J	M	SPT	LPT	LSO	SSO	LWKR	MWKR	LRM	SRM	GEPV
FT06	6	6	83/0.7	79/0.59	60/0.08	71/0.38	94/1	67/0.27	**57/0**	94/1	58/0.03
FT10	10	10	1399/0.66	1534/1	1219/0.21	1410/0.69	1530/0.99	1178/0.11	**1134/0**	1415/0.7	1147/0.03
FT20	20	5	1581/0.46	1610/0.65	1611/0.66	1526/0.09	**1513/0**	1588/0.5	1662/1	1595/0.55	1539/0.17
LA01	10	5	920/0.44	889/0.38	846/0.29	1078/0.74	1210/1	735/0.08	747/0.1	1027/0.65	**694/0**
LA02	10	5	958/0.85	898/0.43	904/0.47	912/0.52	966/0.91	875/0.26	905/0.48	979/1	**838/0**
LA03	10	5	770/0.37	748/0.26	747/0.25	808/0.56	897/1	704/0.04	787/0.45	834/0.69	**696/0**
LA04	10	5	811/0.23	848/0.4	799/0.17	939/0.83	976/1	790/0.13	783/0.1	880/0.55	**762/0**
LA05	10	5	827/0.74	787/0.6	**610/0**	845/0.8	905/1	612/0.01	612/0.01	661/0.17	612/0.01
LA06	15	5	1369/0.77	1105/0.31	**928/0**	1268/0.6	1498/1	926/0	968/0.07	1439/0.9	**926/0**
LA07	15	5	1128/0.41	1145/0.47	**1017/0**	1141/0.46	1282/0.97	1031/0.05	1039/0.08	1289/1	1039/0.08
LA08	15	5	1168/0.54	1102/0.37	**959/0**	1256/0.76	1348/1	1011/0.13	1023/0.16	1134/0.45	1019/0.15
LA09	15	5	1332/0.74	1111/0.3	1005/0.09	1232/0.54	1384/0.84	1066/0.22	986/0.06	1463/1	**957/0**
LA10	15	5	1367/0.74	1136/0.32	**958/0**	1291/0.6	1509/1	1052/0.17	1031/0.13	1279/0.58	1010/0.09
LA11	20	5	1625/0.8	1476/0.48	1297/0.09	1664/0.89	1653/0.86	1316/0.13	**1256/0**	1715/1	**1256/0**
LA12	20	5	1330/0.48	1222/0.27	1127/0.09	1350/0.51	1423/0.65	1167/0.17	1140/0.11	1606/1	**1080/0**
LA13	20	5	1642/1	1246/0.19	**1154/0**	1530/0.77	1517/0.74	1191/0.08	1225/0.15	1522/0.75	1183/0.06
LA14	20	5	1663/0.79	1429/0.29	**1292/0**	1594/0.65	1669/0.81	1292/0	1297/0.01	1759/1	**1292/0**
LA15	20	5	1538/0.25	1516/0.21	1492/0.16	1510/0.2	1900/1	**1415/0**	1493/0.16	1778/0.75	1466/0.11
LA16	10	10	1557/1	1244/0.33	**1089/0**	1183/0.2	1371/0.6	1118/0.06	1124/0.07	1547/0.98	1216/0.27
LA17	10	10	1236/0.68	1145/0.51	**860/0**	1261/0.72	1416/1	1004/0.26	895/0.06	1295/0.78	915/0.1
LA18	10	10	1259/0.75	1264/0.76	989/0.04	1182/0.55	1353/1	983/0.02	1027/0.14	1174/0.53	**975/0**
LA19	10	10	1352/0.94	1140/0.36	1058/0.13	1208/0.54	1302/0.8	1089/0.22	1061/0.14	1375/1	**1009/0**
LA20	10	10	1331/0.59	1390/0.72	1199/0.28	1513/1	1447/0.85	1076/0.004	**1074/0**	1463/0.89	1105/0.07
LA21	15	10	1719/0.84	1519/0.48	1336/0.15	1610/0.65	1806/1	1314/0.11	1304/0.09	1760/0.92	**1253/0**
LA22	15	10	1392/0.43	1409/0.46	1251/0.19	1434/0.5	1736/1	**1135/0**	1168/0.05	1686/0.92	1221/0.14
LA23	15	10	1480/0.54	1330/0.27	1351/0.3	1717/0.96	1737/1	1258/0.14	1214/0.06	1587/0.73	**1183/0**
LA24	15	10	1561/0.88	1472/0.7	**1111/0**	1532/0.82	1624/1	1178/0.13	1181/0.14	1618/0.99	1164/0.1
LA25	15	10	1691/0.74	1382/0.3	1207/0.05	1562/0.56	1849/0.97	1209/0.05	**1173/0**	1869/1	1205/0.05
LA26	20	10	1856/0.65	1746/0.48	1568/0.2	1952/0.8	1989/0.85	**1439/0**	1535/0.15	2084/1	1460/0.03
LA27	20	10	2004/0.73	1776/0.35	1665/0.16	1955/0.65	2161/1	1595/0.04	1619/0.08	2009/0.74	**1571/0**
LA28	20	10	2013/0.65	1668/0.2	**1514/0**	2007/0.64	2145/0.82	1631/0.15	1562/0.06	2283/1	1569/0.07
LA29	20	10	1993/0.77	1695/0.35	1488/0.07	2008/0.79	2154/0.99	1452/0.02	1555/0.16	2161/1	**1441/0**
LA30	20	10	2100/0.63	1893/0.4	1643/0.13	2322/0.87	2444/1	1566/0.05	**1520/0**	2110/0.64	1556/0.04
LA31	30	10	2352/0.45	2392/0.49	**1900/0**	2555/0.65	2783/0.87	2057/0.16	1987/0.09	2912/1	1987/0.09
LA32	30	10	2653/0.73	2609/0.68	2059/0.07	2731/0.81	2899/1	1993/0	2005/0.01	2804/0.9	**1992/0**
LA33	30	10	2292/0.66	2302/0.67	**1863/0**	2501/0.98	2514/1	1973/0.17	2005/0.22	2514/1	1973/0.17
LA34	30	10	2564/0.73	2480/0.63	**1940/0**	2491/0.64	2798/1	2016/0.09	2047/0.12	2607/0.78	1987/0.05
LA35	30	10	2488/0.46	2335/0.26	2321/0.24	2594/0.6	2895/1	**2136/0**	2203/0.09	2682/0.72	2141/0.01
LA36	15	15	1851/0.41	1789/0.33	1602/0.12	1831/0.38	2218/0.84	1513/0.01	1514/0.01	2359/1	**1502/0**
LA37	15	15	2075/0.81	1940/0.55	1737/0.17	1919/0.51	2176/1	1680/0.06	1691/0.08	2151/0.95	**1649/0**
LA38	15	15	1819/0.64	1912/0.81	1582/0.23	2024/1	1928/0.83	1456/0.01	**1449/0**	2005/0.97	1558/0.19
LA39	15	15	1790/0.35	2064/0.71	1594/0.1	1908/0.5	2102/0.76	1552/0.04	1651/0.17	2289/1	**1520/0**
LA40	15	15	2048/0.75	1829/0.46	1506/0.02	1867/0.51	2231/1	1604/0.15	**1493/0**	2006/0.7	1497/0.01

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Glossary

O_{ij}: the jth operation of the ith job, where $i = 1, 2, ..., n,\ j = 1,\ 2,\ \ ...,\ |J_i|$
p_{ij}: the processing time of operation O_{ij}
m_{ij}: the machine that has been predefined to perform the operation O_{ij}
TEC: the total energy consumption
DEC: the direct energy consumption
IEC: he indirect energy consumption
PC_{ij}: the cutting power of operation O_{ij}
PU_k: the unload power of machine k
EU_k: the total unload energy consumption of machine k
T: set of global event points symbolizing operations to be sequenced, $T = \{t | t = 1, 2, ..., L\}$
It_k: the idle time of machine k
SM_{kt}: the starting time of machine k at sequence t
CM_{kt}: the completion time of machine k at sequence t
CO_{ij}: continuous variable, the completion time of the operation O_{ij}
$C_{\max}$: continuous variable, makespan or the completion time of the last operation
Y_{ijs}: binary variable. It equals to 1 if O_{ij} is the sth operation in the requested sequence; otherwise, 0
α: the coefficient of Stute power balance equation
β: the coefficient of indirect energy consumption
M: parameter, a big number