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ORIGINAL ARTICLE

An improved electromagnetism-like mechanism algorithm for energy-aware many-objective flexible job shop scheduling

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Abstract
Nowadays, most of the manufacturing industries rely on effective shop floor schedules to improve productivity and to optimize the makespan, production cost, tardiness, etc., which are usually considered in traditional scheduling problems. Recently, in response to the global initiatives for sustainability in manufacturing industries, an increasing number of shop floor schedules have taken energy consumption into account. However, few research works have considered traditional objectives, energy consumption, and other sustainability factors simultaneously in a shop floor schedule. In this paper, a many-objective optimization model for a flexible job shop scheduling problem considering makespan, total energy consumption, and three other indicators is formulated. Then, an improved electromagnetism-like mechanism algorithm is proposed to find the optimal or near-optimal solutions. Finally, a real-life case study is conducted to evaluate the proposed model and the algorithm. The results show that the many-objective model is effective for reducing energy consumption and improving sustainability in the shop floor.

Keywords Electromagnetism-like mechanism algorithm · Energy consumption · Job shop scheduling · Many-objective optimization · Sustainable manufacturing

1 Introduction

With the rapid development of the manufacturing industry, and increasing needs for environmental-friendly production technics, currently the manufacturing companies are facing great challenges to develop their manufacturing systems to a more efficient and sustainable level [1, 2]. To be specific, under such circumstances, the companies should lower their production energy consumption, reduce carbon emissions, and improve energy efficiency, while maintaining a short makespan, and reasonable production cost as well.

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Adopting a proper shop floor scheduling scheme has been proved to be an effective way for the enterprises to optimize their manufacturing efficiency and reliability. A traditional scheduling in a manufacturing process allocates limited resources to several tasks within a certain amount of time, in order to achieve one or multiple objectives such as minimizing makespan, reducing production cost or controlling environmental impacts. Thus, the optimization of shop floor scheduling is of great significance for improving the energy efficiency of general production processes. There are different models of shop floor configurations, such as single machine, parallel machine, flow shop, job shop, and continuous manufacturing. A job shop often handles small to medium-size orders, which is more flexible and reconfigurable, hence plays an important role in smart manufacturing. In this paper, a flexible job shop scheduling problem (FJSP) is studied, in which jobs have different process sequences, and each operation for each job can be processed on different machines. The processing time also varies depending on which machine is chosen.

A lot of research works have been done to solve shop floor scheduling problems. Most of them focus on the traditional objectives such as makespan, production cost, and tardiness. [3–5]. When traditional scheduling objectives cannot meet the increasing needs of sustainable manufacturing, more and more researchers choose to integrate the new objectives of reducing energy consumption and improving energy efficiency into shop floor scheduling studies. For example, Wang et al. [6] studied an identical parallel machine scheduling problem to minimize both the makespan and the total energy consumption. Fu et al. [7] addressed a distributed permutation flow shop scheduling problem also to minimize the makespan and the energy consumption. Liu et al. [8] proposed a bi-objective optimization model that minimizes the non-processing electricity consumption and the total weighted tardiness in a job shop. Lu et al. [9] investigated an energy-efficient permutation flow shop scheduling problem to simultaneously ensure the machine service span and energy saving. Liu et al. [10] proposed a fuzzy flow shop scheduling problem to minimize energy consumption and tardiness. Some researchers also consider adding additional constraints and different situations to better interpret real-life cases. For example, Nagasawa et al. [11] studied a robust flow shop scheduling considering random processing time and minimizing the peak power consumption. Dai et al. [12] studied the FJSP to minimize energy consumption and makespan with transportation constraints.

The studies above mainly consider traditional scheduling objectives or the combination of traditional and energy-related objectives. Recently, in addition to the traditional objectives and the energy-related factors, researchers start to consider and seek to optimize other sustainability-related indicators, such as environmental indicators like carbon dioxide emissions [13–15], social indicators like worker allocation [16], and other mixed indicators [17].

However, research works that consider multiple environmental indicators are still limited. Therefore, in this paper, a many-objective flexible job shop scheduling optimization model is formulated to improve the overall sustainability of the shop floor. The objectives of the model include minimizing makespan, total energy consumption, production cost, and improving processing power efficiency and reducing wasted carbon emission.

To solve the many-objective FJSP, which is NP-hard, a certain or several approximation methods are required. With the advancement of the computing capacity in computer technology since the late twentieth century, the intelligent algorithm prospers and a large number of approximation methods, also known as heuristic algorithms, have helped greatly solve numerous complicated problems [18, 19]. Most of these algorithms are bio-inspired, evolution-based, or physical/chemistry-based approaches [20]. They have shown a great effectiveness in solving optimization and many-objective optimization problems for real or simulated cases [21–27]. The electromagnetism-like mechanism algorithm (EMA) is a heuristic inspired by the attraction–repulsion mechanism of charged particles in a static electric field. It is firstly proposed by Birbil and Fang [28] in 2003 to solve optimization problems, and has been used in many researches ever since. Debels et al. [29] studied a resource-constrained project scheduling problem and incorporated the EMA in their proposed meta-heuristic to provide near-optimal solutions for large instances. Karimi et al. [30] investigated a hybrid flexible flow shop scheduling problem for minimizing the makespan and implemented the EMA in their newly presented evolutionary algorithm. Fathian et al. [31] proposed a hybrid meta-heuristic algorithm based on the EMA to solve the nonlinear programming model for a supply chain design and planning problem. Alinezhad et al. [32] developed a multi-objective optimization model for location-pricing with congested facilities and presented a meta-heuristic based on the EMA to find better solutions. However, the EMA also has limitations when dealing with many-objective FJSP. For instance, the EMA lacks the capacity to record the best solution or solution set throughout the iterations. It also has a relatively high computational complexity, and a fast convergence speed, which may cause premature problems and the loss of diversity in terms of the final Pareto solution set. Hence, an improved electromagnetism-like mechanism algorithm (IEMA) is proposed to solve the scheduling problem studied in this paper to obtain optimal or near-optimal solutions more effectively.

The contributions of this paper are as follows:

1. The proposed many-objective optimization model takes not only traditional and energy factors into account, but also other environmental factors, which further improves the overall sustainability of the manufacturing process.
2. The proposed IEMA improves the computation and searching capability of the original EMA and can find better Pareto solutions to the problem discussed in this paper.
3. A real-life case of a hydraulic valve job shop is studied to verify the effectiveness of the proposed model and algorithm.

The following sections of this paper are outlined as follows. In Sect. 2, the many-objective FJSP along with the corresponding mathematical model are put forward. Section 3 introduces the proposed IEMA. Section 4 includes a real-life case study of a hydraulic valve company to verify the effectiveness of the proposed many-objective model and algorithm. Finally, a conclusion and future research possibilities are presented in Sect. 5.

2 Energy-aware many-objective flexible job shop scheduling problem

2.1 Problem description

In this paper, a flexible job shop scheduling problem is described as follows. A set of n jobs $J = \{J_1, J_2, \dots, J_n\}$ is processed on m machines represented by $M = \{M_1, M_2, \dots, M_m\}$. Each job J_i possesses p_i operations $O_i = \{O_{i1}, O_{i2}, \dots, O_{ip_i}\}$. The process sequence of operations is pre-determined. There are multiple choices for each operation O_{ij} to select a machine for processing. The completion time and the total energy consumption of the task are depended on the choices of machine sets. Besides, the usage of electricity will also generate certain quantities of carbon dioxide during the process.

The assumptions for the FJSP problem are as follows: (1) Each machine can only process one job at a time. (2) Each operation of each job can only be processed on one machine at a time. (3) There are no priorities among different jobs. (4) The processing of an operation will not stop once started. (5) The electricity price is invariant during the scheduled production process.

2.2 Nomenclature

The nomenclature in this paper is presented in Table 1.

2.3 Model formulation

The many-objective FJSP proposed in this paper consider the makespan (MKS), the total energy consumption (TEC), the

Table 1 Nomenclature

Indexes	
i, k	Index of jobs,$\in \{1, 2, \dots, n\}$
j, l	Index of operations,$\in \{1, 2, \dots, p_i\}$
x, y	Index of machines,$\in \{1, 2, \dots, m\}$
w	Index of position,$\in \{1, 2, \dots, q_x\}$
Sets	
A_{ij}	Set of available machines for operation O_{ij}, $A_{ij} \subseteq M$
Constants	
m	Number of machines
n	Number of jobs
σ	Average auxiliary energy consumption per unit time
Variables	
p_i	Number of operations for job J_i
a_{ij}	Number of available machines for operation O_{ij}
q_x	Number of operations processed by machine M_x
T_i	Completion time of job J_i
T_{ijx}	Completion time of operation O_{ij} on machine M_x
t_{ij}	Processing time of operation O_{ij}
t_{ijx}	Processing time of operation O_{ij} on machine M_x
S_{ij}	Starting time of operation O_{ij}
S_{ijx}	Starting time of operation O_{ij} on machine M_x
S_{xw}	Starting time of the wth operation on machine M_x
s_{jx}	Configuring time of the machine M_x for the jth operation
X_{ijx}	$X_{ijx} = \begin{cases} 1, \text{ if operation } O_{ij} \text{ is processed on machine } M_x \\ 0, \text{ if otherwise} \end{cases}$
Y_{ijxw}	$Y_{ijxw} = \begin{cases} 1, \text{ if operation } O_{ij} \text{ is processed on machine } M_x \text{ in } w\text{th position} \\ 0, \text{ if otherwise} \end{cases}$
BP_{jx}	Basic power demand of the machine M_x for maintaining the normal running for the jth operation
OP_{ijx}	Operation power of the machine M_x when processing the operation O_{ij}
IP_x	Idling power of the machine M_x

total production cost (TPC), the wasted carbon dioxide emission (WCE), and the inverted processing power efficiency (IPPE) simultaneously. Their mathematical models are constructed as follows.

1. The makespan is the total production time of a set of jobs, whose function f_1 can be represented by Eq. (1).

$$\mathrm{MKS} = \max_{1\le i\le n} T_i \tag{1}$$

2. The TEC is divided into four parts: the configuration energy consumption (CE), which represents the part of energy required for readjusting and configuring the machines when changing tool positions, jobs and operations; the processing energy consumption (PE) is the part of energy consumed for processing operations; the idling energy consumption (IE) is the energy consumed when machines are running at the idle state; the auxiliary energy consumption (AE), which is the part of energy used for lighting, heating, ventilation, air-conditioning, and other power usage for maintaining the basic working environment. The equations for calculating the four parts of energy consumption are presented by Eqs. (2)–(5) [12], and the TEC can be obtained by Eq. (6).

$$\mathrm{CE} = \sum_{x=1}^{m} \sum_{j=1}^{q_x} BP_{jx} \cdot s_{jx} \tag{2}$$

$$\mathrm{PE} = \sum_{i=1}^{n} \sum_{j=1}^{p_i} \sum_{x=1}^{m} OP_{ijx} \cdot t_{ijx} \cdot X_{ijx} \tag{3}$$

$$\mathrm{IE} = \sum_{x=1}^{m} IP_x \cdot \left(\max_{ij} T_{ijx} - \sum_{i=1}^{n} \sum_{j=1}^{p_i} (T_{ijx} - S_{ijx}) \cdot X_{ijx} \right) \tag{4}$$

$$\mathrm{AE} = \sigma \cdot \max_{1\le i\le n} T_i \tag{5}$$

$$\mathrm{TEC} = \mathrm{CE} + \mathrm{PE} + \mathrm{IE} + \mathrm{AE} \tag{6}$$

3. The TPC consists of two parts: the power usage cost (PUC) and the holding cost (HC). The power usage is considered mainly as electricity usage, which is calculated by multiplying the power consumption by the electricity price (ε). The HC is described as the product of the unit holding cost of the job i $\left(H_i\right)$ and its holding time during the production process. The equations for calculating the two components of the TPC and itself are presented by Eqs. (7)–(9), respectively.

$$\mathrm{PUC} = \varepsilon \cdot \mathrm{TEC} \tag{7}$$

$$\mathrm{HC} = \sum_{i=1}^{n} H_i \cdot \left(\max_{1\le i\le n} T_i - T_i \right) \tag{8}$$

$$\mathrm{TPC} = \mathrm{PUC} + \mathrm{IC} \tag{9}$$

4. The WCE can be obtained by multiplying the worthless power usage by the coefficient of carbon dioxide emission for electricity (λ). The worthless power usage in a production process is mainly the idling power. The WCE is calculated through Eq. (10). The coefficient of carbon dioxide emission for electricity (λ) is taken as $0.785\mathrm{kg/kW \cdot h}$ [13].

$$\mathrm{WCE} = \lambda \cdot \mathrm{IE} \tag{10}$$

5. The processing power efficiency (PPE) is described as the ratio between the processing energy consumption and the total energy consumption, which can be calculated by Eq. (11). The IPPE is defined by Eq. (12), in order to maintain the optimizing direction of all five objective functions.

$$\mathrm{PPE} = \frac{\mathrm{PE}}{\mathrm{TEC}} \tag{11}$$

$$\mathrm{IPPE} = \frac{1}{1 + \mathrm{PPE}} \tag{12}$$

The objectives of the scheduling problem discussed in this paper are therefore minimizing MKS, TEC, TPC, WCE, and IPPE. Thus, they can be described as follows:

$$\min f_1 = \mathrm{MKS} = \max_{1\le i\le n} T_i \tag{13}$$

$$\min f_2 = \mathrm{TEC} = \mathrm{CE} + \mathrm{PE} + \mathrm{IE} + \mathrm{AE} \tag{14}$$

$$\min f_3 = \mathrm{TPC} = \mathrm{PUC} + \mathrm{IC} \tag{15}$$

$$\min f_4 = \mathrm{WCE} = \lambda \cdot \mathrm{IE} \tag{16}$$

$$\min f_5 = \mathrm{IPPE} = \frac{1}{1 + \mathrm{PPE}} \tag{17}$$

Subject to

$$\sum_{x=1}^{m} S_{ijx} \cdot X_{ijx} = S_{ij} \tag{18}$$

$$\sum_{x=1}^{m} t_{ijx} \cdot X_{ijx} = t_{ij} \tag{19}$$

$$S_{i(j-1)} + \sum_{x=1}^{m} t_{i(j-1)} \cdot X_{i(j-1)x} \le S_{ij} \tag{20}$$

$$S_{ijx} \ge T_{(i-1)(j-1)x} \tag{21}$$

$$\sum_{x=1}^{a_{ij}} X_{ijx} = 1 \tag{22}$$

$$\sum_{x=1}^{m} \sum_{j=1}^{p_i} Y_{ijxw} = 1 \tag{23}$$

$$\sum_{w=1}^{q_x} Y_{ijxw} = X_{ijx} \tag{24}$$

$$\left| S_{xw} - t_{ij} \right| \le C \cdot \left(1 - Y_{ijxw}\right) \tag{25}$$

Equations (13)–(17) are objective functions, and Eqs. (18)–(25) are constraints. Equations (18) and (19) indicate the starting time and the processing time of each operation for each job after being assigned to a machine, respectively. Equation (20) ensures the pre-determined processing sequence of operations for each job. Equation (21) ensures that the starting time of the operation O_{ij} processed on machine M_x must be after the completion of the precedent operation $O_{(i-1)(j-1)}$ processed on machine M_x. Equation (22) indicates that each operation of each job can only be processed on one machine at a time. Equation (23) ensures that only one operation can be processed in the same position on each machine. Equation (24) addresses the relation between the two variables X_{ijx} and Y_{ijxw}. Equation (25) ensures that the two starting times S_{ij} and S_{xw} are coherent only if operation O_{ij} is processed in wth position on machine M_x, the coefficient C is a big positive constant.

3 An improved electromagnetism-like mechanism algorithm

The FJSP model formulated in the previous section requires an intelligent algorithm to find optimal or near-optimal solutions. Traditional heuristic algorithms have been proved to be efficient to solve this kind of problem [4, 8]. However, they have pre-mature issues where solutions tend to converge to local optima, and their local searching performance often relies on external searching scheme, such as simulated annealing. In this paper, an IEMA is proposed to solve this problem. The general procedure of IEMA can be represented by Fig. 1. Compared to the original EMA, the IEMA presents the following improvements:

An archiving operation is applied before moving the individuals of the current population, in order to save and update optimal and near-optimal Pareto solution set of each iteration.

The equations and parameters in the calculation procedure are adjusted to adapt to solve the many-objective optimization problem, and to assure a better evolution direction.

A magnetic deflection operation is added after moving the individuals of the current population, in order to further improve the searching ability of the algorithm throughout the whole iteration process.

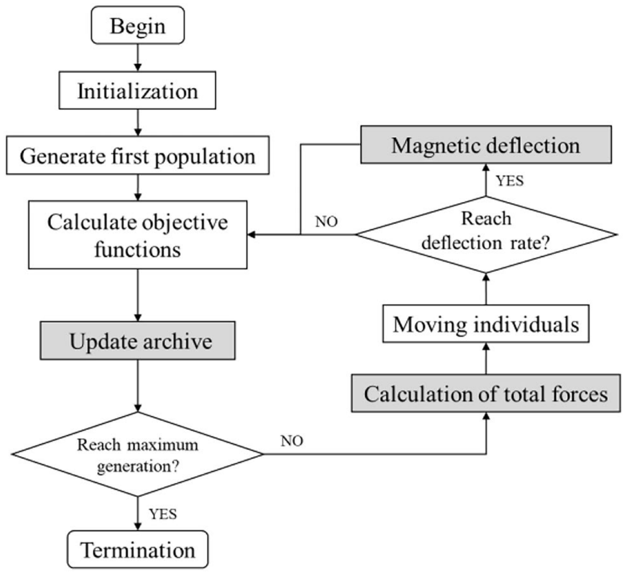

Fig. 1 General procedure of the IEMA

The encoding scheme and the detailed procedure of the major operations of IEMA will be presented in the following subsections.

3.1 Encoding and decoding

The solutions of a flexible job shop scheduling problem need to be encoded before being put into algorithms for computing. In a typical FJSP, two parts of information need encoding: the operation sequence and the machine selection. The operation sequence encoding represents the actual processing sequence of each operation for each job, while the machine selection encoding represents which machine is selected to process each operation. The encoding method used in this paper is shown by an example in Fig. 2. Each operation is assigned by two values: the operation sequence value and the machine selection value. In this example, there are 3 jobs $\{J_1, J_2, J_3\}$ and 9 operations $\{O_{11}, O_{12}, O_{13}, O_{21}, O_{22}, O_{23}, O_{31}, O_{32}, O_{33}\}$. Each operation has its own available machine set. The operation sequence value is randomly generated initially for the first generation. Then, by sorting all 9 operation sequence values by an ascending or descending order, a processing order is thereby formed: $\{O_{21}, O_{31}, O_{11}, O_{32}, O_{22}, O_{12}, O_{23}, O_{13}, O_{33}\}$. The machine selection value is also randomly generated in the beginning. The value of each operation represents which machine in the available machine set is chosen for processing. In the example, the second machine from the available machine set of operation O_{11} is selected to process O_{11}, and the fifth machine from the available machine set of operation O_{13} is selected to process

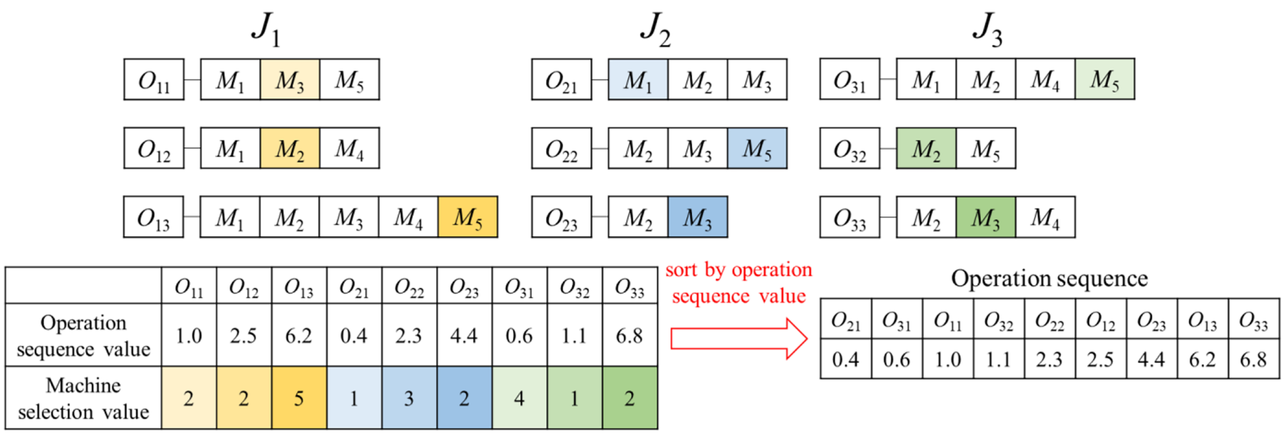

Fig. 2 Encoding method for FJSP

O_{13}. By adopting this encoding method, a scheduling solution can thereby be represented as {(1.0, 2), (2.5, 2), (6.2, 5), (0.4, 1), (2.3, 3), (4.4, 2), (0.6, 4), (1.1, 1), (5.8, 2)}.

The decoding process starts with the encoded representation of a scheduling solution. Firstly, the operation sequence is identified by sorting all the operation sequence value by the default order. Then, the machine on which each operation is processed is determined by the machine selection value assigned to that operation. After assigning each operation to the machines following the decoded sequence, the processing time, energy consumption, and other parameters of each operation can be determined and ready for calculations.

3.2 Improved electromagnetism-like mechanism operation

The improved electromagnetism-like mechanism operation includes three sub-operations: Coulomb force calculation, moving individuals, and magnetic deflection.

The first step is Coulomb force calculation. Same as the original EMA, each solution is defined by its charge and can be seen as a charged particle placed in an electric field. And because of the Coulomb's law, each particle will subject to the Coulomb force due to the presence of other charged particles and will therefore move accordingly. The charge of each particle and the Coulomb force exerted on them can be calculated according to the Coulomb's law [28].

Firstly, the charge of the particles will be determined. However, when dealing with many-objective optimization problems, it is difficult to manipulate the Coulomb force equation directly because it is obtained with a single objective function. Therefore, in this paper, a comprehensive evaluation function (CEF) is defined to replace the objective functions and simplify the computation. The CEF is defined by Eq. (26), and it sums all the objective functions with each of them multiplying a preference coefficient ω_k. These coefficients are given by the decision-maker based on his preferences on each objective function. In this way, the charge q_i of the particle x_i can be calculated by Eq. (27).

$$\mathrm{CEF}(x_i) = \sum\nolimits_k \omega_k \cdot \frac{\max[f_k(x_i)] - f_k(x_i)}{\max[f_k(x_i)] - \min[f_k(x_i)]} \tag{26}$$

$$q_i = \exp\left[-N\frac{\mathrm{CEF}(x_i) - \mathrm{CEF}(x_{best})}{\sum_{i=1}^{N}\left(\mathrm{CEF}(x_i) - \mathrm{CEF}(x_{best})\right)}\right] \tag{27}$$

When calculating the Coulomb force, the original EMA takes the distance between solutions into account. As a consequence, a solution may not be influenced by better ones due to a long distance, which therefore limits the EMA's ability to jump out of the local optima. To avoid such redundancy, the proposed IEMA considers a constant distance d, and the equation for calculating total forces is thus adjusted to Eq. (28). F_i represents the total Coulomb force exerted on particle x_i, which is the sum of all the Coulomb forces resulted from every other particle, which can be positive or negative based on their CEF.

$$F_i = \begin{cases} \sum_{j\neq i}^{N}\left[\left(x_j - x_i\right)\cdot\frac{q_i q_j}{d}\right], CEF(x_j) < CEF(x_i) \\ \sum_{j\neq i}^{N}\left[\left(x_i - x_j\right)\cdot\frac{q_i q_j}{d}\right], CEF(x_j) \geq CEF(x_i) \end{cases} \tag{28}$$

In completion of the calculation of F_i, the particle can then be moved along its direction by a certain step. In order to keep the solution feasible after the movement, the step size is ranged and limited to the solution's upper bound (x_{max}) or lower bound (x_{min}). For the encoding method proposed in this paper, x_{max} can be described as $\{(10, a_{11}), (10, a_{12}), \ldots, (10, a_{ij}), \ldots\}$, while a_{ij} is the number of available machines for operation O_{ij}. And x_{min} can be described as {(0, 1), (0, 1), …, (0, 1), …}. Particularly, if a machine selection value is not an integer after the movement, this value will be replaced by its nearest integer. The pseudocode of Coulomb force calculation and moving individuals is shown by Fig. 3.

The magnetic deflection operation is similar to the mutation operation in the genetic algorithm, which serves as an enhancement of local searching during late iteration process. After moving individuals, the particles have a possibility to be affected by a magnetic field. The affection possibility P depends on their iteration number, or generation number, which is defined in Eq. (29). When affected, each particle will subject to a magnetic force F_{mi} defined in Eq. (30), which is an adapted version of the Lorentz force equation, and results in deflecting the particle toward another direction.

$$P = e^{-\frac{generationnumber}{100}} \tag{29}$$

$$F_{mi} = B \cdot R \cdot q_i \tag{30}$$

B is the magnetic field strength, which can be considered constant for all particles of the same generation. R is the deflection rate, which declines with the increase in generation number. The pseudocode of the magnetic deflection is shown by Fig. 4.

```
// Coulomb force calculation
For (i = 1 to N) do
  Calculate CEF(x_i) and q_i
  F_i = 0
End for
d = 1
For (i = 1 to N) do
  For (j = 1 to N) do
    If (CEF(x_j) < CEF(x_i)) then
      F_i = F_i + (x_j − x_i) q_i q_j / d
    Else
      F_i = F_i + (x_i − x_j) q_i q_j / d
    End if
  End for
End for
// Moving individuals
For (i = 1 to N) do
  λ = random[0, 1]
  If (F_i > 0) then
    y_i = x_i + λ · F_i/||F_i|| · (x_max − x_i)
  Else
    y_i = x_i + λ · F_i/||F_i|| · (x_i − x_min)
  End if
  If (CEF(y_i) < CEF(x_i)) then
    x_i = y_i
  Else
    x_i = x_i
  End if
End for
```

Fig. 3 Pseudocode of force calculation and moving individuals

```
// Magnetic deflection
Calculate P
Generate random number r within [0, 1]
If (r < P) then
  Generate random number B within [0, 1]
  Generate direction D within {-1, 1}
  R = 1 / generation number
  For (i = 1 to N) do
    F_mi = B × R × q_i
    If (D = 1) then
      x_i = x_i + D · F_mi · (x_max − x_i)
    Else
      x_i = x_i + D · F_mi · (x_i − x_min)
    End if
  End for
End if
```

Fig. 4 Pseudocode of magnetic deflection

3.3 Archiving operation

The archiving operation aims to obtain a Pareto solution set. For each generation, the Pareto solutions are stored into an archive. The archive will update when a new generation is produced, by adding new Pareto solutions and removing non-Pareto solutions. For a specific solution, if all of its objective values are greater than any of the other solutions in the same generation, then it should be considered a non-Pareto solution. Otherwise, it will be added into the archive as a Pareto solution. The pseudocode of the archiving operation is shown by Fig. 5.

4 Case Study

In this section, a real-life case of a job shop in a Chinese hydraulic valve company is used to test the general performance of the many-objective optimization model and the proposed IEMA. Firstly, the IEMA's effectiveness of

```
// Archiving operation
For (i, j = 1 to N) do
  If (all objective values of solution x_i > all objective values of solution
     x_j) then
     x_i is marked as non-Pareto solution
  Else
     x_i is added into the archive
  End if
End for
// Archive update
For (i, j = 1 to numbers of solution in archive) do
  If (all objective values of solution x_i > all objective values of solution
     x_j) then
     x_i is removed from the archive
  End if
End for
```

Fig. 5 Pseudocode of archiving operation

Table 2 Processing procedure for each type of component

Job	Procedure
J_1	Milling, drilling, drilling, milling
J_2	Milling, drilling, drilling, milling
J_3	Milling, drilling, milling
J_4	Milling, drilling, drilling, milling
J_5	Milling, drilling, milling
J_6	Milling, drilling, drilling, milling

solving the many-objective optimization model is verified against other widely used heuristics. And then, the performance improvement of the job shop by adopting the many-objective optimization model is analyzed through the Pareto solution set obtained by IEMA.

The case involves a flexible job shop scheduling problem with 6 jobs, 22 operations and 4 machines, including 2 milling machines (M_1, M_2) and 2 drilling machines (M_3, M_4). The job shop uses roughly processed parts to produce major components of different hydraulic valves. The processing procedures of each type of component are listed in Table 2. All the experiments in this section are conducted using MATLAB programming language and performed on a personal computer with Intel Core i7 CPU, 8 GB memory and 2.20 GHz processor. Each experiment is repeated 10 times independently to avoid chance.

4.1 Effectiveness verification of the IEMA

To test the effectiveness of the proposed IEMA, the original EMA, nondominated sorting genetic algorithm II (NSGA-II), particle swarm optimization (PSO), and PSO-SA [4] are used as comparisons. Firstly, the box-plots of the 5 algorithms are analyzed in Fig. 6. A box-plot is used to evaluate the general distribution of a group of data. In a box-plot, the line in the middle of the rectangle represents the median, the two short segments outside the rectangle represent the minimum and the maximum value, and the top and bottom side of the rectangle represent the upper quartile and the lower quartile, respectively. Thus, the 5 box-plots in the figure show the distributions of solutions in 5 Pareto solution sets obtained by different algorithms, respectively. By comparison, the IEMA has the lowest fitness and a more concentrated distribution of solutions.

Secondly, the Pareto fronts of different Pareto solution sets obtained by the algorithms are compared in Fig. 7. The horizontal axis is the makespan, and the vertical axis is the TEC. As shown in the figure, the two objectives conflict with each other. Generally speaking, the lower the TEC, the longer the makespan. The results show that the IEMA has a better Pareto front compared to other algorithms, which means a better capability of finding solutions that minimize makespan and TEC.

The above experiments show that the proposed IEMA can help solutions jump out of their local optima in search of better solutions which have better fitness values. In addition, compared with other algorithms, the IEMA has a better Pareto front with regard to minimizing simultaneously the makespan and TEC, which are two conflicting objectives, and is therefore a better choice to solve our many-objective optimization problem.

4.2 Job shop performance improvement analysis

In order to verify the performance improvement to the real-life job shop by adopting the many-objective optimization model, the IEMA is used to solve the scheduling problem

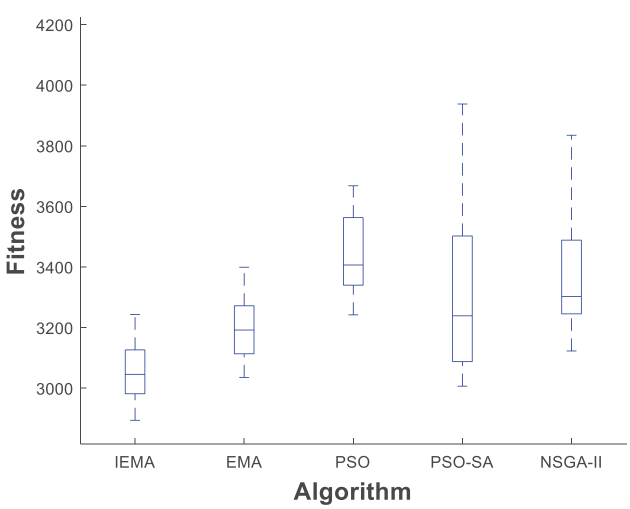

Fig. 6 Boxplots of different algorithms

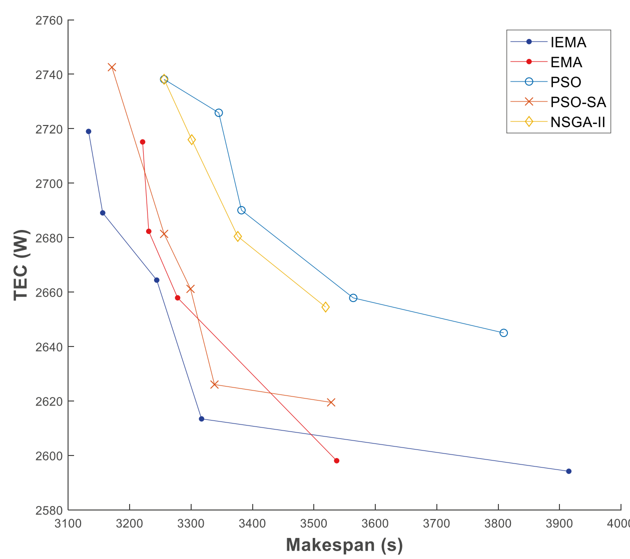

Fig. 7 Pareto fronts of different algorithms

under different situations depending on the decision-maker's preferences. The best-compromised solution of the Pareto solution set in each situation is selected to compare with one another, and also with the default scheduling plan provided by the company, which is optimized for makespan using a basic genetic algorithm. The Gantt chart of the default plan is presented in Fig. 8. Based on the machine number, operation number, and the processing time, the scheduling representation of the default plan can be denoted as: $\{M_1(O_{11}$, 401, O_{31}, 334, O_{61}, 370, O_{51}, 586, O_{33}, 428, O_{53}, 567, O_{64}, 426), $M_2(O_{21}$, 306, O_{41}, 398, O_{24}, 504, O_{14}, 597, O_{44}, 410), $M_3(O_{42}$, 448, O_{43}, 449, O_{23}, 351), $M_4(O_{22}$, 348, O_{12}, 574, O_{13}, 355, O_{32}, 363, O_{52}, 157, O_{62}, 320, O_{63}, 258)$\}$.

The first situation is where the decision-maker decides that the TEC is the most important objective to be optimized. The preference coefficient for TEC is therefore set as the biggest among others. By applying the IEMA to this instance, a Pareto solution set containing several non-dominated solutions is generated and evaluated by their CEF value. The best-compromised solution has the smallest CEF value and is named as the TEC-optimized solution, or TEC-optimized plan. Similar to the first, the second situation is defined as where the decision-maker decides the TPC to be the most important objective. The third and the fourth situation are therefore where the WCE or IPPE is, respectively, the most favored objective. The best-compromised solution under each situation is also selected among their Pareto solution set. They are named as the TPC-optimized, WCE-optimized, and IPPE-optimized solution, respectively. The last two situations are for comparative purpose. The fifth situation is described as equally optimized, where all 5 preference coefficients have the same value. The last situation is the traditional energy-aware optimization model, where the decision-maker only considers makespan and TEC as optimization objectives, and the preference coefficients for

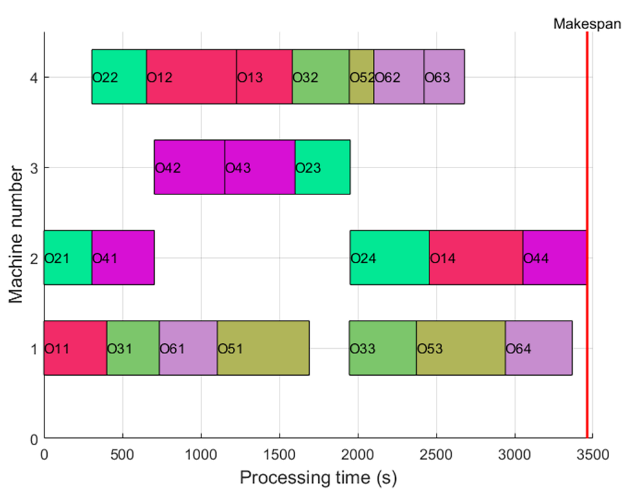

Fig. 8 Default scheduling plan of the job shop

the last three objectives are therefore 0. The objective values of the best-compromised solutions under each situation are listed in Table 3, and their scheduling representations are presented in Table 4.

Compared to the default plan, company can save 10.1% energy consumption if they choose the TEC-optimized plan, or save 35.9% production cost by adopting the TPC-optimized plan, or produce 53.3% less wasted carbon dioxide by adopting the WCE-optimized plan, or have 4% higher processing power efficiency by adopting the IPPE-optimized plan. The equally optimized plan has a similar improvement trend to the WCE-optimized plan, but the variations are subtler. The makespan-TEC only plan successfully improves the two objectives, but the TPC and WCE are higher. As for the improvement ratio of the first four situations, the IPPE-optimized plan has the lowest value compared to other three, while the WCE-optimized plan has the highest amount of improvement. However, it is also noticeable that by using the WCE-optimized plan, the completion time of the production process in the job shop will be significantly delayed from 57.7 min to 71.8 min, and the cost of production will also be increased by 62.0%. Thus, the reduction in carbon dioxide emission will lead to a great decrease in profitability to the company, which makes this plan hardly useful if the company's carbon emission is already at standard. On the other hand, if the company needs to reduce their carbon emission in order to meet the sustainable manufacturing requirements, they can also refer to the TEC-optimized or the IPPE-optimized plan. Both of them can reduce a good amount of carbon emission without delaying the overall production time, whereas the latter still leads to an increase in production cost. As for the TPC-optimized plan, it is the only one among the four optimized plans that saves a considerable amount of production cost, but has the highest WCE and IPPE value at the same time.

In general, it can be seen that the first 5 optimized plans can reduce energy consumption to varying degrees, which means by adopting the proposed many-objective optimization model, the hydraulic valve job shop in the company will

Table 3 Objective values of the best solutions under different situations

Situation	Makespan (s)	TEC (W)	TPC (yuan)	WCE (g)	IPPE
TEC-optimized	3407	2675.1	918.6	125.8	0.543
TPC-optimized	3661	2819.2	641.0	222.0	0.558
WCE-optimized	4307	2715.1	1619.1	76.0	0.546
IPPE-optimized	3350	2700.9	1563.7	105.7	0.541
Equally optimized	4038	2882.0	1131.1	134.1	0.550
Makespan-TEC only	3245	2714.2	1318.0	174.4	0.549
Default plan	3463	2975.2	999.4	162.9	0.550

Table 4 Scheduling representations under different situations

Situation	Scheduling representation
TEC-optimized	{M_1(O_{61}, 370, O_{51}, 586, O_{31}, 334, O_{53}, 567, O_{64}, 426, O_{33}, 428), M_2(O_{11}, 550, O_{41}, 398, O_{21}, 306, O_{14}, 597, O_{24}, 504, O_{44}, 410), M_3(O_{62}, 266, O_{12}, 563, O_{52}, 185, O_{22}, 354, O_{32}, 340), M_4(O_{63}, 258, O_{13}, 355, O_{42}, 360, O_{23}, 379, O_{43}, 436)}
TPC-optimized	{M_1(O_{61}, 370, O_{51}, 586, O_{21}, 391, O_{31}, 334, O_{53}, 567, O_{14}, 612, O_{44}, 402, O_{64}, 426), M_2(O_{11}, 550, O_{41}, 398, O_{24}, 504, O_{33}, 415), M_3(O_{42}, 448, O_{52}, 185, O_{32}, 340, O_{62}, 266), M_4(O_{12}, 574, O_{13}, 355, O_{43}, 436, O_{22}, 348, O_{23}, 379, O_{63}, 258)}
WCE-optimized	{M_1(O_{31}, 334, O_{51}, 586, O_{11}, 401, O_{33}, 428, O_{64}, 426, O_{53}, 567), M_2(O_{21}, 306, O_{41}, 398, O_{61}, 357, O_{44}, 410, O_{24}, 504, O_{14}, 597), M_3(O_{22}, 354, O_{23}, 351, O_{43}, 449, O_{12}, 563, O_{52}, 185), M_4(O_{42}, 360, O_{32}, 363, O_{62}, 320, O_{63}, 258, O_{13}, 355)}
IPPE-optimized	{M_1(O_{61}, 370, O_{51}, 586, O_{31}, 334, O_{53}, 567, O_{64}, 426, O_{24}, 561, O_{44}, 402), M_2(O_{11}, 550, O_{21}, 306, O_{41}, 398, O_{33}, 415, O_{14}, 597), M_3(O_{62}, 266, O_{12}, 563, O_{52}, 185, O_{42}, 448), M_4(O_{63}, 258, O_{22}, 348, O_{32}, 363, O_{13}, 355, O_{23}, 379, O_{43}, 436)}
Equally optimized	{M_1(O_{31}, 334, O_{21}, 391, O_{61}, 370, O_{51}, 586, O_{11}, 401, O_{44}, 402, O_{24}, 561, O_{53}, 567, O_{64}, 426), M_2(O_{41}, 398, O_{14}, 597, O_{33}, 415), M_3(O_{32}, 340, O_{62}, 266, O_{23}, 351), M_4(O_{42}, 360, O_{22}, 348, O_{43}, 436, O_{52}, 157, O_{12}, 574, O_{13}, 355, O_{63}, 258)}
Makespan-TEC only	{M_1(O_{61}, 370, O_{11}, 401, O_{51}, 586, O_{31}, 334, O_{24}, 561, O_{64}, 426, O_{53}, 567), M_2(O_{21}, 306, O_{41}, 398, O_{14}, 597, O_{33}, 415, O_{44}, 410), M_3(O_{62}, 266, O_{12}, 563, O_{52}, 185, O_{42}, 448), M_4(O_{22}, 348, O_{23}, 379, O_{63}, 258, O_{13}, 355, O_{32}, 363, O_{43}, 436)}

consume less energy and therefore, have a positive impact on the environment and potentially reduce costs as well. In addition, compared to the traditional energy-aware model, the TEC-optimized plan generated by the many-objective optimization model has better TEC, TPC, and WCE reduction. However, in order to further reduce production cost, the company risk generating more carbon dioxide and having a lower processing power efficiency. Thus, the prior recommendation for the company is the TEC-optimized plan, which has better results in all five objectives and improves the overall sustainability and profitability of the production process in the shop floor.

5 Conclusion

This paper considers an energy-aware many-objective flexible job shop scheduling problem. In order to solve this problem, firstly, a many-objective optimization model including makespan, TEC, TPC, WCE, and IPPE is constructed. Then, in order to optimize the above five objectives, an improved electromagnetism-like mechanism algorithm is proposed to find optimal or near-optimal solutions for the optimization problem. Finally, a real-life job shop case is studied to test the performances of the proposed IEMA and the many-objective optimization model. The results of the experiments show that the IEMA can solve the many-objective optimization problem more effectively compared to other heuristics. In addition, the real-life job shop can have a better performance by adopting the many-objective optimization model and choosing the proper optimized plan to suit their needs.

However, not all aspects are considered in this paper and thus further research is needed. For example, a dynamic scheduling should be considered in the future to better adapt to potential changes in reality. Moreover, the computation time of the IEMA could be further improved, and the model could also be more precise and robust to better describe real cases.

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Code availability The code supporting the results of this work is available upon reasonable request.

Declarations

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Consent to participate Not applicable.

Consent for publication Not applicable.

Conflicts of interest The authors declare no competing interests.

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