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Unified Multi-Objective Genetic Algorithm for Energy Efficient Job Shop Scheduling

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ABSTRACT In recent years, people have paid more and more attention to traditional manufacturing's environmental impact, especially in terms of energy consumption and related emissions of carbon dioxide. Except for adopting new equipment, production scheduling could play an important role in reducing the total energy consumption of a manufacturing plant. Machine tools waste a considerable amount of energy because of their underutilization. Consequently, energy saving can be achieved by switching machines to standby or off when they lay idle for a comparatively long period. Herein, we first introduce the objectives of minimizing non-processing energy consumption, total weighted tardiness and earliness, and makespan into a typical production scheduling model-the job shop scheduling problem, based on a machine status switching framework. The multi-objective genetic algorithm U-NSGA-III combined with MME (a heuristic algorithm combined with the MinMax (MM) and Nawaz–Enscore–Ham (NEH) algorithms) population initialization method is used to solve the problem. The multi-objective optimization algorithm can generate a Pareto set of solutions so that production managers can flexibly select a schedule from these non-dominated schedules based on their priorities. Three sets of numerical experiments have been carried out on the extended Taillard benchmark to verify this three-objective model's effectiveness and the multi-objective optimization algorithm. The results show that U-NSGA-III has obtained better Pareto solutions in most test problem instances than NSGA-II and NSGA-III. Furthermore, the non-processing energy consumption is reduced by 46%-69%, which is 13-83% of the total energy consumption.

INDEX TERMS Job shop scheduling, energy efficiency, unified multi-objective genetic algorithm, machine status switching.

I. INTRODUCTION

The problem of energy shortages and climate change has become increasingly prominent in recent years. In order to alleviate the pressure caused by energy shortages and climate deterioration, energy conservation and emission reduction campaigns have been launched in many countries. The 2018 Industrial Energy Data Book showed that the industrial sector was the most significant energy user of all the end-user sectors, accounting for 32.6% of the total energy consumption [1]. Accordingly, energy saving has been an active campaign in the manufacturing industry to reduce energy consumption during the production process, such as shutting off idle machines for cost-saving considerations and environmental protection. Regarding the issue of energy conservation in the manufacturing industry, the researchers studied the law of energy consumption in the manufacturing process, including processing [2], assembly [3], [4] and disassembly [5], [6].

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Our research focuses on a multi-objective scheduling approach to job shop scheduling problems aiming to reduce makespan, total energy consumption, and tardiness/earliness costs. Most current energy and tardiness-related job shop scheduling researches do not consider the earliness cost [7], [8]. One of the commonly used objectives of job shop scheduling is earliness and tardiness. In a given job schedule, if any of the jobs are completed before their due date, it will create undesirable effects such as insufficient warehouse space, inventory carrying costs, storage and insurance costs, and product deterioration [9]. In practical production, especially in the just-in-time (JIT) manufacturing environment, earliness and tardiness are important criteria [10]. The second commonly used optimization objective is makespan, another very applicable criterion in the job shop environment [11]–[13]. However, there is no report about optimizing the three objectives (makespan, energy consumption, tardiness & earliness) simultaneously so far for job shop scheduling. Based on previous research [10], [14], [15], compared to developing more energy-effective machines, there exists a more significant energy reduction margin at the system-level where shop floor scheduling optimization and machine tools operation strategies can be applied as the energy-saving approach. This is especially suitable for large-scale production environments to improve efficiency and energy utilization, thereby increasing manufacturing enterprises' profitability [16]. In this paper, we propose a multi-objective model for job shop scheduling problems to minimize the non-processing energy consumption (NEC) with operational status switching of machine tools, total weighted tardiness & earliness (TWET), and makespan (C_{max}). The Unified Non-dominated Sorting Genetic Algorithm-III(U-NSGA-III) [17] is adopted to achieve the tri-objective job scheduling problem. The experiments show that U-NSGA-III effectively deals with the multi-objective energy efficiency-oriented job scheduling problem, reducing 46%-69% of the non-processing energy consumption. The main novelties and contributions of this paper include the following:

(1)This is the first time that three objectives, including makespan, total weighted tardiness and earliness, and non-processing energy consumption, have been optimized simultaneously in a job shop scheduling problem. And we demonstrate the necessity of optimizing these objectives simultaneously through bi-objective experiments.

(2)We studied job shop's energy-saving strategy and established an energy consumption model based on the energy-saving strategy.

(3)We applied a modern multi-objective genetic algorithm U-NSGA-III to solving the energy-efficient job shop scheduling problem. This is the first time that this algorithm is used in a job shop scheduling problem. To improve algorithm's performance, we combined the operating-based coding, MME [18] initial population generating, two-point crossover, and random mutation method to improve the algorithm. Besides, we applied the Taguchi method to select the optimal parameter for U-NSGA-III.

In the remainder of this paper, a brief literature review related to current research is presented in Section 2. In Section 3, we describe the research problem and present the tri-objective job shop scheduling model. The U-NSGA-III is then explained in detail in Section 4. And then, the instance sets, comparison metrics, and computational results are discussed in Section 5. Finally, Section 6 provides conclusions.

II. LITERATURE REVIEW

Energy saving in manufacturing has mainly focused on developing energy-efficient machines, optimizing process planning and cutting parameters, and job scheduling algorithms. Flum *et al.* [19] developed a Twin-Control energy efficiency module to support machine tool builders in choosing an optimal machine configuration regarding both the investment and the energy costs, to provide machine users with customized machine tools with the lowest total cost. Kroll *et al.* [20] discussed lightweight design approaches' general influence on energy efficiency in machine tools and restrictions on the maximum mass reduction for structural components. And the results showed that structural lightweight design could achieve mass reductions up to 30% of the structural component, which could directly lead to 30%-50% lower electrical power losses of a servo drive. Li *et al.* [21] applied the HBMOA algorithm to solve the problem of minimizing energy consumption and makespan by optimizing process routes and cutting parameters. Wang *et al.* [22] established a dual-objective optimization model to select milling parameters to minimize the power consumption and process time. Zhang and Ge [23] proposed a new planning strategy from the perspective of reducing energy consumption. Although energy-efficient machine development and process route redesign can save energy consumption in manufacturing shops, it needs mass capital investment and cannot be implemented promptly.

Mouzon *et al.* [24] made an earlier attempt to improve the production scheduling method for energy saving in manufacturing workshops. They found that the running of non-bottleneck machines in the idle state consumed a large amount of energy that could be reduced by turn-on and turn-off scheduling framework. This framework has been further extended in recent research. Bruzzone *et al.* [25] presented an energy-aware scheduling algorithm to realize energy savings for a given fixed original job assignment and sequencing flexible flow shop. Dai *et al.* [26] applied this turn-on/off strategy to a flexible flow shop scheduling problem. A genetic simulated annealing algorithm was used to minimizing the total energy consumption and makespan. Aghelinejad *et al.* [27] introduced the turn-on/off framework to single-machine scheduling problems. The meta-heuristic method was used to minimizing the total energy consumption cost under time varied electricity prices. An alternative energy-saving framework based on machine speed scaling was proposed by Bunde [28]. Fang *et al.* [29] applied this framework in a flow shop scheduling problem with a constraint on peak power consumption and proposed two-mixed integer programming models for the problem. In this paper, the turn-on/off framework is extended and applied to job scheduling for energy-saving in workshops. A previous study [30] has shown four states during machine operation: working, idle, standby, and off. When a machine tool is idle, it can be switched to standby or off depending on the specific situation, rather than only be turned off.

Tardiness and earliness are also critical manufacturing scheduling criteria involving due dates. Studies that aim at minimizing the tardiness and earliness criterion can be found in mono- and bi-objective scheduling. Cheng and Huang [31] developed a modified genetic algorithm (GA) with distributed release time control (GARTC) mechanism to minimize the total earliness and tardiness time in an unrelated parallel machine scheduling problem for jobs with specific due dates and dedicated machines. Fu *et al.* [32] addressed a two-agent stochastic flow shop deteriorating scheduling problem with the objectives of minimizing the makespan and the total tardiness. Li *et al.* [33] proposed a mixed integer programming model and an improved multi-objective teaching learning-based optimization algorithm to minimize the makespan and total earliness & tardiness in job shop robotic cell scheduling problem. Yazdani *et al.* [10] applied a new hybrid imperialist competitive algorithm(HICA) to the job shop scheduling problem with a single objective of minimizing the maximum earliness and tardiness. Liu *et al.* [7] applied NSGA-II to solve the multi-objective model total non-processing electricity consumption and total weighted tardiness job shop scheduling problems. Piroozfard *et al.* [8] presented a multi-objective flexible job shop scheduling problem with objectives of minimizing total carbon footprint and total late work criterion. Considering each job's different importance, the total weighted tardiness and earliness model is employed in this research.

Concerning the optimization techniques on the multi-objective job shop scheduling problem, many approaches that imitate nature, social behaviors, etc., have been widely applied in job shop scheduling, such as ant colony optimization [34], particle swarm optimization [35], evolutionary algorithm [36], tabu search [37], simulated annealing [38], migrating birds optimization algorithm [39]. Although there exist some researchers attempting to solve the multi-objective job shop problem using machine learning methods, such as Wang and Tang proposed a machine-learning-based multi-objective memetic algorithm (ML-MOMA) for the discrete permutation flow shop scheduling problem [40], Zhang *et al.* introduced particle swarm optimization (PSO) and neural network (NN) to solve the job-shop scheduling problem (JSP) [34]. However, machine learning methods are more commonly used to solve image processing problems and fault diagnosis [43]–[46]. The genetic algorithm has been successfully applied to solve different kinds of multi-objective optimization problems [47]. However, limited studies used the genetic algorithm to tackle optimization problems with multiple conflicting objectives in job shop scheduling problems [48].

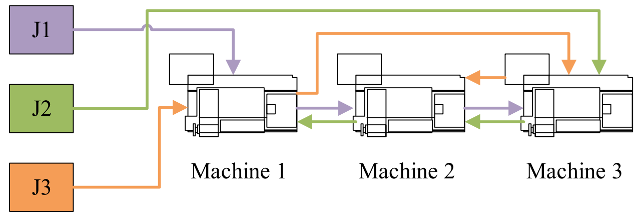

FIGURE 1. The layout of job shop scheduling.

Table1 summarizes some studies on the job shop scheduling problem from the number of objectives, scheduling criterion, author, algorithm, etc. Based on the conducted literature review, most researchers have not considered earliness-based objectives. Besides, there is no research about optimizing makespan, TWET, and NEC together in recent years in job shop scheduling. Therefore, approaches are needed to address environment-based objectives in more complex scheduling problems.

III. PROBLEM DESCRIPTION AND MATHEMATICAL MODEL

A. JOB SHOP MODEL DESCRIPTION

The $n \times m$ job shop scheduling problem can be described as follows (Figure 1): There are n jobs with specific processing routes, which need to be processed on m machines. The machining process satisfies the following assumptions: (1) All jobs and machines are available at time zero. (2) Each job has m processing steps, and each step must be completed on a specific machine. (3) Each job visits each machine exactly once according to its own predefined sequence and preemption of the jobs is not allowed. (4) Each machine can only process one job at a time, and each job can only be machined by one machine at a time. (5) The machining process cannot be interrupted until it is completed. (6) Job's transport time is ignored. As shown in Figure 1, there are 3 different machines and 3 different jobs that need to be processed. The connecting lines and arrows of different colors represent the machine sequence of specific jobs on the production line. Each job needs to be processed by all machine tools, but the processing order of the jobs on the machine tools is different. Solving the JSSP problem is to find a proper processing sequence to determine the processing order of each job on each machine under specific process requirements. The JSSP problem's optimization is to find the optimal sequence in all feasible machining sequences for a specific production performance index, such as makespan and energy consumption. Note that symbols used in this paper and their meanings are shown in Table 2.

B. ENERGY CONSUMPTION MODEL WITH ENERGY-SAVING OPERATION STRATEGY

1) EVALUATING THE OPERATIONAL STATUS OF A MACHINE TOOL

Machine tool energy consumption can be modeled in various ways, such as the function, the composition system, components, operation status, and energy consumption attributes.

TABLE 1. The summary of studies on job shop scheduling.

Number of objectives	Scheduling criterion	Author, Year, and Reference	Algorithm	Summary
One	Total earliness& tardiness costs	Dos *et al*. (2010) [68]	Evolutionary Algorithm	- Presented a combination of evolutionary algorithm and mathematical programming with an efficient local search procedure for a just-in-time job-shop scheduling problem.
One	Total weighted tardiness	Zhang *et al.* (2012) [69]	Two-stage particle swarm optimization	- Proposed a two-stage particle swarm optimization algorithm for SJSSP with the objective of minimizing the expected total weighted tardiness.
One	Energy cost	Masmoudi *et al.* (2019) [70]	Heuristic algorithm	- Minimized production costs in terms of energy, while respecting a power peak limitation, along with more traditional production constraints.
One	Total energy cost	Kim *et al* (2017) [71]	Metaheuristic	- Proposed a simulation-based machine shop operations scheduling system for minimizing the energy cost without sacrificing productivity.
Two	Total non-processing electricity consumption, total weighted tardiness	Liu et *al*. (2014) [7]	NSGA-II	- Developed the model for multi-objective job shop scheduling problem and solved it by NSGA-II.
Two	Energy consumption, makespan	Dai *et al*. (2015) [12]	Modified genetic algorithm	- Proposed an energy-aware mathematical model for job shops that integrated process planning and scheduling - MGA generated interesting results and could be used to improve the energy efficiency of sustainable manufacturing processes.
Two	Total non-processing electricity consumption, total weighted tardiness	Liu *et al*. (2016) [14]	Novel multi-objective genetic algorithm	- Introduced a model for the bi-objective optimization problem that minimized the total non-processing electricity consumption and total weighted tardiness in a job shop.
Two	Total weighted tardiness, energy consumption	Zhang and chiong (2016) [72]	Genetic algorithm	- Proposed a multi-objective genetic algorithm incorporated with two problem-specific local improvement strategies to solve this bi-objective optimization problem.
Two	Total carbon footprint, total late work	Piroozfard *et al.* (2018) [8]	Improved multi-objective genetic algorithm	- Proposed an improved multi-objective evolutionary algorithm for solving the newly extended bi-objective problem.
Three	Makespan, mean flow time, mean tardiness	Udomsakdigool and Voratas (2011) [13]	Ant colony algorithm	- Presented ant colony algorithm for solving the multi-objective job shop scheduling problem.
Three	Makespan, tardiness, mean flow time	Ong *et al*. (2013) [73]	Intelligent Water Drops	- IWD is improved and customized to solve SOJSSP and MOJSSP problems.
Four	Makespan, average flow time, maximal tardiness, total tardiness	Huang and Süer （2015） [74]	Dispatching rule based genetic-algorithm with fuzzy satisfaction	- Proposed FRGA to solve the multi-objective manufacturing scheduling problem with four objectives.

In this research, the energy consumption model is built based on the machine's operating status, including off, standby, idle and working. The description of machine tools' operating state is shown in Table 3.

Figure 2 displays the machine tool energy-consuming transition diagram with ramp-up and ramp-down. Colors of different states represent power levels. The power values rise along with the order of off, standby, idle, and working. It is

TABLE 2. The meaning of parameters used in this paper.

Parameter	Meaning
N	Set of n jobs, $N = \{1, i, \ldots, n\}$
M	Set of m machines, $M = \{1, \ldots, j, \ldots, m\}$
O_i	Set of operations of job i, $O_i = \{1, \ldots, k, \ldots, n_i\}$, $n_i = m$
$O_{i,k}$	Operation k of job i
$pt_{i,j,k}$	Processing time in machine j of operation k of job i
$x_{i,j,k}$	1, if the process O_{ik} is processed on the machine j; Otherwise,0. $\sum_{k=1}^{n_i} x_{i,j,k}=1$
$S_{i,k}$	Starting time of operation k of job i
$C_{i,k}$	Completion time of operation k of job i
C_{max}	Makespan of a schedule
α_i	Tardiness penalty coefficient of job i
β_i	Earliness penalty coefficient of job i
T_i	Tardiness of job i
E_i	Earliness of job i
d_i	Due date of job i
$P_{W,j}$	Working power of machine j
$P_{I,j}$	Idle power of machine j
$P_{S,j}$	Standby power of machine j
$P_{rampup,off,j}$	Switching power for machine j to switch from idle to off state and again idle
$P_{rampup,standby,j}$	Switching power for machine j to switch from idle to standby state and again idle
$t_{I,j}$	Time of machine j in idle state
$t_{W,j}$	Time of machine j in working state
$t_{S,j}$	Time of machine j in standby state
$t_{rampup,off,j}$	Switching time for machine j to switch from idle to off state and again idle
$t_{rampup,standby,j}$	Switching time for machine j to switch from idle to standby state and again idle

TABLE 3. The description of machine tool operating status.

Status	Description
Off	Machine tool is off, and all machine parts are in no energy consumption state.
Standby	Electric cabinet of machine tool is powered on and small amount of power is needed to feed basic unit and control unit. Machine tool is not ready to process jobs.
Idle	Significant amount of power is required to run basic unit, control unit, auxiliary equipment and drive unit of each axis. Machine tool is ready to process jobs.
Working	Each axis is operating, and machine tool is processing the job.

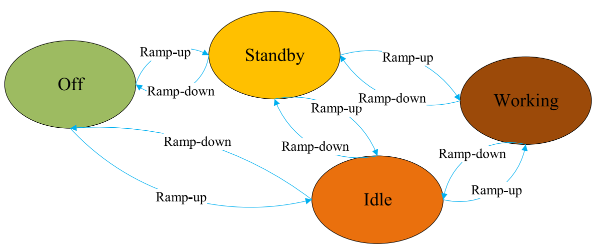

FIGURE 2. Machine tool state switching diagram.

clearly shown that energy consumption from off to working state is progressively increased in unit time.

2) ENERGY-SAVING OPERATION STRATEGY OF MACHINE TOOLS

In a job shop environment, considering that the job's process phase is constrained by the previous process phase's completion time, the machine will keep idle waiting for the

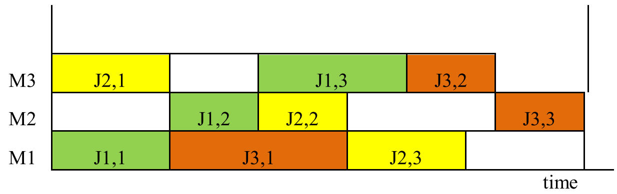

FIGURE 3. Gantt chart of a job shop scheduling example.

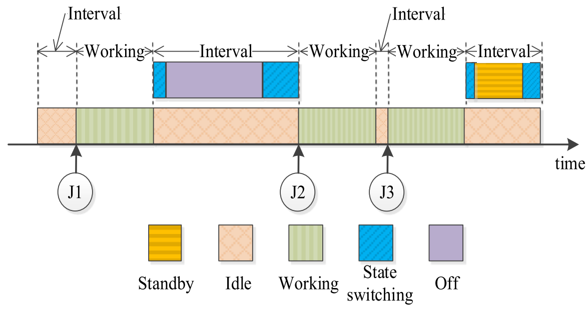

FIGURE 4. Machine tool running track.

next job arrival after machining the current job. During this period, the machines still require a certain amount of energy consumption to keep running. Figure 3 shows a Gantt chart of a 3 × 3 job shop scheduling example. In the Figure, (J2,1) means the first operation of job 2. It is displayed that there exists a certain amount of non-processing time (the white box in Figure3) consumed energy in the entire machining process of most machine tools.

The average working, idle, and standby power of M1, M2, and M3 are represented in Table 4 (data from [49]). From this table, we can find that the three states' power consumption decrease progressively from working to standby. Based on the example in Figure 3 and the data in Table 4, we can calculate the proportion of non-processing energy consumption in the total energy consumption of machines. After calculation, the non-processing energy consumption of machine tools accounts for 31.70% $\left(= 2931 \times 6 + 2293 \times 9 + 861 \times 4 / \left(\begin{array}{l} 3207.5 \times 12 + 2931 \times 6 + 3034.6 \times 9 \\ +2293 \times 91716.9 \times 14 + 861 \times 4 \end{array}\right)\right)$ in this schedule. Figure 4 and Figure 5 show the machine tool running track and schematic diagram of the power before and after using the energy-saving operation strategy. As can be seen from the two figures, if we switch a machine into standby or off state by a particular strategy when it keeps in an idle state for a long time, a large amount of energy can be saved. So, the switching policy of machines should be studied.

According to the machining interval time and energy consumption of the machine, we can decide to keep the machine tool idle or switch to standby or off. Assuming that the only form of energy consumed is electrical energy, we define the energy strategy formula as follows:

(1) Machines should be kept idle, if:

$$P_{I,j} \cdot \left(S_{i,j} - C_{i-1,j}\right) \leq P_{rampup,s\tan dby,j} \cdot t_{rampup,s\tan dyby,j}$$

TABLE 4. Power information of machines.

Machine number	Machine category	Machine model	Average working power (P_W/W)	Idle power (P_I/W)	Standby power (P_S/W)
M01	Vertical Machining Center	VGC1500	3207.5	2936	1569
M02	Vertical Machining Center	TH5656	3034.6	2293	1478
M03	Lifting Milling Machine	X5032	1716.9	861	85

$$+P_{S,j}\cdot\left(S_{i,j}-C_{i-1,j}-t_{rampup,s\tan dby,j}\right) \quad (1)$$

&

$$P_{I,j}\cdot\left(S_{i,j}-C_{i-1,j}\right) \le P_{rampup,off,j}\cdot t_{rampup,off,j} \quad (2)$$

(2) Machines should be switched to standby, if:

$$P_{rampup,s\tan dby,j}\cdot t_{rampup,s\tan dyby,j} + P_{S,j}\cdot\left(S_{i,j}-C_{i-1,j}-t_{rampup,s\tan dyby,j}\right) < P_{I,j}\cdot\left(S_{i,j}-C_{i-1,j}\right) \quad (3)$$

&

$$P_{rampup,s\tan dby,j}\cdot t_{rampup,s\tan dyby,j} + P_{S,j}\cdot\left(S_{i,j}-C_{i-1,j}-t_{rampup,s\tan dyby,j}\right) < P_{rampup,off,j}\cdot t_{rampup,off,j} \quad (4)$$

(3) Machines should be switched to off and then on, if:

$$P_{rampup,off,j}\cdot t_{rampup,off,j} < P_{I,j}\cdot\left(S_{i,j}-C_{i-1,j}\right) \quad (5)$$

$$P_{rampup,off,j}\cdot t_{rampup,off,j} < P_{rampup,s\tan dby,j}\cdot t_{rampup,s\tan dyby,j} + P_{S,j}\cdot\left(S_{i,j}-C_{i-1,j}-t_{rampup,s\tan dyby,j}\right) \quad (6)$$

The machine tool energy consumption in the job shop environment can be calculated according to the machining's average power and time. Before adopting the energy-saving strategy, the energy consumption model of the job shop is:

$$E_{total}=\sum_{j=1}^{m}\sum_{i=1}^{n}\sum_{k=1}^{n_i}x_{i,j,k}\cdot P_{W,j}\cdot pt_{i,j,k} + \sum_{j=1}^{m}\left(C_{\max}-\sum_{i=1}^{n}pt_{i,j}\right)\cdot P_{I,j} \quad (7)$$

After adopting the energy-saving strategy, the energy consumption model is:

$$E_{total}=\sum_{j=1}^{m}\sum_{i=1}^{n}\sum_{k=1}^{n_i}x_{i,j,k}\cdot P_{W,j}\cdot pt_{i,j,k} + \sum_{j=1}^{m}\begin{pmatrix}P_{I,j}\cdot t_{I,j}+P_{S,j}\cdot t_{S,j}+n_{rampup,s\tan dby,j}\\ \cdot P_{rampup,s\tan dyby,j}\cdot t_{rampup,s\tan dby,j}\\ +n_{rampup,off,j}P_{rampup,off,j}\cdot t_{rampup,off,j}\end{pmatrix} \quad (8)$$

Comparing the formula (7) and (8), it is clear that the difference between the energy consumption before and after adopting the energy-saving strategy is the non-processing consumption. So, in this paper, non-processing energy consumption is one of three objectives.

C. FORMULAION OF ENERGY-EFFICIENT JOB SCHEDULING OBJECTIVES

In the energy-efficient job shop scheduling problem of this paper, there are three conflicting objectives, including the non-processing energy consumption (NEC), makespan (Cmax), total weighted earliness, and tardiness (TWET). These three objectives are chosen because NEC is a necessary metric to quantify the impact of energy efficiency on a job shop scheduling problem. At the same time, Cmax and TWET are classical performance metrics indicating the overall production time and total weighted tardiness and earliness cost, respectively.

$$\min\ C_{\max}=\max(C_{i,k}),\forall i\in[1,n],k\in[1,m] \quad (9)$$

$$\min\ TWET=\sum_{i=1}^{n}(\alpha_i T_i+\beta_i E_i) \quad (10)$$

$$\min NFC=\sum_{j=1}^{m}\begin{pmatrix}P_{I,j}\cdot t_{I,j}+P_{S,j}\cdot t_{S,j}+n_{rampup,s\tan dby,j}\\ \cdot P_{rampup,s\tan dyby,j}\cdot t_{rampup,s\tan dby,j}\\ +n_{rampup,off,j}P_{rampup,off,j}\cdot t_{rampup,off,j}\end{pmatrix} \quad (11)$$

S.T.

$$C_{i,k}\le C_{i,k+1}-pt_{i,j,k+1},\quad \forall i,j,k \quad (12)$$

$$C_{i,k}\ge C_{l,h}+pt_{i,j,k}\vee C_{l,h}\ge C_{i,k}+pt_{l,j,h},\quad \forall i,j,k,l,h \quad (13)$$

$$C_{i,k}-S_{i,k}=pt_{i,j,k},\quad \forall i,j,k \quad (14)$$

$$S_{i,k}\ge 0,\quad \forall i,k \quad (15)$$

$$T_i=\max\{C_{\max}-d_i,0\} \quad (16)$$

$$E_i=\max\{d_i-C_{\max},0\} \quad (17)$$

The objective function (9), (10), and (11) can calculate the makespan, the total weighted tardiness, and earliness (TWET), non-processing energy consumption (NEC). We applied the same objective function and constraint condition with classical job shop scheduling researches. By optimizing this objective, the completion time of a batch of jobs can be reduced. The TWET model is to minimize total weighted early and tardy costs. We refer to the tardiness and earliness calculation methods in literature [50]–[52], and we set different penalty coefficients α_i and β_i. To reduce the tardiness of jobs as much as possible, we set a significant tardiness penalty coefficient. For the NEC model, we referred to the method proposed by Mouzon [24] to turn off the non-bottleneck period machine and save energy consumption. And we extended this method by dividing four different operating states of machine tools. Formula (12) is a constraint that indicates the precedence relations among the operations of a job. Formula (13) is a machine constraint that indicates that each machine can process at most one job at a time. Constraint

(14) indicates that once an operation is started, it cannot be preempted until it is completed. Constraint (15) expresses the fact that the start time of each operation is positive. Formula (16) and (17) are the calculation methods for tardiness (T_i) and earliness (E_i) of a job.

IV. U-NSGA-III ALGORITHM

A. OVERVIEW OF THE U-NSGA-III ALGORITHM

In this study, Unified Non-dominated Sorting Genetic Algorithm-III (U-NSGA-III) proposed by Seada and Deb [53] in 2014 is chosen and improved as the optimization algorithm. U-NSGA-III is a unified evolutionary optimization algorithm that allows a user to work with a single code to achieve optimizations with different objective dimensions (i.e., single, multiple, and many-objective). So we can use the U-NSGA-III to illustrate the necessity of optimizing three objectives (makespan, TWET, and NEC) together. The U-NSGA-III is based on the structure of NSGA-III, which is a practical algorithm for many-objective problems. It can provide a set of optimal solutions that collectively represent the trade-offs between the conflicting objectives. As a result, decision-makers can prioritize and select optimal trade-offs from the global set of optimal solutions. In the view of the problem that no explicit selection operator on P_t in the process of creating Q_t and too small population size when NSGA-III is used to solving mono-objective and multi-objective problems, U-NSGA-III alleviates these difficulties through using a population size N which is larger than the number of reference points (H) and introducing a niching-based tournament selection operator. The niching-based tournament selection operator added in U-NSGA-III is as follows. If two solutions to be compared are related to the same reference direction, choose the solution from the better non-dominated rank. In this case, if both solutions belong to the same non-dominant front simultaneously, the solution closer to the reference direction (i.e., the solution with a smaller perpendicular distance) is selected. Otherwise, if the two solutions to be compared come from two cross-reference directions, one of them is randomly selected to introduce multiple niches in the population. The flow chart of U-NSGA-III is shown in Figure 6. The simple pseudocode of U-NSGA-III is as follows [17]:

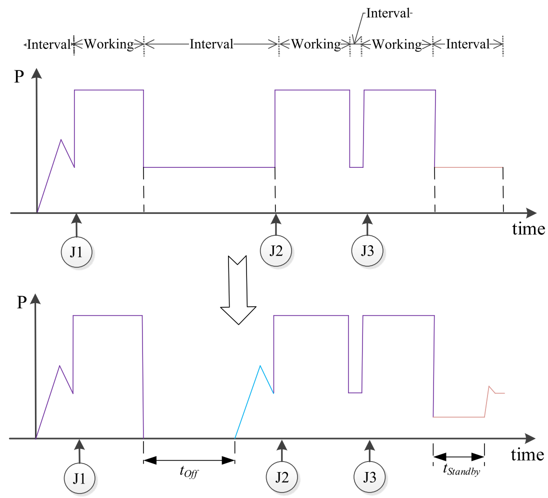

FIGURE 5. Schematic diagram of the power.

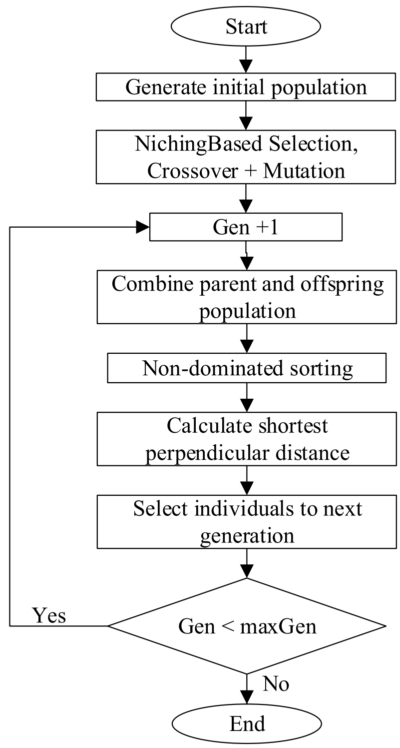

FIGURE 6. Algorithm flow chart for U-NSGA-III.

B. ENCODING OF JOB SCHEDULES

The job schedule encoding used in our algorithm is an operation-based representation. A chromosome is a permutation of a set of operations, representing an order to arrange them in a certain schedule. The same ID represents processing operations of the same job, and the frequency of the ID indicates the number of processing operations of the job. Figure 7 shows an example of a job shop problem with two jobs, where both jobs have three processes. The first number "2" in the chromosome [2, 1, 2, 2, 1, 1] represents the first process of job 2. This approach avoids the complicated repair procedures to deal with the infeasibility of the chromosomes [54]. In the 2×3 example, a random arrangement of numbers 1 and 2 can always generate a feasible solution.

C. POPULATION INITIALIZATION

The initial population quality has a significant impact on the performance of an evolutionary algorithm. Reasonable initial solutions can significantly improve the convergence rate and solution quality of the algorithm [55]. In order to ensure the quality and diversity of the initial population, the MME algorithm [18] and the random generation method are combined to generate the initial population in this paper.

Algorithm 1 Algorithm U-NSGA-III Generation t of U-NSGA-III Procedure

Input: H structured reference points Z^s or supplied aspiration points Z^a, parent population P_t
Output: P_{t+1}
$S_t = \varphi, i = 1$
$P'_t =$ NichingBasedSelection(Pt)
$Q_t =$ Crossover+Mutation(P'_t)
$R_t = P_t \cup Q_t$
$(F_1, F_2, \ldots F_n) =$ Non-dominated-sort(R_t)
repeat
    $S_t = S_t \cup F_i$ and $i = i + 1$
until $|S_t| \geq N$
Last front to be included: $i = l$
if $|S_t| = N$ **then**
    $P_{t+1} = S_t$, break
else
$P_{t+1} = \bigcup_{i=l}^{l-1} F_i$
Number of individuals to be chosen from F_l: $K = N - |P_{t+1}|$
Normalize objectives and create reference set Z^r: Normalize(f^n,S^t, Z^r, Z^s, Z^a)
Associate each member in St with a reference point: $[\pi(s); d(s)]$ =Associate (S_t, Z^r)
$\pi(s)$: closest reference point, d: distance between s and $\pi(s)$
Compute niche count of reference point $j \in Z^r$: $P_j = \sum_{s \in St/Fl}((\pi(s) = j)\ ?\ 1 : 0)$
Choose K members one at a time from F_l to construct P_{t+1}:
Niching $(K, P_j, \pi, d, Z^r, F_l, P_{t+1})$
end if

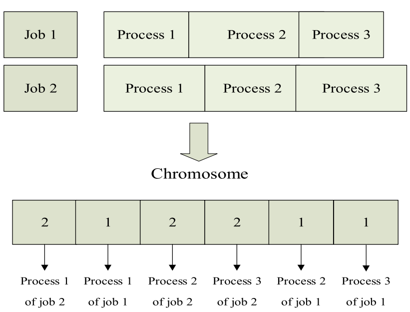

FIGURE 7. Chromosome coding in job shop scheduling.

D. CROSSOVER OPERATION BASED ON A CHROMOSOME ENCODING

In the genetic algorithm, the crossover operation is one of the main ways to create new populations. A crossover operation can be applied to the parents who are randomly picked if a uniformly distributed random number generated between 0 and 1 is less than crossover probability (Pc) [26]. In this study, we select a two-point crossover operation. The operation steps are as follows:

(1) Choose two intersections randomly, exchange the genes between the two intersections of two parents.

(2) Repair chromosomes by deleting excess genes and adding under-quantity genes.

For example, the genetic codes of the two parents' chromosomes P_1 and P_2 are "213112323" and "131233122". Randomly generate two cross positions 3 and 6, and exchange the segments between the intersections for getting "211233323" and "133112122". Two feasible gene sequences "211233123" and "133112322" can be obtained by repairing the gene position whose number of occurrences is not equal to three.

E. MUTATION OPERATION BASED ON A CHROMOSOME ENCODING

A set of matrices composed of uniformly distributed numbers between 0 and 1 with the same dimension as the parent population is generated. When a specific value in the random number matrix is less than the mutation probability, then the corresponding position in the parent population matrix needs to be mutated.

The steps of mutation are as follows:

(1) Move the gene from this position to the last position in this chromosome.

(2) Move all the genes which are behind this position forward by one position.

V. EXPERIMENTS AND RESULTS

The algorithm of this paper was coded in Python language. The experiments were on a Dell Precision workstation with the following configuration: Intel Corei5, 2.19 GHz CPU, and 8 GB RAM. There are three key parameters in the U-NSGA-III, i.e., the crossover probability P_c, and the mutation probability P_m, the population size N. In order to investigate the effect of parameter setting, we refer to the experimental design method in [56] and carry out the Taguchi method of design-of-experiment in 15×15 instance. For each parameter we set four levels, i.e., $N \in \{40, 80, 100, 120\}$, $P_c \in \{0.4, 0.6, 0.8, 0.9\}$ and $P_m \in \{0.05, 0.1, 0.2, 0.3\}$. According to the orthogonal array $L_{16}(4^3)$, we test the performance of the U-NSGA-III with 16 combinations. In order to compare the advantages and disadvantages of each parameter combination, the RV and MID (Mean Ideal Distance) results are shown in Table 5. RV is defined as below: we aggregate all the non-dominated solutions obtained by 16 aggregated sets. The percentage of solutions from each aggregated set can be regarded as the score of each combination, denoted as RV. The larger RV indicates the better parameter combination. According to the parameter testing results, we set the algorithm's experimental parameters as follows: the population size was 100, the crossover probability was 0.9, and the mutation probability was 0.1.

A. TEST INSTANCES

In our paper, the standard benchmarked job shop scheduling instances from Taillard [57] were extended in order to include

TABLE 5. Investigation of parameter effect.

Experiment number	Factor level			MID	RV
	N	Pc	Pm		
1	40	0.4	0.05	2371.425	7.11%
2	40	0.6	0.1	2103.59	4.60%
3	40	0.8	0.2	1519.689	5.02%
4	40	0.9	0.3	896.5346	2.51%
5	80	0.4	0.1	590.2755	5.86%
6	80	0.6	0.05	980.8984	7.53%
7	80	0.8	0.3	760.7601	5.02%
8	80	0.9	0.2	3010.726	4.18%
9	100	0.4	0.2	**476.9627**	9.62%
10	100	0.6	0.3	1384.411	2.92%
11	100	0.8	0.05	566.5547	2.09%
12	100	0.9	0.1	487.8842	**15.06%**
13	120	0.4	0.3	752.5984	8.37%
14	120	0.6	0.2	699.639	10.46%
15	120	0.8	0.1	1085.638	4.60%
16	120	0.9	0.05	711.0914	5.02%

all the necessary information for the presented mathematical model, including the due date of each job, tardiness & earliness penalty coefficient of each job, power consumption in idle, standby & working states, and ramp-up power & time of each machine. The instances from E. Taillard contain the following information: the number of jobs, number of operations for each job, processing time of each operation on the corresponding machine, and processing sequence of operations of each job. The new data required for the tri-objective model are generated and explained as follows. By studying different papers [58]–[60], we found that pure numbers have only relative importance with respect to the ratios among the different kinds of power requirements. Therefore, referring to the parameters in Literature [10], [61], [62] and the actual parameters in Table 4, power consumption, switching time & power for each machine, due date, and tardiness/earliness penalty coefficient for each job are provided as follows:

$P_{W,j} = 0.9\sim1$kw; $P_{I,j} = 0.6\sim0.7$kw; $P_{S,j} = 0.3\sim0.5$kw; $P_{rampup,off,j} = P_{rampup,standby,j} = 0.8$kw

$$d_i = \gamma \cdot \sum_{i=1}^{n}\sum_{k=1}^{n_i} x_{ijk}pt_{ijk} \tag{18}$$

where γ is random number between 1.8 and 2.3.

$$\beta_i = 1/\alpha_i \tag{19}$$

where α_i is randomly selected from 1, 5 and 10.

$$t_{rampup,s,\tan dby,j} = \frac{1}{2}\cdot t_{rampup,off,j} = \frac{1}{2m}\cdot\sum_{J=1}^{M}\sum_{k=1}^{n_i} x_{ijk}pt_{ijk} \tag{20}$$

B. COMPARISON METRICS FOR ALGORITHM EVALUATION

To assess algorithms' performance, three different comparison metrics including Diversification Metric, Mean Ideal Distance, and Mean Normalized Objective Function are considered, where these performance criteria are elucidated as follows.

(1) Diversification Metric (DM): DM, which is computed by formula (21), is used for evaluating the spread of the solution sets for algorithms. A higher value of DM indicates a better algorithm [63].

$$DM = \sqrt{\sum_{j=1}^{m}(\max(f_j) - \min(f_j))^2} \tag{21}$$

where f_j is the value of the jth objective function and m is the number of objectives ($m = 3$ in this paper).

(2) Mean Ideal Distance (MID): MID is the metric to evaluate the proximity between the Pareto solutions ($f_{1,i}, f_{2,i}, f_{3,i}$) and the ideal point ($f_{1,best}, f_{2,best}, f_{3,best}$). The formula of MID is:

$$MID = \frac{\sum_{i=1}^{n}\sqrt{(f_{1,i}-f_{1,bset})^2+(f_{2,i}-f_{2,bset})^2+(f_{3,i}-f_{3,bset})^2}}{n} \tag{22}$$

where $f_{1,i}$, $f_{2,i}$, and $f_{3,i}$ are the function values of ith Pareto solution, $f_{1,best}$, $f_{2,best}$, and $f_{3,best}$ are the best fitness values of three objectives, and n is the total number of obtained non-dominated schedules. A lower value of MID indicates a better algorithm [63].

(3) Mean Normalized Objective Function (MNOF): The MNOF value of the algorithm is calculated as: (23), as shown at the bottom of the next page, where A is the set of optimization algorithms, $\min_{j\in A} f_{1,j}$, $\min_{j\in A} f_{2,j}$, $\min_{j\in A} f_{3,j}$ are the best fitness for three objectives obtained by all algorithms, $\max_{j\in A} f_{1,j}$, $\max_{j\in A} f_{2,j}$, $\max_{j\in A} f_{3,j}$ find the worst fitness for three objectives obtained by all algorithms. Lower values of MNOF are preferred [10].

TABLE 6. Best, median and worst value of U-NSGA-III with random and mme initialization method.

Serial number	Scenarios	Objectives
1	S1	makespan and TWET
2	S2	makespan and NEC
3	S3	TEC and TWET
4	S4	makespan, TWET, and TEC

C. ANALYSIS OF RESULTS

To verify the feasibility of the proposed model and algorithm, the following four sets of numerical experiments are carried out.

(1) Initialization method experiments:

This set of experiments is used to illustrate the effect of the initialization method–MME.

(2) Bi-objective experiments:

This set of experiments is used to compare the quality of the solutions produced by bi-objective and tri-objective

TABLE 7. Four scenarios in multi-objective experiments.

instance	Objectives / EI / Initialization method	Makespan			TWET			NEC		
		Best	Median	Worst	Best	Median	Worst	Best	Median	Worst
15×15-1	Random	1524	1601	1667	664.6	786.48	1593.66	2859.18	**2964.05**	3218.43
	MME	**1485**	**1549**	1689	**317.52**	**478.3**	988.4	**2809.09**	3132.17	3499.53
15×15-2	Random	1563	1632	1893	579.94	931	11566.90	2859.64	**3118.5**	3593.13
	MME	**1513**	**1577.5**	1841	**428.3**	**645.83**	6160.71	**2788.16**	3159.92	3297.89

optimization to prove the necessity of optimizing three objectives simultaneously.

(3) Tri-objective experiments:

Compare the best, median and worst values of Pareto solutions generated by NSGA-II, NSGA-III, and U-NSGA-III testing in Taillard benchmark arranging from 20jobs-15machines to 50jobs-20machines to provide the evidence for evaluating the performance of algorithms.

(4) Comparative experiment of our multi-objective scheduling based energy-saving strategy:

The comparative experiment is carried out by computing the NEC before and after employing the machine status switching approach to illustrate the energy-saving strategy's effect.

1) INITIALIZATION METHOD EXPERIMENTS

In order to illustrate the effect of MME initialization method, we design the comparative experiments in 15×15 benchmark. The best, median and worst values of Pareto solutions generated by U-NSGA-III with random and MME initialization method are listed in Table 7. Form the table, we can find that U-NSGA-III with MME method obtain all of the best minimum values of three objectives in 15×15.1 and 15×15.2 instances. The results indicate that the U-NSGA-III with MME method can provide good initial population and obtain better Pareto solution.

2) BI-OBJECTIVE EXPERIMENTS

Through the literature research, we find that, researchers have never considered the three optimal objectives (makespan, earliness & tardiness, and energy efficiency) together in job shop scheduling. They usually optimize any two objectives of them to obtain results. But we think the makespan, total weighted earliness & tardiness (TWET), non-processing energy consumption (NEC) are all essential and should be optimized together. Four scenarios of experiments arranged from bi-objective and tri-objective in 15 × 15 benchmark to demonstrate our idea,. The four Scenarios are listed in Table 6.

We choose any two of the three objectives to compose three scenarios (S1, S2, and S3) and obtain the best schedule result used the U-NSGA-III algorithm. And then, we input the schedule into an objective evaluation code for calculating the values of the third objective. We test the results in 15 × 15.1 and 15 × 15.2 instances by the U-NSGA-III algorithm. The experiment results, which are obtained in the same iterations, are shown in Table 8 (EI means evaluation index). Boldface in Table 8 represents the minimal best value obtained by the algorithm. From scenarios S1, S2, and S3 in Table 8, we find that if we choose two objectives to optimize, the objective value that is not controlled will be larger. The experimental results in the three scenarios are consistent with this law. For example, in 15 × 15.1 instance, if we choose makespan and NEC as the optimal objectives in S2, the best value of TWET is higher 108.57% and 118.56%, the median value is higher 51.28% and 74.86% than values in S1and S3, respectively. In S4 of Table 8, the result of the tri-objective is listed. Comparing S4 with S1, S2, and S3, we find that S4 gets the minimum best value makespan and TWET. And the best value of NEC in S4 is only 1.12% above the minimum value 2777.90 in S2. In addition, the U-NSGA-III algorithm is a unified evolutionary optimization algorithm that allows a user to work with a single code to achieve optimizations with different objective dimensions (i.e., single, multiple, and many-objective). So the result in table 8 illustrates that it is necessary to simultaneously optimize the three objectives.

3) TRI-OBJECTIVE EXPERIMENTS

In order to analyze the performance of the U-NSGA-III algorithm in the tri-objective job shop scheduling problem, it is compared with NSGA-II and NSGA-III which are commonly used in multi-objective scheduling problems. Through literature research, we find that many studies on multi-objective workshop scheduling problems choose NSGA-III and NSGA-II as the comparison algorithm [48], [64]. In addition, Yang *et al.* [65] proved that NSGA-II could get better solutions than MOEA/D (multi-objective evolutionary algorithm based on decomposition)

$$MNOF = \frac{1}{n} \cdot \sum_{i=1}^{n} \sqrt{(\frac{f_{1,i} - \min_{j\in A} f_{1,j}}{\max_{j\in A} f_{1,j} - \min_{j\in A} f_{1,j}})^2 + (\frac{f_{2,i} - \min_{j\in A} f_{2,j}}{\max_{j\in A} f_{2,j} - \min_{j\in A} f_{2,j}})^2 + (\frac{f_{3,i} - \min_{j\in A} f_{3,j}}{\max_{j\in A} f_{3,j} - \min_{j\in A} f_{3,j}})^2} \tag{23}$$

TABLE 8. Best, median and worst value of pareto solution in four scenarios.

Instance	Scenarios	Objectives / EI Algorithm	Makespan			TWET			NEC		
			Best	Median	Worst	Best	Median	Worst	Best	Median	Worst
15×15-1	S1	U-NSGA-III	1486	1577	1666	352.96	510.9	768.9	3054.16	3265.10	3389.40
	S2	U-NSGA-III	1499	1537	1579	736.16	772.90	1262.88	**2777.90**	2953.98	3109.42
	S3	U-NSGA-III	1531	1669	1802	336.82	442	707.9	2892.62	3108.73	3442.35
	S4	U-NSGA-III	**1485**	1549	1689	**317.52**	478.3	988.4	2809.09	3132.17	3499.53
15×15-2	S1	U-NSGA-III	**1503**	1550	1612	760.16	794.9	836.1	3007.19	3174.61	3511.14
	S2	U-NSGA-III	1547	1581	1710	905.44	1354.34	3594.6	2858.65	2944.76	3273.10
	S3	U-NSGA-III	1570	1592	1841	458.9	688.6	6160.71	**2788.16**	3004.68	3370.04
	S4	U-NSGA-III	1513	1577.5	1841	**428.3**	645.83	6160.71	**2788.16**	3159.92	3297.89

TABLE 9. Best, median and worst value of pareto solution for NSGA-II, NSGA-III and U-NSGA-III.

instance	Objectives / EI Algorithm	Makespan			TWET			NEC		
		Best	Median	Worst	Best	Median	Worst	Best	Median	Worst
20×15-1	NSGA-II	1823	1838.5	1869	3942.45	5318.56	7342.36	4043.33	4438.00	4767.96
	NSGA-III	1800	1866	1904	3418.69	5714.42	8965.60	3765.02	4209.95	4570.79
	U-NSGA-III	**1687**	1798	1876	**2473.79**	3542.31	7082.97	**3763.92**	3845.85	4056.47
20×15-2	NSGA-II	**1740**	1817	1940	3682.47	5274.21	7261.35	3838.31	4068.27	4454.14
	NSGA-III	1841	1902	1934	7143.29	7604.07	8073.82	3946.18	4268.08	4599.42
	U-NSGA-III	1763	1846	1897	**2346.11**	6700.83	8835.05	**3778.39**	3885.46	4292.37
20×20-1	NSGA-II	2284	2371	2532	3099.89	4628.67	9186.98	4943.47	5521.51	5994.95
	NSGA-III	**2190**	2320.5	2471	1551.57	3195.06	9429.05	4966.79	5352.81	5561.94
	U-NSGA-III	2195	2236	2627	**1436.33**	1858.23	11475.94	**4891.60**	5161.16	5561.94
20×20-2	NSGA-II	2202	2248	2349	2170.61	2682.71	5376.95	6171.12	6562.59	6953.11
	NSGA-III	2312	2365	2466	3668.91	5841.21	7730.86	6249.08	6636.72	7010.80
	U-NSGA-III	**2123**	2235	2330	**1997.81**	2169.26	3422.69	**6089.07**	6154.02	6597.40
30×15-1	NSGA-II	2514	2647	2723	70522.33	80019.33	92328.33	4185.05	4524.51	4650.09
	NSGA-III	2557	2627.5	2751	67257.33	75387.33	88835.34	4288.98	4659.38	4841.56
	U-NSGA-III	**2449**	2489	2693	**43597.73**	51330.33	62880.33	**3883.98**	4464.57	5108.19
30×15-2	NSGA-II	2639	2811.5	2864	108978	128597	145339	3891.67	4266.53	4646.91
	NSGA-III	2546	2546	2546	88806	88806	88806	4127.90	4127.90	4127.90
	U-NSGA-III	**2546**	2751	2889	**81701**	127114	138252	**3850.72**	4099.59	4544.03
30×20-1	NSGA-II	3017	3446.5	3849	97003.5	157809	192784	6677.53	7025.13	7118.52
	NSGA-III	3115	3195	3297	102804.5	115089	129720.5	6549.55	6987.99	7127.84
	U-NSGA-III	**2977**	3108	3772	**77271.5**	98999.5	177502.5	**6425.72**	7020.69	7542.80
30×20-2	NSGA-II	2966	3121	3229	105467.33	118166.7	140495.7	6598.66	6681.50	7407.80
	NSGA-III	2909.	3021.5	3111	73374.7	89144.2	127274.7	6552.89	7086.40	7249.06
	U-NSGA-III	**2909**	2949	3170	**72174.81**	82227.7	127274.7	**6552.89**	7091.69	7249.06
50×20-1	NSGA-II	4296	4362.5	4402	464912.5	470661.0	484497.5	7697.73	8175.37	8516.53
	NSGA-III	4348	4439	4629	475197.5	482603.5	511877.5	7924.25	8304.65	8804.21
	U-NSGA-III	**4268**	4313	4549	**446004.5**	461483.5	482623.5	**7355.44**	7605.08	8429.29
50×20-2	NSGA-II	4248	4293.5	4460	424687.5	446704.5	484684.5	7662.00	7806.65	8326.40
	NSGA-III	4226	4332	4459	446285.5	456681.5	493740.5	7780.75	7955.87	8432.60
	U-NSGA-III	**3956**	4442.5	4537	**361405.5**	458390	501890.5	**7553.93**	7811.38	8039.04

in flexible job shop scheduling problems by comparative experiments. Ahmadi *et al.* [66] applied two evolutionary algorithms, NSGA-II and NRGA, to solve multi-objective flexible job shop scheduling problems. The results indicated NSGA-II performed better on most criteria. So in this paper, we choose NSGA-II and NSGA-III as the comparison algorithm. The U-NSGA-III algorithm is run ten independent times for each instance. Table 9 shows the best, median, and worst results of the three algorithms tested in different Taillard benchmark scales. It can be seen from the table that the algorithm U-NSGA-III obtained the best solutions of 8 out of 10 examples, indicating the best results obtained by U-NSGA-III are better than the other two algorithms, and reflecting the better search quality of U-NSGA-III. Decision-makers can find the exact optimum according to their scheduling cases. And, 20 × 15.2 and 20 × 20.1 instance, the optimal best makespan values are obtained by NSGA-II and NSGA-III respectively. The best makespan obtained by U-NSGA-III is only 1.32% and 0.23 % above 1740 and 2190.

TABLE 10. Experimental outcomes of NSGA-II, NSGA-III and U-NSGA-III based on comparison metrics.

Instance	DM			MID			MNOF		
	NSGA-II	NSGA-III	U-NSGA-III	NSGA-II	NSGA-III	U-NSGA-III	NSGA-II	NSGA-III	U-NSGA-III
20×15-1	3476.58	**5606.094**	4622.32	3048.44	3376.68	**2009.44**	1.0852	1.0213	**0.6687**
20×15-2	3636.98	1140.73	**6510.64**	**3141.54**	5267.81	3541.49	**0.7217**	1.1895	0.7878
20×20-1	6182.215	7904.93	**10071.23**	3963.25	**2569.94**	3474.25	0.8709	**0.6432**	0.6701
20×20-2	3303.594	**4135.62**	1526.94	1143.73	3689.04	**508.49**	0.7057	1.1937	**0.4264**
30×15-1	**21811.96**	21585.96	19322.96	35626.99	32831.07	**10510.70**	1.1214	1.1022	**0.7360**
30×15-2	36369.54	0	**56556.29**	46141.03	**7111.04**	32719.43	1.1779	**0.3656**	0.9042
30×20-1	95785.13	26922.83	**100240.4**	67510.06	38106.99	**30103.83**	5.9462	3.3858	**2.9531**
30×20-2	35038.70	53904.87	**55104.91**	47903.90	22589.72	**21704.74**	0.8607	0.8406	**0.7191**
50×20-1	19602.40	36691.63	**36635.82**	26577.23	46008.25	**20421.73**	4.0877	7.0444	**3.2092**
50×20-2	60001.05	47460.05	**140487.0**	89291.90	102214.1	**86136.51**	0.9060	1.0026	**0.8764**
Average	28520.8149	20535.2714	**43107.851**	32434.807	26376.464	**21113.061**	1.74834	1.77889	**1.1951**

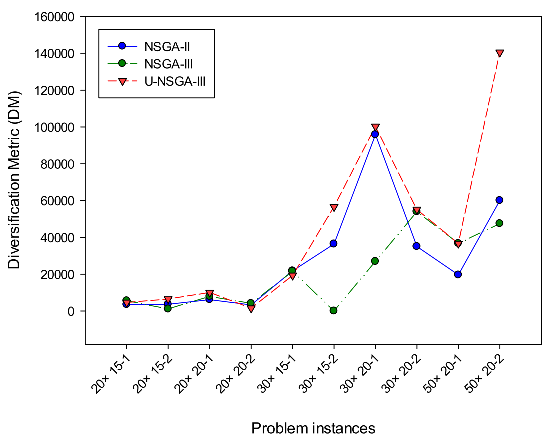

FIGURE 8. Diversification metric for problem instances.

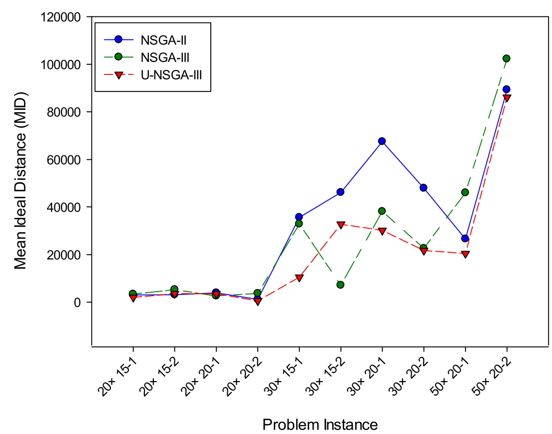

FIGURE 9. Mean ideal distance for problem instances.

To further compare the advantages and disadvantages of the proposed algorithm and the other two algorithms, three metrics, i.e., DM, MID, and MNOF, are introduced to compare each algorithm's effects. The computational outcomes for the ten instances are presented in Table 10, which consists of the problem instances and values of the performance criteria (DM, MID, and MNOF) for each of the multi-objective algorithms. According to Table 10, the U-NSGA-III has generally obtained better non-dominated schedules as compared to the other two algorithms. For example, the non-dominated Pareto solutions generated by U-NSGA-III in the 50 × 20.2 instance show better results compared to solutions generated by NSGA-II and NSGA-III. Specifically, in the first comparison metrics, U-NSGA-III obtained the best value of DM=140487.0; however, other algorithms got lower results. The higher value of DM shows a better extension and spread of U-NSGA-III. The second metric results (MID = 86136.51) also indicate U-NSGA-III is an excellent algorithm, while other algorithms have higher values (a lower value of MID is preferable). Besides, according to the third metric MNOF, U-NSGA-III has got the best value of 0.8764. However, NSGA-II and NSGA-III obtained 0.9060 and 1.0026, respectively (a lower value of MNOF is better). In the same way, results of other test instances can be explained and expounded in detail.

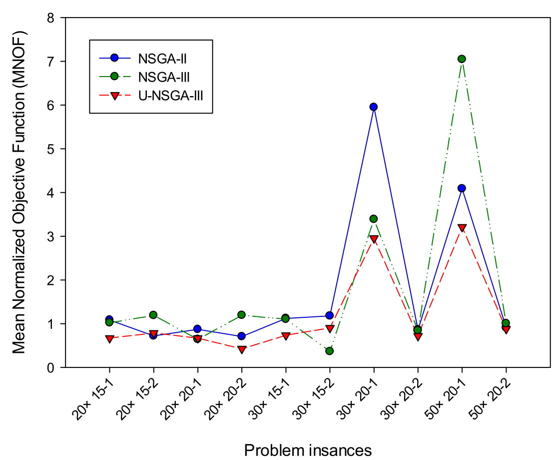

FIGURE 10. Mean normalized objective function for problem instances.

Figures 8-10, present the three comparison metrics for the problem instances. As shown in Figure 8, the U-NSGA-III has obtained better results in most problem instances except 20 × 15.1, 20 × 20.2, and 30 × 15.1 regarding the first metric DM. Based the Figure 9, U-NSGA-III can obtain better results in seven test problem instances for the second comparison metric MID, while in the other three instances, it performs worse than either NSGA-II or

TABLE 11. The comparison of non-processing energy consumption.

Instance	*E1*	*E2*	Energy saving ratio *f* (%)
20×15-1	7013.84	3763.93	46.34
20×15-2	7351.073	3778.39	48.60
20×20-1	15834.96	4891.60	**69.11**
20×20-2	14261.73	6089.08	57.30
30×15-1	9085.80	3883.99	57.25
30×15-2	9534.06	3850.72	59.61
30×20-1	18642.70	6425.72	65.53
30×20-2	17991.82	6552.89	63.58
50×20-1	22402.58	7355.44	67.17
50×20-2	19526.31	7553.93	61.31

NSGA-IIII. Whereas the average values of MID in Table 10 (MID = 32434.807, 26376.464, 21113.061 for NSGA-II, NSGA-III, and U-NSGA-III, respectively) point out U-NSGA-III is better than NSGA-II and NSGA-III. According to Figure 10, U-NSGA-III performs better in seven of ten problem instances. However, the average values of MNOF indicate that U-NSGA-III performs better. It is noted that MID and MNOF are critical performance metrics of multi-objective algorithms as they are directly related to the quality of the obtained non-dominated schedules.

4) COMPARATIVE EXPERIMENT OF ENERGY-SAVING STRATEGY

In order to illustrate the effect of energy-saving strategies, comparative experimental results are listed in Table 11. In this table, E1 represents the NEC without the energy-saving strategy; E2 represents the best NEC with the energy-saving strategy obtained by U-NSGA-III. And the energy-saving ratio is computed by the formula $f = (E1 - E2)/E1$. From Table 11, more than 46% of energy can be saved by using energy-saving job scheduling strategies. As the instances' scale increased, the non-processing energy consumption can be saved more significantly, reaching over 65% in instance 30×20.1, 50×20.1, and 20×20.1. Considering that non-processing energy consumption can consist of 13-83% of total energy consumption [24], [67], the 65% reduction here can significantly reduce the energy bill for manufacturing enterprises.

VI. CONCLUSION

In modern manufacturing, more and more attention is paid to reducing energy consumption as well as maintaining good scheduling performance in terms of traditional scheduling objectives. In this paper, we proposed a multi-objective genetic algorithm for the energy-efficient job scheduling problem, including three objectives: non-processing energy consumption (NEC), makespan (C_{max}), and total weighted earliness & tardiness (TWET) by combining scheduling with the status switching of machines. We use the multi-objective genetic algorithm U-NSGA-III with high-quality population initialization using the MME algorithm and random generating method. The performance of U-NSGA-III is tested in an extended Taillard job shop benchmark comparing with the other two algorithms, namely, NSGA-II and NSGA-III. The results indicate that U-NSGA-III can obtain most of the optimal values for the three objectives. Besides, the quality of the Pareto solutions obtained by U-NSGA-III is respectively evaluated from the aspect of the boundary extension in the generated non-dominated schedules (DM), the closeness between the Pareto solutions and the ideal point (MID), the reliability (MNOF). Furthermore, the initialization method experiments, bi-objective experiments, and comparative experiment of energy-saving strategy are performed to illustrate the effect of the MME initialization method, the necessity of optimizing three objectives simultaneously, and the energy-saving strategy's effect. To the best of our knowledge, this is the first attempt to optimize the three objectives simultaneously, including the energy efficiency target. The results show that our energy-efficiency-oriented multi-objective job scheduling algorithms can achieve significant energy saving with 46%-69% saving in non-processing energy consumption. Our methods can be easily extended to solve other kinds of manufacturing shop scheduling problems for energy saving, such as classical flow shop scheduling and flexible job shop scheduling. Although the effectiveness of the proposed job shop energy-saving method has been proven, further research is still needed. Some reasonable assumptions simplify the model in this study, however, the actual production scheduling problem is more complicated because of some uncertain factors or unexpected conditions, such as time uncertainty, random arrival or cancellation of orders, changes in delivery dates, and machinery breakdown. So in the follow-up work, we will focus on the research of production workshop scheduling models that can handle more realistic production conditions to improve the applicability of energy-saving scheduling theory and schemes. In addition to that, future studies should also consider cost control in workshop manufacturing and the environmental impact of the manufacturing process.

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