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Energy-efficient scheduling problem under speed-scaling and power-saving machine states

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Abstract— **This paper addresses the problem of scheduling different non-preemptive jobs on a single machine under time of use electricity tariffs consideration. The considered machine has three main states (OFF, ON, Idle) and two transition states (Turn-on and Turn-off). Each of these machine's states as well as the processing jobs, consume a specific amount of energy. Moreover, a speed-scalable case of the problem is considered, in which jobs can be processed at an arbitrary speed with a trade-off between speed and energy consumption. First, a mixed-integer linear programming model with the objective of minimizing total energy consumption costs formulates this scheduling problem. Then, since this problem is strongly NP-hard, different approximate optimization methods are investigated to provide near-optimal solutions. Finally, an extensive computational study is carried out to establish the efficiency of the proposed algorithms. The obtained results show, how a well-tuned genetic algorithm combined with an adequate local search procedure constitutes an efficient method for solving this energy-aware scheduling problem.**

I. INTRODUCTION

In the last few years, economic and societal developments have led to a rapid increase in energy consumption. The industrial sector is one of the most important consumers of energy in most industrial countries ([6]). Figure 1 illustrates this fact for the case of the United States and also shows that this trend tends to continue in the future. Therefore, it is more than necessary to focus on the industrial sector for the minimization of energy consumption and the reduction of greenhouse gas emissions. Since the turn of the millennium, in almost every industrial nation, electricity prices, one of the main energy sources used in manufacturing firms, have been rising continuously (see Fig. 1). This is mainly a result of taxes and duties to support the integration of renewable energies and the turning away from low-cost electricity generated by nuclear power.

As a consequence, the energy costs relative to the production activities increase, which causes less competitiveness compared to countries with cheaper electricity prices. Therefore, improving energy efficiency and saving electricity plays a very important role in modern industries. These issues have encouraged many researchers all around the world to study the efficiency improvement of a production system in electricity consumption to reduce production costs and environmental impact simultaneously.

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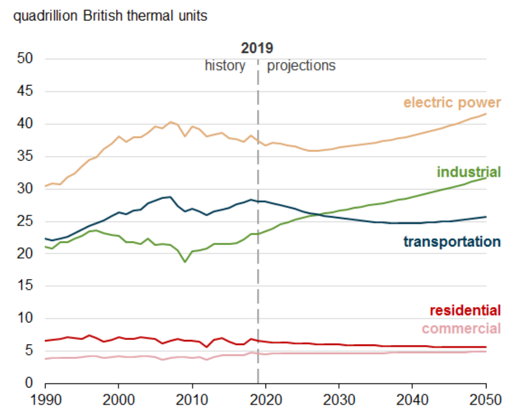

Fig. 1. Projection of energy consumption by sector in the United States (source: AEO2020 Reference case)

II. RELATED LITERATURE

A large amount of literature has been dedicated to energy-efficient scheduling problems. These different works have shown that integrating energy management strategies with the scheduling of production systems is an effective way to improve energy efficiency and reduce production costs.
A quick check of the related literature shows that there are different methods to integrate energy concepts in production scheduling problems. For example, [14] presented a literature review of decision support models for energy-efficient production planning. [3] introduced several options on how enterprise-wide optimization concepts can integrate energy management and scheduling. Recently, [2] published a comprehensive literature review of production scheduling for intelligent manufacturing systems with energy-related constraints and objectives. They analyzed synthesized the existing achievements, current research status, and introduced some perspectives especially intelligent strategies for solving the energy-efficient scheduling problems.

In this study, we are attempted to categorize the literature into two main parts. The first one investigates the works interested in reducing energy consumption and the second class reviews the papers which deal with the reduction of the energy consumption costs (operational costs).

The energy consumption of a manufacturing system can be analyzed in different perspectives such as machine-level, product-level, and system-level ([9]). Machine-level studies focus on developing and designing more efficient machines and equipment, whereas in the product-level, the researchers

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concentrate on product design to reduce energy consumption values. However, in the system-level, manufacturers can achieve a significant reduction in energy consumption by using decision models and optimization techniques to apply to production planning and scheduling decision levels ([9]). Since the machine redesign and product redesign need enormous financial investments, the system-level perspective is addressed in this study to present some decreasing energy consumption methods.

Generally, the energy consumption of a production system at the system-level is composed of the amount of energy consumed during the non-processing states and the processing state. Start-up, the transition between different states, shut down and idle states are different types of non-processing states. In the real world, the amount of energy that the machine consumes is dependent on its states. Moreover, several characteristics may change the energy consumption of the machine during the processing (ON) states such as type of the machine, type of the processing job, and the processing speed of the machine. Consequently, The energy consumption of a system can be machine-dependent, or (and) state-dependent, or (and) job-dependent, or (and) speed-dependent. Among the studies which deal with the state factor, [16] developed a model and algorithm in a single machine system that minimize the energy consumption of the system by selecting the idle or switched on or off states between two consecutive jobs. Moreover, in some cases, the authors addressed energy consumption minimization simultaneously with another classical scheduling objective, like minimization of makespan, total weighted completion time, or total tardiness. Among the studies which consider the speed factor, [10] and [11] studied the complexity of a deadline-based scheduling problem under a variable processing speed for the preemptive and non-preemptive cases, intending to find a feasible schedule that minimizes the energy consumption. [18] examined the trade-off between total energy consumption and total weighted tardiness in a single machine environment with sequence-dependent setup times, where different jobs can be operated at varying speed levels.

In practice, electricity suppliers in different countries propose variable pricing to balance the electricity supply and demand to improve the reliability and efficiency of electrical power grids. The most common categories of time-varying rates are Time-Of-Use (TOU), Critical Peak Pricing (CPP), Peak Time Rebates (PTR), and Real-Time Pricing (RTP). In some papers, the authors just assumed the time-dependent energy cost to compute the total energy consumption cost. They reduced the total energy cost by shifting the on-peak hour energy consumption to the off-peak hour ([4], [5]).

In some papers, the authors investigated the effects of different factors such as machine-dependent, speed-dependent, or state-dependent on the machine's energy consumption, in addition to the time-dependent energy cost. For example, [7], [11] and [12] investigated the total cost minimization when the machine has variable speed and energy consumption. [6] analyzed the complexity of the scheduling problem of processing jobs with arbitrary power demands which must be processed at a uniform speed or speed-scalable single machine to minimize total electricity costs under TOU electricity tariffs. [8] proposed a mathematical model to minimize energy consumption costs for single machine scheduling by considering variable energy prices during a production shift and unique energy consumption for each state of the machine. For this purpose, they made decisions at the machine level to determine the state of the machine at each period as well as specifying the sequence of the jobs in the process state of the machine. [13] studied the same problem as that one proposed by [8]. They proposed two mathematical models. The first one considers a predetermined fixed order for the processing jobs to improve the previous mathematical model, and the second one finds the optimal schedule for the machine state and job's sequence simultaneously. The authors proposed also a new heuristic algorithm and a genetic algorithm to solve this problem. The complexity analysis of several energy-oriented multi-state single-machine scheduling problems addressed in the literature is presented in [19]. [17] worked on a non-preemptive single-machine scheduling problem under TOU electricity tariffs. They proposed a mixed-integer multi-objective mathematical programming model and several new holistic genetic algorithms to minimize the total tardiness and total energy cost.

This paper investigated how to improve the energy efficiency of manufacturing processes or a machine by changing the processing jobs' sequence, processing speed on the machine, and by turning off and then turning on the machine, or put it in idle state for obtaining better energy-efficient production strategies. We focus on total energy consumption costs minimization. This problem was introduced, for the first time, by [1] without proposing any optimization method to solve it. To the best of our knowledge, very few publications are addressed in the literature to deal with this energy-aware scheduling problem.

The remainder of this manuscript is organized as follows. Section 3 describes the considered problem with its different assumptions. A new mathematical model is also presented to formulate the problem. Section 4 describes detailed steps for the development of a memetic algorithm for solving the problem. Section 6 addresses and analyzes a large numerical study, based on several instances, to evaluate the efficiency of the proposed methods. Finally, section 7 summarizes the contributions and presents some perspectives for future directions of this study.

III. Problem formulation

The problem considered in this paper can be formally described as follows. There are n jobs to be proceeded by a single machine during a horizon of time with T periods characterized by different electricity tariffs. This machine or processor has 3 main states (ON, OFF, and Idle), and the possible transitions between OFF and ON states (named Ton and Toff) are considered (Figure 2). The machine consumes a specific amount of energy (e_s) in state

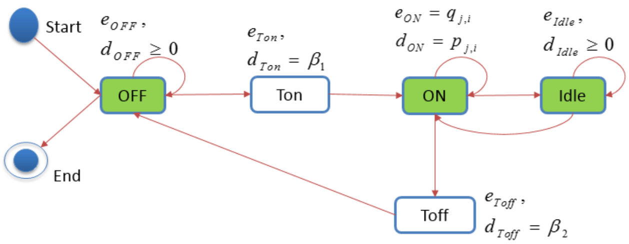

Fig. 2. Machine states and possible transitions.

s ($s \in \{ON,\ OFF,\ Idle,\ Ton,\ Toff\}$). It must stay in the same state for a specific number of periods which depends on the state (d_s; $\ s \in \{ON,\ OFF,\ Idle,\ Ton,\ Toff\}$). Without loss of generality, the energy consumption of the machine in state OFF for this study is assumed to be equal to 0 ($e_{OFF} = 0$). Moreover, the energy consumption of the machine during state ON depends also job-dependent.

Since a speed-scalable machine is addressed in this work, so there are different possibilities for processing each job. That means for each job $j = 1, ..., n$ with v_j possible speeds, there are different values for the processing time as $P_j = \{p_{j,1}, \cdots, p_{j,v_j}\}$, and for each $p_{j,i}$, a corresponding energy consumption $q_{j,i}$ is associated. $Q_j = \{q_{j,1}, \cdots, q_{j,v_j}\}$ is the set of the different energy consumptions of job $j = 1, ..., n$. To ensure the logical trade-off between speed and energy consumption, the following relations are considered:

$$p_{j,1} > p_{j,2} > \cdots > p_{j,v_j} \quad ; \forall j \in \{1, \cdots, n\} \tag{1}$$

$$q_{j,1} < q_{j,2} < \cdots < q_{j,v_j} \quad ; \forall j \in \{1, \cdots, n\} \tag{2}$$

As it is illustrated in Figure 2, the machine must be in OFF state during the initial and final periods. When it is decided to turn on the machine, this transition takes β_1 periods and it consumes e_{Ton} units of energy per period. Then the machine is in ON state and is ready to process a job $j = 1, ..., n$ with speed $i = 1, ..., v_j$, that takes $p_{j,i}$ periods and consumes $q_{j,i}$ corresponding units of energy per period. Once the job is processed completely, there are three possibilities for the machine: it may stay in ON state and process the next job; it can go to Idle state for one period or more and also, the machine can go to OFF state. Regarding the energy consumption and the unit of energy price, any of these possibilities may be selected. Note that, in this study, the transition time between Idle and ON states, and its energy consumption are neglected. Besides, the transition between Idle and OFF states is not allowed. Therefore, when the machine is in the Idle state, for the next period, it may stay in Idle state or pass to ON state. The objective of this study is to find the most economical production schedule in terms of energy consumption costs during the time horizon.

To describe this mathematical model, the parameters and decision variables are defined and then, the objective function and constraints are explained.

Parameters:

T: Total number of periods.

t	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	Cost
c_t	0	8	8	8	4	4	4	3	3	3	2	2	2	2	2	10	10	10	10	3	3	3	2	2	2	2	6	6	3	3	3	5	5	
ON							16	12	12	15	10	8	8	8	8							9	6	6	6	6								
OFF	0	0	0	0													0	0	0									0	0	0	0	0	0	
Idle																																		
Turn on					20	20														15	15													
Turn off																10											6							
The schedule	Off				Ton		J1-1			J2-3		J3-2				Toff	Off			Ton		J4-3		J5-2			Toff	Off						206

Fig. 3. An example of the problem

c_t: Unit of energy price in period $t = 1, ..., T$.
n: Number of jobs.
v_j: Number of possible processing speeds for job j (speed $i = \{1, \cdots, v_j\}$).
$p_{j,i}$: Processing time of job $j = 1, ..., n$ with speed $i = 1, ..., v_j$ (in a number of periods).
$q_{j,i}$: Energy consumption of job $j = 1, ..., n$ per period which is associated to $p_{j,i}$.
s: States of the machine (s=1 for ON state, s=2 for OFF state, and s=3 for Idle state).
E_s: Energy consumption of the machine during state s.
$E_{ss'}$: Energy consumption of the machine in transiting from state s to state s'.
$d_{ss'}$: Number of periods that must elapse for switching from state s to state s' ($s \neq s'$).

Decision variables:

In this formulation, two binary decision variables are used to describe the state of the machine in each period, and two binary decision variables are also used to define the status of the jobs in each period.

$$\alpha_{s,t} = \begin{cases} 1 & ; \text{If the machine is in state } s \text{ during period } t \\ 0 & ; \text{ Otherwise} \end{cases}$$

$$\beta_{ss',t} = \begin{cases} 1 & ; \text{ If the machine is in transition } ss' \text{ in period } t \\ 0 & ; \text{ Otherwise} \end{cases}$$

$$x_{j,i} = \begin{cases} 1 & ; \text{ If job } j \text{ is processed with speed } i \\ 0 & ; \text{ Otherwise} \end{cases}$$

$$y_{j,i,t} = \begin{cases} 1 & ; \text{If job } j \text{ is processed with speed } i \text{ in period } t \\ 0 & ; \text{Otherwise} \end{cases}$$

Mathematical model:

$$Min \sum_{t=0}^{T} c_t \left(\sum_{j=1}^{n} \sum_{i=1}^{v_j} q_{j,i} \cdot y_{j,i,t} + \sum_{s=2}^{3} E_s \cdot \alpha_{s,t} + \sum_{s=1}^{3} \sum_{s'=1}^{3} E_{ss'} \cdot \beta_{ss',t} \right) \tag{3}$$

s.t.

$$\sum_{j=1}^{n} \sum_{i=1}^{v_j} y_{j,i,t} = \alpha_{1,t} \qquad ; \forall t \in \{1, \cdots, T\} \tag{4}$$

$$\sum_{s=1}^{3} \alpha_{s,t} + \sum_{s=1}^{3} \sum_{s'=1}^{3} \beta_{ss',t} = 1 \qquad ; \forall t \in \{0, \cdots, T\} \tag{5}$$

$$\alpha_{s,t} \leq \sum_{s'=1|d_{ss'}=0}^{3} \alpha_{s',t+1} + \sum_{s=1|d_{ss''}\geq 1}^{3} \sum_{s''=1}^{3} \beta_{ss'',t+1}$$
$$; \forall t \in \{0, \cdots, T-1\}, \forall s \in \{1, 2, 3\} \tag{6}$$

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$$\beta_{ss',t} \leq \beta_{ss',t+1} + \alpha_{s',t+1} \\ ;\forall t \in \{0, \cdots, T-1\}, \forall s, s' \in \{1, 2, 3\} | d_{ss'} \geq 1 \tag{7}$$

$$\sum_{t'=t+1}^{t+d_{ss'}} \beta_{ss',t'} \geq (\alpha_{s,t} + \beta_{ss',t+1} - 1) \cdot d_{ss'} \\ ;\forall t \in \{0, \cdots, T-1\}, \forall s, s' \in \{1, 2, 3\} | d_{ss'} \geq 1 \tag{8}$$

$$\beta_{ss',t} + \beta_{ss',t+d_{ss'}} \leq 1 \\ ;\forall t \in \{0, \cdots, T-t_{ss'}\}, \forall s, s' \in \{1, 2, 3\} | d_{ss'} \geq 1 \tag{9}$$

$$\sum_{j=1}^{n} \sum_{i=1}^{v_j} y_{j,i,t} \leq 1 \qquad ;\forall t \in \{0, \cdots, T\} \tag{10}$$

$$\sum_{t'=0}^{t-p_{j,i}} y_{j,i,t'} + \sum_{t'=t+p_{j,i}}^{T} y_{j,i,t'} \leq p_{j,i} \cdot (1 - y_{j,i,t}) \\ ;\forall t \in \{p_{j,i}, \cdots, T-p_{j,i}-1\}, \forall j \in \{1, \cdots, n\} \\ ,\forall i \in \{1, \cdots, v_j\} \tag{11}$$

$$\sum_{i=1}^{v_j} x_{j,i} = 1 \qquad ;\forall j \in \{1, \cdots, n\} \tag{12}$$

$$\sum_{t=0}^{T} y_{j,i,t} \geq p_{j,i} \cdot x_{j,i} \quad ;\forall j \in \{1, \cdots, n\}, \forall i \in \{1, \cdots, v_j\} \tag{13}$$

$$\alpha_{2,t} = 1 \qquad ;t \in \{0, T\} \tag{14}$$

$$\alpha_{s,t},\ \beta_{ss',t},\ x_{j,i},\ y_{j,i,t} \in \{0, 1\} \tag{15}$$

In this model, the objective is to minimize the total energy consumption cost of the system, which depends on the unit of electricity price in each period, as well as, the energy consumption of the machine in each period that depends on the processing jobs, the processing speeds, and the machine states (equation (3)). Equation (4) indicates that the machine may process at most one job per period, and if the machine processes job j during period t, it must be in ON state ($s = 1$). Equation (5) expresses that in each period the machine must be in one of the possible states (ON, OFF, Idle, Ton, and Toff). Equations (6) and (7) limit the machine's state in each period regarding it's state in the previous period by taking into account the required number of periods for each state ($d_{ss'}$). Equations (8) and (9) identify a lower and upper number of required periods for Ton and Toff states. Equation (10) imposes the constraint that the machine can process at most one job per period. Equation (11) translates the non-preemption constraints of the jobs. Equation (12) imposes the constraint that each job must be processed with only one speed. Equation (13) specifies the processing time of each job, regarding its processing speed. Equation (14) identifies that the machine is in OFF state during the initial and final periods.

To analyze the complexity of this problem, we can refer to a simple version of this problem which is studied in the literature. The complexity of a speed-scalable single machine scheduling problem, when the machine has just two states (ON and OFF), $(1, TOU|speeds, q_j|TEC)$ has been already studied in [6]. The authors proved that the problem is NP-hard. So, we can conclude that the general version of this problem which is presented in this work, with three main states and two transition states, $(1, TOU|states, speeds, q_j|TEC)$ is also NP-hard. Therefore, exact methods are not able to solve large size instances of this NP-hard problem in reasonable computational times. To tackle this issue, different approximate optimization methods are investigated to provide near-optimal solutions. The detailed description of these algorithms and their performance evaluation are presented in the following sections.

1	1	1	1	2	2	110	110	110	230	230	320	320	320	320	4	1	1	1	2	2	430	430	520	520	520	4	1	1	1	1	1	1

Fig. 4. The chromosome of our genetic algorithm

IV. Resolution method: Memetic Algorithm (MA)

Meta-heuristics techniques are also used to solve NP-hard problems. They are usually inspired by the natural process. Genetic Algorithms are one of these techniques which have been successfully applied to scheduling and sequencing problems to find good solutions ([15]).

The first step to implement a genetic algorithm for a specific problem is to define several concepts such as chromosome, initial population, parent selection method, crossover and mutation operators, and the stopping criteria. In the following subsections, these concepts are defined for the studied problem.

A. Initial population and Chromosome representation

Any solution of this problem is a schedule consisting of a horizon time from period 0 to period T, that defines the machine's state during each period. So, in this paper, each chromosome of the genetic algorithm is represented by $T+1$ genes and each gene identifies the machine's state in a period. To distinguish the machine's states, each state is represented by a specific number as $OFF = 1$, $Ton = 2$, $Toff = 3$, and $Idle = 4$. Besides, an integer number greater than 100 ($k > 100$) represents that the machine is in ON state. In the other words, if in period t, the machine processes the job j with speed i, in the related chromosome, the gene t fills with a number $(100 * j + 10 * i)$. Figure 4 represents the corresponding chromosome of the presented instance in Figure 3. Since in this instance the number of periods is 32, so this chromosome consists of 33 genes. The number 230 in 10th gene means that during period 9 the machine processes job 2 with speed 3. Also, the number 4 in 27th gene means that, during period 26, the machine is in Toff state.

After the construction of the chromosomes, the genetic algorithm's procedure starts with a randomly generated initial population. In this study, the proposed genetic algorithm uses an initial population that is randomly generated. In other words, for each individual, at first, the period that the machine is in the first Ton state must be selected randomly. Then, the job's number and its processing speed will be chosen randomly. After completing the job, the machine's state must be selected among ON, Toff, and Idle states arbitrarily. These procedures must be continued to process

all of the jobs until the last period. Finally, the objective value of the problem will be computed as a fitness function to classify the quality of the generated chromosome.
For completing the procedure of the genetic algorithm, it is necessary to choose it's main parameters based on the studied problem. These parameters are population size, crossover rate, mutation rate, a crossover operator, a mutation operator, and the number of iterations. The performance of the algorithm depends on the selection of these parameters.

B. Crossover and mutation

In this work, the roulette wheel selection operator has been chosen as the parents' selection operator to produce the new offspring. In the literature, two approaches are mostly used as the crossover operator such as single-point and double-point, which both of them are studied in this paper, and the more efficient approach is selected. For these approaches, the cut point(s) will be randomly generated from the period's index. In the single-point method, the first offspring will be composed of the first parent from the beginning to the cut point, and the second parent from the first gene after the cut point to the end of the chromosome. The second offspring will be obtained in the same way and by reversing the parents. After producing the children, a correction procedure must be done to convert the not feasible solutions to the feasible ones. For this purpose, the correction's procedure starts from the first gene and ends in the last gene. It verifies the value of each gene regarding the previous and the values of the next genes by respecting the duration of each state and the processing time of each job regarding it's selected speed.In the double-point method, the first offspring will be composed of the first parent from the beginning to the first cut point, the second parent from the next gene after the first cut point to the second cut point, and the first parent from the next gene after the second cut point to the end of the chromosome. The second offspring will be obtained in the same way and reverse the parents. Finally, a correction procedure is also required to convert the not feasible solutions to the feasible ones.

Besides, for the mutation method, a chromosome from the initial population will be randomly selected and the mutation will be performed on the selected gene by swapping its value. Then, it is necessary to check the feasibility of the obtained offspring and correct the not feasible ones like for the crossover method. The final step in the first iteration of the genetic algorithm is to update the initial population for the next iteration. For this purpose, the best chromosomes in terms of the fitness function must be selected from all the initial population and the obtained chromosomes by crossover and mutation methods in the previous iteration.

In this paper, a Taguchi orthogonal array is utilized instead of a full factorial experimental design for determining the best parameters of the genetic algorithm. This approach is presented in the following.

TABLE I
DESIGN FACTORS AND THEIR LEVELS

Factor	level1	Level2	Level3
Crossover operator	single-point	double-point	-
Mutation operator	swap	reverse	insert
Crossover rate	0.7	0.8	0.9
Mutation rate	0.05	0.10	0.15
Population size	50	100	150
Iteration number	50	100	150

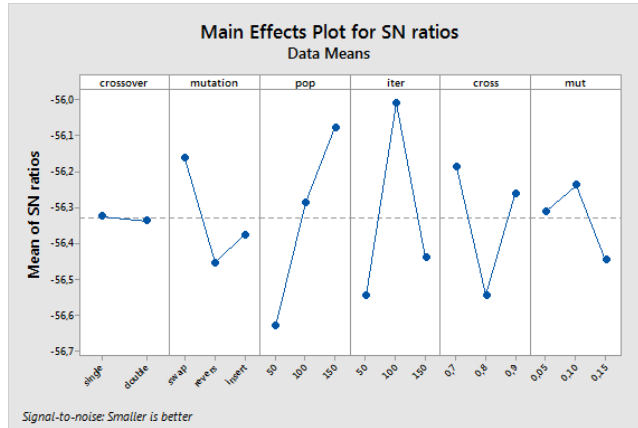

Fig. 5. Parameters tuning by Taguchi method

C. Taguchi method for parameters setting

An experimental design method is developed by Genichi Taguchi to increase the efficiency of implementation and evaluation of experiments. In Taguchi method, experimental results are converted to a signal/noise (S/N) ratio, which can be calculated in three different ways, such as 'small value is good', 'great value is good' and 'nominal value is good'. In this way, a level of the factor which has the highest ratio represents better performance.

1) Design factors and their levels: In this study, Taguchi method is applied to reduce the number of experiments. For this purpose, six factors are selected and their most used values in the literature are considered. One of them has two levels and the others have three levels (Table I). So, we applied the L_{18} (one two-level and up to seven three-levels) orthogonal array. Moreover, to achieve accuracy, experiments were repeated five times for each problem.

2) Data analysis: The result of Taguchi method analysis is given in Figure 5. As a result, single-point is selected as the crossover method to produce two new children, and the crossover rate is selected equal to 0.7 (70%). The mutation rate is selected equal to 0.1 (10%), and the initial population size and the number of iterations are considered equal to 150 and 100, respectively.

D. Local Search procedure

To improve the quality of the obtained solutions by the genetic algorithm for this problem, a local search procedure is also introduced to provide a memetic algorithm to solve the scheduling problem. The local search procedure is applied to increase the quality of the 15 best chromosomes of the population at each iteration (10% of the population size). For this purpose, a new solution will be created by increasing the processing speed of one job as much as one unit, and consequently, processing all the remaining jobs earlier. This procedure must be repeated for all the jobs in their sequence order. Since, in this problem n jobs must be performed by the machine, so, at most n new solutions can be created from each initial solution, and then, the solution with the best objective function must replace the initial one. The pseudo-code for the local search procedure is demonstrated by Algorithm 1. Finally, the initial population for the next iteration must update regarding the best-obtained solutions in the current iteration.

Algorithm 1: The Local Search procedure

```
At the end of each iteration find the 15 best solutions;
for i=1 to 15 do
    Get the initial solution x_i;
    for j=1 to n do
        if speed_j < speed_max(v_j) then
            Create the new solution (y_i), by doing the
              job j with speed speed_j + 1;
            When the job j is performed, do the
              remaining jobs, the same as solution x_i;
            Compute the objective function of y_i;
            if obj(y_i) < obj(x_i) then
                Replace the solution (x_i), by the new
                  one (y_i);
```

V. Numerical experiments

The performances of the proposed methods in this paper have been examined by several numerical instances inspired from the literature [8]. For this purpose, the genetic algorithm and the memetic algorithm have been coded by C++ language in Visual Studio 2015, and ILOG CPLEX 12.5 is used to solve the instances with the exact method (Branch and Cut) on a computer with a 2.6 GHz Intel Core i5 processor and 8 GB of RAM. Through some examination, we find that the computational performances of the presented methods are mainly influenced by the following parameters: the number of jobs, speeds, and periods (n, v, T); the processing times $(p_{j,i})$; the energy consumption of the jobs $(q_{j,i})$; the electricity prices (c_t). For each size of the instances (n, v, T) ten different examples are randomly generated. For this purpose, the processing times and the energy consumptions of the jobs are generated randomly from the uniform distribution on $1, 2, ..., 8$ ($p_{j,i} \in [1, 8]$ and $q_{j,i} \in [1, 8]$), and the unit of energy price for each period are generated from the uniform distribution on $1, 2, ..., 10$ ($c_t \in [1, 10]$). The computation time with CPLEX, for all the experiments was set to 1 hour or 3600 seconds.

For the problems smaller than 15 jobs, 5 speeds, and 120 periods, CPLEX was able to find the optimal solutions. Therefore, the results of the proposed algorithms are compared with the optimal solution. In general, for the small size problems, genetic algorithm find the solutions with the gap of 7.5% on average, while this gap for the memetic algorithm is equal to 2.7%. The average computation time of small size problems for genetic, and memetic algorithms are equals to 15.64 s, and 18.50 s, respectively. Whereas, the average computation time for CPLEX is equal to 271.01 seconds.

For the problems larger than 20 jobs, 5 speeds and 160 periods, CPLEX was not able to find the optimal solution. We just compared the obtained solutions by these three algorithms. It must be mention that, in all the cases, the memetic algorithm finds the best solution. The average gap between the genetic algorithms' solutions and the obtained solution by MA, is about 18.4%. These large gaps between GA to MA, demonstrate that the efficiency of the GA will decrease when we increase the size of the instance. On the other hand, these results show the high performance of the MA comparing to two other methods. The average computation time of these problems for genetic, and memetic algorithms are equals to 34.37 s, and 61.59 s, respectively.

VI. Conclusion

As addressed in the literature, in actual machining processes, machine tools stay in an idle state for most of the time and consume energy with the idle state. Therefore, optimizing simultaneously the scheduling of jobs and machine states represents an effective issue and has a huge potential for energy saving. To the best of our knowledge, our paper is one of the first to consider a speed-scalable and multi-states single machine scheduling problem with the objective of minimizing total energy consumption costs. This paper investigated how to improve the energy efficiency of manufacturing processes or a machine by changing the job processing sequence, job processing speed on the machine and by turning off and then turning on idle the machine for obtaining better energy-efficient production strategies. A mixed integer linear programming model consumption to minimize total energy consumption costs was developed to describe the problem. Then, since the considered problem is NP-hard, several approximate optimization methods have been developed to solve medium and large-scale instances in reduced computational times. Finally, an extensive computational study has been conducted to verify the effectiveness of the proposed energy-oriented memetic algorithm.

The results presented in this paper may be useful for future research on energy-oriented scheduling problems in more complex production systems. There are many directions for future research to extend this work. It could be interesting to consider more assumptions for this problem like set-up time before each job and real time pricing for electricity tariffs.

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REFERENCES

[1] AGHELINEJAD, MohammadMohsen, OUAZENE, Yassine, et YALAOUI, Alice. Energy optimization of a speed-scalable and multi-states single machine scheduling problem. In : New trends in emerging complex real life problems. Springer, Cham, 2018. p. 23-31.
[2] GAO, Kaizhou, HUANG, Yun, SADOLLAH, Ali, et al. A review of energy-efficient scheduling in intelligent production systems. Complex & Intelligent Systems, 2020, vol. 6, no 2, p. 237-249.
[3] MERKERT, Lennart, HARJUNKOSKI, Iiro, ISAKSSON, Alf, et al. Scheduling and energy–Industrial challenges and opportunities. Computers & Chemical Engineering, 2015, vol. 72, p. 183-198.
[4] TAN, Yuanyuan et LIU, Shixin. Models and optimisation approaches for scheduling steelmaking–refining–continuous casting production under variable electricity price. International Journal of Production Research, 2014, vol. 52, no 4, p. 1032-1049.
[5] TAN, Mao, DUAN, Bin, SU, Yongxin, et al. Optimal hot rolling production scheduling for economic load dispatch under time-of-use electricity pricing. Submitted for publication, 2015.
[6] FANG, Kan, UHAN, Nelson A., ZHAO, Fu, et al. Scheduling on a single machine under time-of-use electricity tariffs. Annals of Operations Research, 2016, vol. 238, no 1, p. 199-227.
[7] ALBERS, Susanne et FUJIWARA, Hiroshi. Energy-efficient algorithms for flow time minimization. ACM Transactions on Algorithms (TALG), 2007, vol. 3, no 4, p. 49-es.
[8] SHROUF, Fadi, ORDIERES-MERÉ, Joaquin, GARCÍA-SÁNCHEZ, Alvaro, et al. Optimizing the production scheduling of a single machine to minimize total energy consumption costs. Journal of Cleaner Production, 2014, vol. 67, p. 197-207.
[9] LUO, Hao, DU, Bing, HUANG, George Q., et al. Hybrid flow shop scheduling considering machine electricity consumption cost. International journal of production economics, 2013, vol. 146, no 2, p. 423-439.
[10] ANTONIADIS, Antonios et HUANG, Chien-Chung. Non-preemptive speed scaling. Journal of scheduling, 2013, vol. 16, no 4, p. 385-394.
[11] ANTONIADIS, Antonios, HUANG, Chien-Chung, et OTT, Sebastian. A fully polynomial-time approximation scheme for speed scaling with sleep state. In : Proceedings of the twenty-sixth annual ACM-SIAM symposium on discrete algorithms. Society for Industrial and Applied Mathematics, 2014. p. 1102-1113.
[12] BAMPIS, Evripidis, KONONOV, Alexander, LETSIOS, Dimitrios, et al. From preemptive to non-preemptive speed-scaling scheduling. Discrete Applied Mathematics, 2015, vol. 181, p. 11-20.
[13] AGHELINEJAD, MohammadMohsen, OUAZENE, Yassine, et YALAOUI, Alice. Production scheduling optimisation with machine state and time-dependent energy costs. International Journal of Production Research, 2018, vol. 56, no 16, p. 5558-5575.
[14] BIEL, Konstantin et GLOCK, Christoph H. Systematic literature review of decision support models for energy-efficient production planning. Computers & Industrial Engineering, 2016, vol. 101, p. 243-259.
[15] KODAGANALLUR, Viswanathan, SEN, Anup K., et MITRA, Subrata. Application of graph search and genetic algorithms for the single machine scheduling problem with sequence-dependent setup times and quadratic penalty function of completion times. Computers & Industrial Engineering, 2014, vol. 67, p. 10-19.
[16] TARAKÇI, Elif, ZAIM, Abdül Halim, et ÖZTAŞ, Oğuzhan. Design of a genetic algorithmic approach for reducing energy consumption in single machine production systems. Journal of International Trade, Logistics and Law, 2018, vol. 4, no 1, p. 101-110.
[17] RUBAIEE, Saeed, CINAR, Suna, et YILDIRIM, Mehmet Bayram. An energy-aware multiobjective optimization framework to minimize total tardiness and energy cost on a single-machine nonpreemptive scheduling. IEEE Transactions on Engineering Management, 2018, vol. 66, no 4, p. 699-714.
[18] FATIH TASGETIREN, M., ÖZTOP, Hande, ELIIYI, Uğur, et al. Energy-efficient single machine total weighted tardiness problem with sequence-dependent setup times. In : International Conference on Intelligent Computing. Springer, Cham, 2018. p. 746-758.
[19] AGHELINEJAD, Mohammadmohsen, OUAZENE, Yassine, et YALAOUI, Alice. Complexity analysis of energy-efficient single machine scheduling problems. Operations Research Perspectives, 2019, vol. 6, p. 100105.