POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)

URL: http://dergipark.org.tr/politeknik

Energy-based scheduling optimization to minimize the total energy consumption and the total tardiness in a single machine manufacturing system with the sequence-dependent setup times

Sıra bağımlı hazırlık süreli tek makineli üretim sisteminde toplam enerji tüketimini ve toplam teslim gecikme süresini minimize etmek için enerji odaklı çizelgeleme optimizasyonu

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Bu makaleye şu şekilde atıfta bulunabilirsiniz(To cite to this article): Tarakcı E., Zaim A. H. and Oztas O., "Energy-based scheduling optimization to minimize the total energy consumption and the total tardiness in a single machine manufacturing system with the sequence-dependent setup times", ***Politeknik Dergisi***, *(*): *, (*).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.1075096

Energy-Based Scheduling Optimization To Minimize The Total Energy Consumption And The Total Tardiness In A Single Machine Manufacturing System With The Sequence-Dependent Setup Times

Highlights

- *Energy-based scheduling problem in manufacturing systems.*
- *An energy-based genetic optimization method is proposed.*
- *The energy-based genetic optimization method provides effective performance.*

Graphical Abstract

In this study, the total energy consumption and the total tardiness are minimized in a single machine. The energy-based genetic optimization method is used and effective results are obtained.

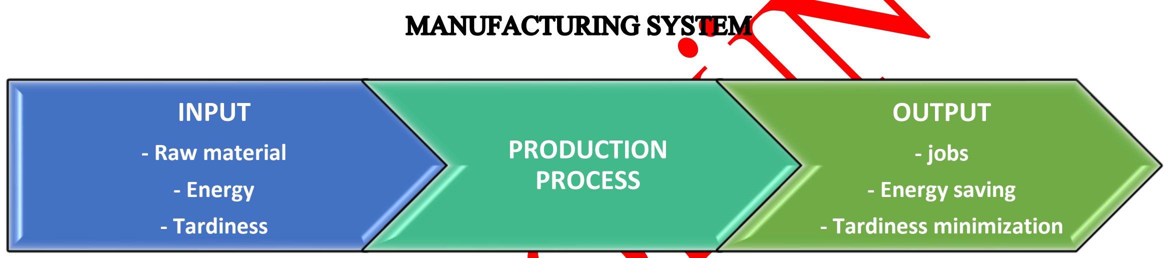

Figure. Graphical Abstract

Aim

It is aimed to perform an energy-based scheduling optimization in manufacturing systems.

Design & Methodology

The different job problems is solved by proposed the energy-based genetic optimization method, which is a heuristic method, the analytical solution and the GAMS.

Originality

Performances of proposed the energy-based genetic optimization method, the analytical solution and the GAMS are evaluated.

Findings

The proposed energy-based genetic optimization method provides feasible solutions in a much shorter time than the analytical solution and the GAMS in the different job problems.

Conclusion

The results and calculation times demonstrate the effectiveness of the proposed energy-based genetic optimization method.

Declaration of Ethical Standards

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Energy-Based Scheduling Optimization To Minimize The Total Energy Consumption And The Total Tardiness In A Single Machine Manufacturing System With The Sequence-Dependent Setup Times

Research Article / Araştırma Makalesi

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(Geliş/Received : 17.02.2022 ; Kabul/Accepted : 05.05.2022 ; Erken Görünüm/Early View : 27.06.2022)

ABSTRACT

Nowadays, reducing energy consumption is an important target for energy-intensive manufacturing systems due to many reasons such as global warming, legal obligations and lowering company expenses. Therefore, this paper focuses on energy-based scheduling problem in manufacturing systems. A mixed-integer nonlinear programming (MINLP) model is developed for a single machine scheduling problem with the sequence-dependent setup times and different arrival times in order to minimize the total energy consumption and the total tardiness. An energy-based genetic optimization (EGOP) method is proposed by adopting the genetic algorithm (GA) approach, which is a heuristic method to solve the problem. The objective values and the computation times are compared with the analytical solution and the General Algebraic Modeling System (GAMS) solution so as to evaluate the performance of the proposed method. As a result, it is seen that the proposed EGOP method provides effective results.

Keywords: Energy consumption, genetic algorithm, job scheduling, sequence-dependent setup time.

Sıra Bağımlı Hazırlık Süreli Tek Makineli Üretim Sisteminde Toplam Enerji Tüketimini Ve Toplam Teslim Gecikme Süresini Minimize Etmek İçin Enerji Odaklı Çizelgeleme Optimizasyonu

ÖZ

Günümüzde küresel ısınma, yasal zorunluluklar ve şirket giderlerinin düşürülmesi gibi birçok nedenden dolayı enerji yoğun üretim sistemleri için enerji tüketimini azaltmak önemli bir hedef haline gelmiştir. Bu nedenle, bu makalede üretim sistemlerinde enerji odaklı çizelgeleme problemine odaklanılmıştır. Sıra bağımlı hazırlık süreli (SBHS) tek makineli bir üretim sisteminde farklı geliş zamanlarına sahip işlerin toplam enerji tüketimini ve toplam teslim gecikme süresini minimize etmeyi sağlayan bir karma tamsayılı doğrusal olmayan programlama (MINLP) modeli geliştirilmiştir. Problemi çözmek için sezgisel bir yöntem olan genetik algoritma (GA) tabanlı enerji odaklı genetik optimizasyon (EGOP) yöntemi önerilmiştir. Önerilen yöntemin performansını değerlendirmek için amaç değerleri ve hesaplama süreleri analitik çözüm ve General Algebraic Modeling System (GAMS) çözüm ile karşılaştırılmıştır. Sonuç olarak, önerilen EGOP yönteminin etkili sonuçlar verdiği görülmüştür.

Anahtar Kelimeler: Enerji tüketimi, genetik algoritma, iş çizelgeleme, sıra bağımlı hazırlık süresi.

1. INTRODUCTION

Due to global climate changes and limited energy resources, it has become a necessity to integrate energy management into decision-making processes in manufacturing systems in order to reduce dependence on fossil fuels and CO_2 emissions [1]. In addition, energy management has become a key issue in manufacturing systems as customers prefer greener products and new environmental regulations are made [2]. As a result of all these, various approaches and solutions have been developed for energy efficiency in manufacturing systems in recent years. Preventions have been tried to be taken by increasing the efficient factor components or avoiding inefficient components [3]. In the literature, energy efficiency studies in the manufacturing system

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can be grouped under two headings: First, some studies aim to minimize energy consumption through technological advances in production processes. Second, other studies plan to decrease energy consumption by adjusting the management parameters of the production process, which is called energy-efficient production planning. Energy-efficient production planning models aim to minimize energy-oriented objectives such as energy consumption, energy costs or greenhouse gas emissions, along with traditional production planning objectives such as inventory holding cost, installation cost or total completion time. Since production planning generally does not require large investments, energy efficient production planning has become more popular in practice instead of technological infrastructure investments aimed at increasing energy efficiency in production systems. Therefore, there has been an increase in the number of scientific studies in this field in recent years [4].

Reducing setup times is a significant work for better production performance in a manufacturing system. The total setup time depends on the number of setups and each setup time. A long setup time affects the completion time of each job and hereby the tardiness and the number of tardy jobs. In addition, frequent setups and long setup times cause idle energy consumption. A more effective production approach should be integrated into manufacturing systems to reduce idle energy consumption [5].

The setup times can be included in the processing times of the jobs in scheduling problems. If energy-efficient scheduling is planned in the manufacturing system, the inclusion of setup times in the processing time of jobs will not make it possible to achieve energy-efficient scheduling. The total sequence-dependent setup time, which varies according to the scheduling of the jobs, directly affects the energy consumed by the manufacturing system. Also, when the machine does not process the job, the state of the machine is another important factor affecting the energy behavior of the system. Especially, when the machine does not process a job, the decision to turn off/on or run the machine at idle is of great importance in terms of energy saving in manufacturing systems.

A scheduling problem that minimizes the total tardiness and the total energy consumption of the jobs with different arrival times is an NP-hard (Non-Polynomial-hard) problem [6]. Scheduling problems that take into account sequence-dependent setup times are among the most difficult classes of scheduling problems [7]. As a result, this scheduling problem with sequence-dependent setup times and different arrival times that aims to minimize the total tardiness and the total energy consumption is also an NP-hard problem. This paper aims to develop an energy-efficient scheduling with the sequence-dependent setup times for a single machine manufacturing system. Moreover, the proposed multi-objective MINLP mathematical model decides on the state of the machine when the machine does not process. A heuristic method, GA-based EGOP, is proposed to solve this NP-hard scheduling problem. Thus, the literature is contributed. Since the problem is a multi-objective optimization problem, non-dominated solutions are obtained on the pareto front. The weighted additive utility function is used to determine the best solution among these pareto solutions.

One of the important studies in the field of scheduling was done by Mouzon et al. (2007) who proposed a model for reducing energy consumption. The study is based on the fact that non-bottleneck machines consume large amounts of energy while idling. So, they developed methods to minimize the energy consumption of production equipment by operational methods. In other words, they aimed to reduce the total energy consumption while optimizing other production planning targets. They also designed a multi-objective mathematical programming model to minimize the energy consumption and the total completion time on a single CNC machine. The study showed that energy saving can be achieved by the decision to run idle or turn off non-bottleneck machine [8]. In another study, Mouzon and Yildirim (2008) used a new greedy randomized multi-objective adaptive search metaheuristic solution method to solve an NP-hard problem that minimizes the total energy consumption and the total tardiness in a single machine. They obtained the best solution among non-dominanted solutions by using Analytical Hierarchical Method [6]. Fang et al. (2011) recommended a multi-objective mixed-integer programming model for a flow shop scheduling problem that minimizes the makespan, the carbon footprint and the peak total power consumption [9]. Dai et al. (2013) developed an energy-efficient model for flexible flow shop scheduling. They used a genetic-simulated annealing algorithm that shows the relationship between the makespan and the total energy consumption to obtain the feasible solution in the model. Experimental results demonstrated that there is a conflicting relationship between the makespan and the energy consumption [10]. Bruzzone et al. (2012) offered a mixed-integer programming model for flexible flow shops. As a result, by altering the original designing for an energy-aware scheduling target, they were able to reduce shop floor power's peak by an acceptable worsening of the tardiness and the makespan [11]. Shrouf et al. (2014) developed a mathematical model that optimizes energy consumption costs in a single machine production system by deciding to idle, process or turn off the machine according to the changing energy prices during the day. They used the GA method to solve the model. They compared it with an analytical method to evaluate the solutions obtained by GA. As a result, they showed that production planning according to lower energy pricing during the day contributes to energy saving with the GA in large-scale problems [12]. Fang et al. (2016) designed a single machine scheduling problem to minimize the total electricity cost of processing jobs under different electricity tariffs. They analyzed the computational performance of different approximation algorithms in randomly generated samples [13]. Lee et al. (2017) proposed a dynamic control algorithm to achieve energy saving of a single machine depending on time-changing electricity pricing without changing daily price rates during the season. They generated a new MINLP model that aimed to adjust the arrival times of jobs, the earliness and the tardiness of jobs and the energy consumption costs of the machine. They developed an efficient heuristic approach based on continuous-time variable control models and algorithm to solve the problem. They ensured efficient solutions in a very short computation time thanks to the scaled heuristic algorithm that provides flexibility for production strategies and can be applied to different production fields [14]. Li et al. (2020) aimed to minimize the makespan, the total carbon emission and the machine loading by designing a multi-objective flexible job-shop scheduling problem with variable processing speed constraint. To solve this optimization problem, they created an improved artificial bee colony algorithm [15]. Zhou et al. (2020) researched the energy-efficient scheduling of a single batch processing machine with non-identical job sizes and release times based on the time-of-use electric tariff in order to optimize the total electricity cost and the makespan. They solved this multi-objective scheduling problem using a hybrid meta-heuristic algorithm [16].

There are many scheduling studies taking into account sequence-dependent setup times in the literature. Nailwal et al. (2015) aimed to minimize the operational cost of the machines arising from sequence-dependent setup times of the jobs in a two-stage flow shop problem. Possibilities were assigned to the machines that have different features for processing different jobs. This problem focused on the impact of the breakdown interval on the total elapsed time and as a result of this on the operational cost when jobs were processed [17]. Varmazyar and Salmasi (2012) intended to minimize the number of tardy jobs in flow shop scheduling problems with sequence-dependent setup times. They developed a mixed-integer linear programming model for this problem and used different meta-heuristic algorithms based on tabu search and the imperialist competitive algorithm while solving the problem. After small, medium and large random test problems were solved by meta-heuristic algorithms, a detailed statistical experiment based on the split-plot design was implemented to determine the best metaheuristic algorithm. They stated that the imperialist competitive algorithm obtained worse solutions than other algorithms in small and medium-sized problems, but the hybrid algorithm based on the tabu search and the imperialist competitive algorithm performed better than other algorithms in large-sized problems [18]. Velez-Gallego et al. (2016) investigated the job scheduling problems with arbitrary release dates and sequence-dependent setup times on a single machine in order to minimize the makespan. They were able to achieve feasible solutions with low computational cost thanks to a beam search heuristic [19]. Li et al. (2018) aimed to minimize the makespan and the energy consumptions in the hybrid flow shop scheduling problem with the setup energy consumptions [20]. Lu et al. (2017) developed a permutation flow shop scheduling problem with sequence-dependent setup time and controllable transportation time in order to minimize the makespan and the total energy consumption. They generated an energy saving scenario that extends the working life of the machines and saves energy. Then, they solved the problem with a hybrid multi-objective backtracking search algorithm and compared the results of the used algorithm with NSGA-II and MOEA/D. They succeeded in proving that used algorithm has a better performance [21].

The framework of this article is formed as follows. An energy-based mathematical model is developed in the second chapter. The steps of the EGOP heuristic method are explained in the third chapter. Different job sets are solved by the EGOP method, the analytical solution and the GAMS, then the results are compared in the fourth chapter. In the last chapter, results are evaluated and recommendations are mentioned.

2. PROBLEM DESCRIPTION AND MATHEMATICAL MODEL

2.1 Problem Description

In this paper, a multi-objective scheduling problem is designed to minimize the total tardiness and the total energy consumption of the jobs in a single machine manufacturing system.

Setup times of the jobs are mostly included in the processing times of the jobs in manufacturing systems. Although the scheduling of all jobs changes, the total processing time does not change. The processing energy consumption of the machine per unit time is the same, so the amount of energy required to process all jobs does not change. If energy efficiency is desired, the amount of energy consumed during sequence-dependent setup times will be significant. If the job scheduling changes the total sequence-dependent setup time will change and this will affect the energy consumption behavior of the system. In addition, whether the machine runs at idle during the remaining time excluding the sequence-dependent setup time between two consecutive jobs is another important factor affecting the energy consumption of the system. Therefore, this paper proposes a mathematical model to reduce energy consumption by deciding job scheduling and whether the machine runs at idle or is turned off/on.

The break-even duration (T_{BED}) is defined as the minimum time required for turning off/on the machine. If the idle energy consumption and idle time of the machine is greater than the energy consumption and time required for turning off/on the machine, the machine must be turned off to consume less time and less energy [22]. Equation (1) is given as:

$$T_{BED} = \max\,(E_{on\text{-}off} / P_I\,,\; T_{on\text{-}off}) \tag{1}$$

There are two decisions that affect total energy consumption behavior in the multi-objective model. The first decision is the scheduling of jobs. The second is that the machine runs at idle or is turned off/on.

The research problem is explained on a 3 jobs problem with the single machine. The processing times, the arrival times, the due dates and the sequence-dependent setup times in hours are given below in Table 1 and Table 2. The idle energy consumption per unit time (P_I) is 10 kW, the setup energy consumption per unit time (P_H) is 20 kW, the energy consumption when the machine is turned off and then on ($E_{on\text{-}off}$) is 30 kW.h, the time for turning off/on the machine ($T_{on\text{-}off}$) is 1 h and T_{BED} is calculated below and 3 h. These values are randomly generated.

$$T_{BED} = \max\,(E_{on\text{-}off} / P_I\,,\; T_{on\text{-}off}) = \max\,(30 / 10,\, 1) = 3 \text{ h}$$

Table 1. Processing times, arrival times and due dates of the 3 jobs problem

Jobs	Processing time	Arrival time	Due date
j_1	3	0	12
j_2	2	14	27
j_3	4	8	18

Table2. Sequence-dependent setup times of the 3 jobs problem

Sequence-dependent setup time	j_1	j_2	j_3
j_0	2	1	2
j_1	0	1	5
j_2	4	0	4
j_3	3	1	0

When the previous job is completed, if the subsequent job is in the manufacturing system for processing, the subsequent job is processed without delay after the setup time between consecutive jobs is completed. However, if the subsequent job is not yet in the manufacturing system when the previous job is completed, it is decided to run or turned off/on the machine during the remaining time after excluding setup time between consecutive jobs to avoid excessive energy consumption. In addition, the setup process can be completed before a job arrives in the manufacturing system.

Gantt chart for some feasible solutions is demonstrated in Fig. 1. The total tardiness and the total energy consumption calculated as a result of scheduling are given in Table 3. When the results are examined, it can be seen that Solution1 is better than Solution4 and Solution3 is better than Solution2. In addition, the total tardiness of Solution1 is smaller than the total tardiness of Solution3 and the total energy consumption of Solution3 is smaller than the total energy consumption of Solution1. The results in Solution1 and Solution3 show that the two objectives are in an opposite correlation with each other.

The total energy consumption of Solution1 and the total energy consumption of Solution3 are the energy consumption during sequence-dependent setup times due to different job scheduling. Different total energy consumption values are obtained as a result of two different schedules. It clearly shows that different schedules change the total setup energy consumption and the sequence-dependent setup times should be considered in an energy-efficient model.

Some feasible solutions are shown in Fig. 2. Solution1 and Solution3 marked in red on the Pareto front are non-dominanted solutions. The decision-maker may choose one of these non-dominant Pareto solutions. At this stage; depending on the priority of the manufacturing system, the decision-maker can choose one of these two non-dominanted solutions or make a decision using a method. The weighted additive utility function is preferred to decide on the best solution in this paper.

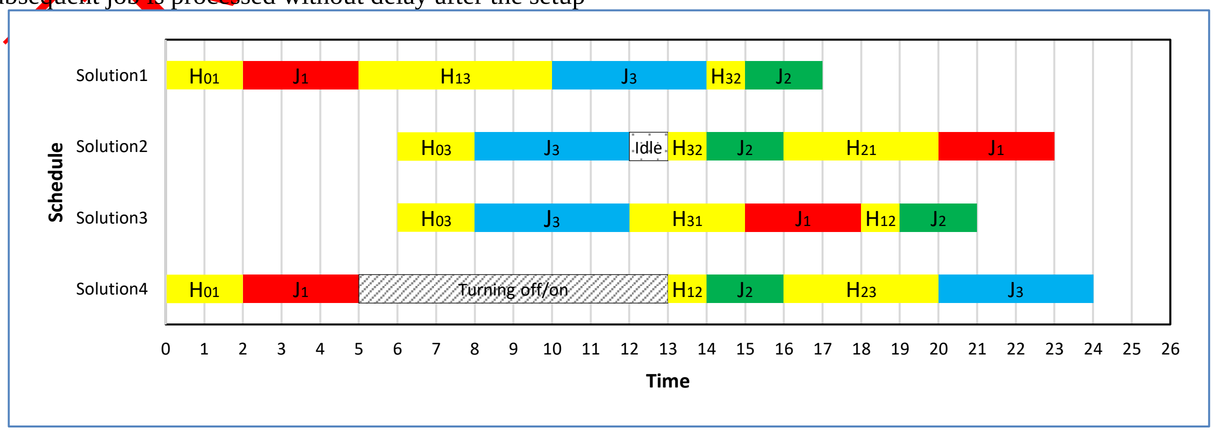

Fig. 1. Gantt chart for some feasible solutions of the 3 jobs problem

Table 3. Total tardiness and total energy consumption values of the 3 jobs problem

Solution	Total tardiness	Total energy consumption
Solution1	0	160
Solution2	11	150
Solution3	6	120
Solution4	6	170

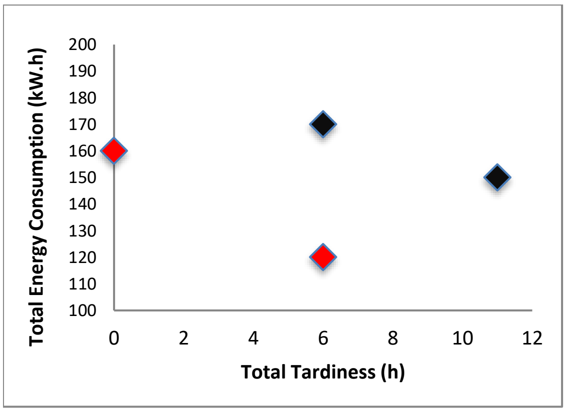

Fig. 2. Some feasible solutions for the 3 jobs problem

2.2 Problem Assumptions

- The processing time, the arrival time, the due date and the sequence-dependent setup times of each job are known before scheduling.
- The machine can process one job at a unit time.
- A job cannot be interrupted until it is completed.
- Jobs are independent of each other.
- The machine is always available in the manufacturing system.
- Each job is processed once.
- The objective function calculates energy consumption during the total sequence-dependent setup time, idle time and turning off/on time of the machine. The energy consumption during the total processing time, the initial turning on time and the last turning off time of the machine is not taken into account as these are the same for all schedules.
- The average energy consumption of the sequence-dependent setup time per unit time is fixed.
- The time required for turning off/on the machine and the average energy consumption during that time are fixed.
- The average idle energy consumption of the machine per unit time is fixed.

2.3 Mathematical Model

A multi-objective mathematical model that minimizes the total tardiness and the total energy consumption in a single machine manufacturing system is presented below.

Parameters and decision variables

- n is the number of jobs
- i and j are the index of jobs (i and $j = 1,2,...,n$)
- P_j is the processing time for job j
- C_j is the completion time for job j
- d_j is the due date for job j
- r_j is the arrival time for job j
- T_j is the tardiness for job j
- S_j is the starting time for job j
- H_{ij} is the sequence-dependent setup time between consecutive job i and job j
- P_I is the idle energy consumption per unit time when the machine runs at idle
- P_H is the setup energy consumption per unit time when the job is in setup
- $E_{on\text{-}off}$ is the energy consumption when the machine is turned off and then on
- $T_{on\text{-}off}$ is the minimum time for turning off/on the machine
- T_T is the total tardiness when all jobs are processed
- E_T is the total energy consumption when all jobs are processed
- α_{ij} is the remaining time after excluding setup time between consecutive job i and job j
- Y_{ij} is the state of the machine during the remaining time after excluding setup time between two consecutive jobs (job i and job j are two successive jobs) when the machine runs at idle

$$Y_{ij} = \begin{cases} 0, & \textit{If the machine runs at idle} \\ 1, & \textit{If the machine is turned off} \end{cases}$$

- $$X_{ij} = \begin{cases} 1, & \textit{If job i is processed just before job j} \\ 0, & \textit{otherwise} \end{cases}$$

Objective functions

$$\min \left(\sum_{j=1}^{n} \max \left(Cj - dj, 0 \right) \right) \quad \forall j = 1,2,\dots,n \qquad (2)$$

$$\min \Big(P_H \sum_{i=0}^{n} \sum_{j=1 \neq i}^{n} Hij \,.\, Xij + \left(P_I \sum_{i=1}^{n} \sum_{j=1 \neq i}^{n} \left((Sj - Ci) - Hij \right) (1 - Yij)\, Xij + \sum_{i=1}^{n} \sum_{j=1 \neq i}^{n} (Eon - off)\, Yij\, Xij \right) \Big) \qquad (3)$$

Constraints

$$((Sj - Ci) - Hij) = \alpha_{ij} \tag{4}$$

$$Y_{ij} = \begin{cases} 0\,, & \alpha_{ij} \leq T_{BED} \quad \forall j = 1,2,\dots,n \\ 1\,, & \alpha_{ij} > T_{BED} \quad \forall i = 0,1,2,\dots,n \neq j \end{cases} \tag{5}$$

$$S_j \geq r_j \qquad \forall j = 1,2,\dots,n \tag{6}$$

$$S_j = \begin{cases} C_i + H_{ij}\,, & r_j \leq C_i + H_{ij} \\ r_j\,, & r_j > C_i + H_{ij} \end{cases}$$

$$\forall j = 1,2,\dots,n \qquad \forall i = 0,1,2,\dots,n \neq j \tag{7}$$

$$\textstyle\sum_{i=0}^{n} Xij = 1 \qquad \forall j = 1,2,\dots,n \neq i \tag{8}$$

$$C_j = S_j + P_j \qquad \forall j = 1,2,\dots,n \tag{9}$$

$$S_j \geq 0 \qquad \forall j = 1,2,\dots,n \tag{10}$$

$$C_0 = 0 \tag{11}$$

Equation (2) indicates the objective to minimize the total tardiness of all jobs. Equation (3) states the objective to minimize total energy consumption. Equation (4) defines the remaining time after excluding setup time between consecutive jobs. Equation (5) means that if the remaining time after excluding setup time between consecutive jobs is less than the break-even duration, the machine should run at idle, but if it is greater than the break-even duration, the machine should be turned off. Equation (6) describes that a job cannot be processed on the machine before it arrives in the manufacturing system. Equation (7) shows that when the previous job and then the sequence-dependent setup between consecutive jobs are completed, if the subsequent job is in the manufacturing system, it starts to be processed; otherwise, the arrival time of the subsequent job is equal to the starting time of this job. Equation (8) indicates the status of consecutive jobs. Equation (9) ensures that the completion time of a job is equal to the sum of the starting time and the processing time of that job. Equation (10) imposes that the starting time of a job is equal to or greater than zero. Equation (11) guarantees that the completion time of a default job at the initial position in a job scheduling is zero.

3. STRUCTURE OF PROPOSED EGOP METHOD

In this paper, the EGOP method based on GA, a heuristic method, is developed to solve the multi-objective optimization problem. The flow chart of the EGOP method is presented in Fig. 3.

3.1 Encoding Representation

Since the problem is a scheduling problem, each job is expressed with an integer. Integers from 1 to n are generated in scheduling for n jobs. These numbers represent jobs, that is, genes. Each of the different sequences of n jobs symbolizes a solution, namely a chromosome. The chromosome consists of as many genes as the number of jobs. For example, in a single machine problem with 5 jobs, the numbers 1, 2, 3, 4, 5 represent jobs and each of the different sequences such as 12345, 25431, 54321 indicates a solution for the problem.

3.2 Generation Of The Initial Population

All individuals of the initial population are randomly generated under certain constraints. If the first job at the time zero is available in the manufacturing system or the sequence-dependent setup still remains when the job arrives in the manufacturing system, the job is processed as soon as the setup is completed. However, if the arrival time of the first job is greater than the sequence-dependent setup time, the arrival time of the first job is equal to the starting time of this job. The setup is completed just before processing. Moreover, the machine is turned on just before the setup of the first job. If the second job is available in the manufacturing system at the completion time of the first job, the second job is processed after the sequence-dependent setup. However, if the second job is not available in the manufacturing system, the second job is processed when it arrives at the manufacturing system. Other jobs in the sequence are scheduled in the same way.

3.3 Fitness Function

Fitness functions are used to determine the quality of solutions in the relevant population. GA evaluates solutions according to their fitness function. The higher fitness value of an individual is, the higher the chance of being chosen in the next generation is. In general, fitness depends on the objective function. In this paper, *U(k)'* (Equation 15) is transformed into a fitness function *F(k)* for solution *k* (Equation 12) as follows [10]:

$$F(k) = 1 / U(k)' \tag{12}$$

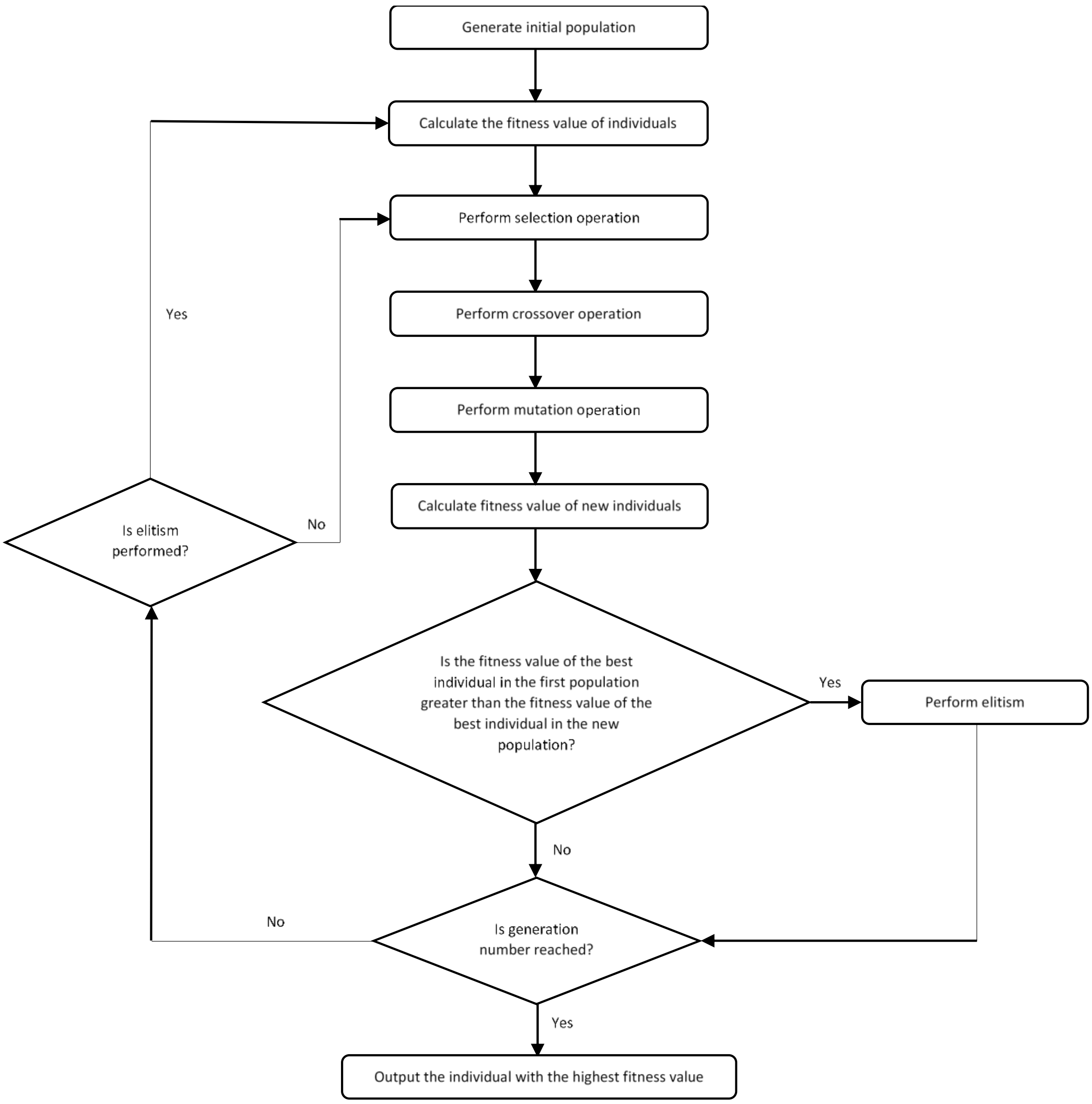

Fig. 3. Flow chart of the EGOP method

3.4 Selection Operation

Reproduction operations allow better individuals in a population to replicate more [23]. The aim is to eliminate individuals with lower fitness values and to reproduce individuals with higher fitness values more [24].

In this paper, the stochastic universal sampling is used as the selection operation. Although individuals with higher fitness value are more likely to be included in the next generation, individuals with lower fitness value can also be prevented from disappearing completely in this method. This allows the algorithm to search at more points and obtain a better solution [25]. Steps of the stochastic universal sampling selection operation are described below:

i. The roulette wheel is divided into n equal parts for n chromosomes in the population.
ii. Fitness values are found for each chromosome and the probability function (Equation 13) is calculated as follows [26]:

$$P_k = F_k / \left(\sum_{k=1}^{n} F_k\right) \tag{13}$$

F_k = Fitness function of chromosome k
P_k = Probability function of chromosome k
n = Population size

iii. Individuals are placed on the wheel according to their probability values. A random number is generated. Other numbers are calculated by adding 1/n to the generated number. Chromosomes are selected according to the numbers falling into the area covered by the chromosomes.

3.5 Crossover Operation

In this paper, the order-based crossover [25] is converted into a suitable crossover operation considering the nature of the problem. The steps of the crossover operation are described below:

i. Individuals are selected in the current population according to the determined crossover rate.
ii. Selected individuals are matched randomly.
iii. Random numbers 0 and 1 are generated for each gene of the first individual. At this stage, genes are selected according to which of 0 and 1 is more, to eliminate the possibility of no crossover operation. The values of the selected genes are marked in the second individual. The genes selected in the first individual replace genes marked in the second individual, respectively. The same crossover operation is applied to the second individual.
iv. The offspring replace parent individuals.

An example of the crossover operation for 6 jobs is illustrated in Fig. 4. Random numbers 1 and 0 are generated for the first parent. The 1st, 4th, 5th and 6th genes (2, 1, 3 and 6 jobs) indicated by the number '1' in the first parent are selected. 2, 1, 3 and 6 jobs are determined in the second parent. 2, 1, 3 and 6 jobs in the first parent replace the same jobs in the second parent, respectively. Thus, the second child is obtained. The same procedure is also applied in order to obtain the first child.

	Stage1	Stage2
Parents:	P_1: 2-4-5-1-3-6 1 0 0 1 1 1	P_2: 5-2-6-4-1-3 1 0 0 1 1 1
	P_2: 5-***2***-***6***-4-***1***-***3***	P_1: 2-***4***-***5***-***1***-***3***-6
Offspring:	C_2: 5-2-1-4-3-6	C_1: 2-5-4-1-3-6

Fig. 4. An example for order-based crossover operation

3.6 Mutation Operation

The arbitrary two-job change [25] is chosen as the mutation operation. The steps of the mutation operation are described below (Fig. 5):

i. Individuals are selected in the current population according to the determined mutation rate.
ii. Two genes are randomly selected from each individual and then these genes are displaced.
iii. The Offspring replace parent individuals.

Parent:	P_1: 6-**3**-5-2-4-**1**
Offspring:	C_1: 6-1-5-2-4-3

Fig. 5. An example for arbitrary two-job change mutation operation

3.7 Elitism

Elitism is a method applied to preserve elite solutions so that they do not disappear during the evolutionary process. This method can generally accelerate the convergence of GAs [27]. The steps of the elitism operation are described below:

i. S_k is identified as the best solution in the population P_k.
ii. The algorithm is performed for the population P_k. S_{k+1} is determined as the best solution in the population of P_{k+1}.
iii. If S_k is better solution than the solution S_{k+1}, the worst solution in the population P_{k+1} is removed from the population and the best solution S_k in the population P_k is added to the population P_{k+1} [28].

3.8 Stopping Criterion

The generation number is selected as the stopping criterion in this paper. The algorithm stops when it reaches the specified number of generations. The individual with the best fitness value in the final population becomes the solution to the problem [26].

4. COMPUTATIONAL PERFORMANCE AND DISCUSSION

In this chapter, different job problems are solved by the EGOP method, the analytical solution and the GAMS. The obtained results are analyzed.

4.1 Analysis Of Proposed EGOP Method In The Scope Of 5 Jobs Problem

In order to make the proposed EGOP method more understandable, the 5 jobs problem is analyzed. The processing times, the arrival times and the sequence-dependent setup times of the jobs are created between [1, 10], [0, 50] and [1, 5] for the datasets of all scheduling problems, respectively. The due dates of the jobs is generated between [($P_j + r_j + H_{max}$), ($P_j + r_j + H_{max} + 4\sum_{j=1}^{n} P_j/n$)] values with the formula taken from Kurose and Ross (2013) [29]. The idle energy consumption per unit time is 10 kW, the setup energy consumption per unit time is 20 kW, the energy consumption when the machine is turned off and then on is 30 kW.h and the time for turning off/on the machine is 1 h. These values are randomly generated and T_{BED} is 3 h. The same values are used in all problems.

The processing times, the arrival times, the due dates and the sequence-dependent setup times for a 5 jobs problem are given below in Table 4 and Table 5. Control parameter values are given in Table 6. The results of the EGOP method, the GAMS and the analytical solution are obtained using the MATLAB program on a computer with Intel (R) Core (TM) I5-3470 CPU 3.20 GHz, 4.00 GB RAM and 64-bit processor.

Table 4. Processing times, arrival times and due dates of the 5 jobs problem

Jobs	Processing time	Arrival time	Due date
j_1	8	0	32
j_2	10	4	30
j_3	8	2	33
j_4	3	10	22
j_5	10	4	31

Table 5. Sequence-dependent setup times of the 5 jobs problem

Sequence-dependent setup time	j_1	j_2	j_3	j_4	j_5
j_0	2	1	5	2	5
j_1	0	1	4	5	1
j_2	4	0	2	4	3
j_3	3	1	0	1	5
j_4	3	2	4	0	5
j_5	1	3	2	2	0

Table 6. Control parameter values of the 5 jobs problem

Parameter	Value
Population size	10
Crossover rate	1
Mutation rate	0.5
Generation number	5

There are feasible and non-dominanted pareto solutions in multi-objective optimization problems. A number of non-dominanted pareto solutions can be achieved to minimize the total tardiness and the total energy consumption. Various approaches have been improved to solve multi-objective optimization problems. In this paper, the weighted additive utility function, which is one of the best-known methods due to its simplicity, wide usage and ability to determine non-dominanted solutions, is used to decide the best solution of the multi-objective problem. f_{1k} and f_{2k} are the first and second objective functions of chromosome k in the population, respectively. The weighted additive utility function $U(k)$ (Equation 14) for chromosome k with two objectives can be defined as follows [10]:

$$U(k) = w_1 f_{1k} + w_2 f_{2k} \tag{14}$$

w_1 and w_2 are the importance weights of each objective function. The sum of the weights should generally be equal to one ($w_1 + w_2 = 1$) and each of the weights is a positive number ($w_1 \geq 0$; $w_2 \geq 0$).

The weight of each objective is determined by the decision-maker. All objective functions are converted into a single objective function in order to solve easily. In addition, it is difficult to assess importance weights because the objective functions are in different scales. All objective functions can be normalized and compared on the same scale. The weighted additive utility function with normalized objective functions ($U(k)'$) (Equation 15) can be defined as follows [10]:

$$U(k)' = w_1 f_{1k}' + w_2 f_{2k}' \tag{15}$$

f_{1k}' and f_{2k}' are normalized objective functions of f_{1k} and f_{2k}, respectively. The normalized f_{1k}' and f_{2k}' (Equation 16 and Equation 17) are defined below:

$$f_{1k}' = f_{1k} / \sum_{k=1}^{n} f_{1k} \tag{16}$$

$$f_{2k}' = f_{2k} / \sum_{k=1}^{n} f_{2k} \tag{17}$$

Table 7 shows the solutions obtained by the EGOP method for the 5 jobs problem. The total energy consumption of Solution6 is smaller than the total energy consumption of Solution10. The total tardiness of Solution10 is smaller than the total tardiness of Solution6. Solution6 and Solution10 are non-dominated solutions. At this stage, one of the solutions is selected using the weighted additive utility function. It is decided that importance weights are equal and 0.5. Solution6 is obtained as the best solution. The computation time is 0.172 s.

Table 7. Total tardiness and total energy consumption values obtained by EGOP method for the 5 jobs problem

Solution	Total tardiness	Total energy consumption
Solution1	36	300
Solution2	39	200
Solution3	55	380
Solution4	42	200
Solution5	43	260
Solution6	30	160
Solution7	38	300
Solution8	56	260
Solution9	32	160
Solution10	27	180

Fig. 6 shows all solutions obtained by the analytical solution for the 5 jobs problem under the constraints of the model. Red dots are non-dominated solutions on the pareto front. The total tardiness and the total energy consumption of these non-dominated solutions are given in Table 8. Solution1 is obtained as the analytical solution using the weighted additive utility function. The computation time is 0.103 s. In addition, the same problem is solved by the GAMS. The total tardiness and the total energy consumption is obtained as 30 and 160, respectively. The computation time is 45.981 s. The EGOP method finds the solution obtained by both the GAMS and the analytical solution in a short time.

Table 9. Processing times, arrival times and due dates of the 6 jobs problem

Jobs	Processing time	Arrival time	Due date
j_1	8	25	57
j_2	7	45	82
j_3	5	35	63
j_4	6	35	65
j_5	5	6	18
j_6	9	10	25

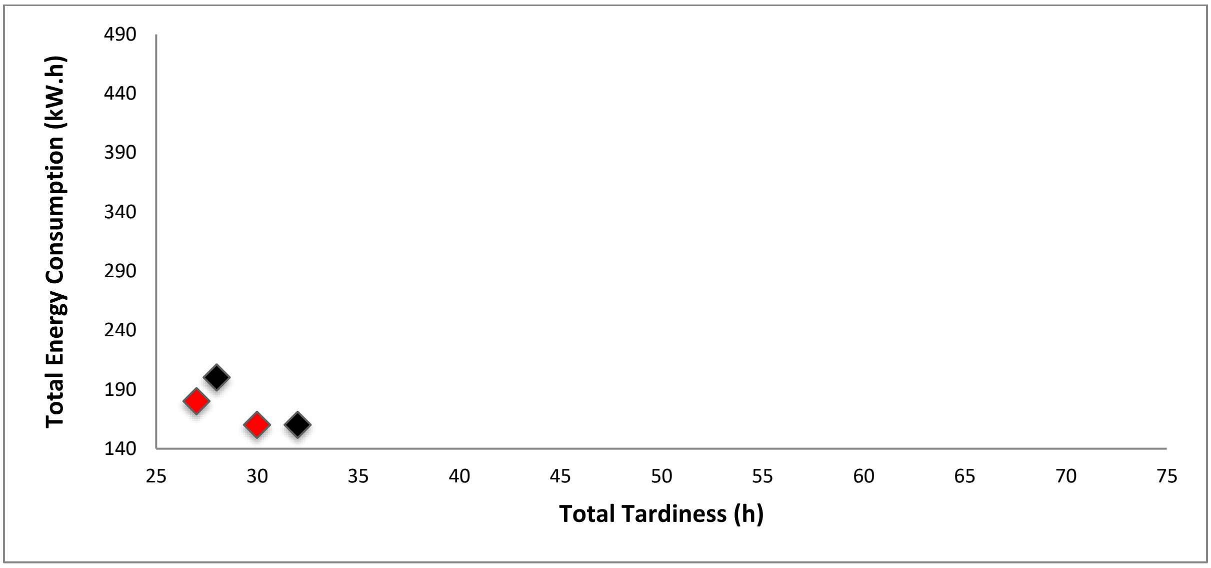

Fig. 6. All solutions obtained by analytical solution for the 5 jobs problem

Table 8. Non-dominated solutions obtained by analytical solution for the 5 jobs problem

Solution	Total tardiness	Total energy consumption
Solution1	30	160
Solution2	27	180

4.2 Evaluation Of Proposed EGOP Method

To evaluate the effectiveness of the EGOP method in terms of results and the computation times, the 6, 7 and 8 jobs problems are solved by the EGOP method, the GAMS and the analytical solution. The processing times, the arrival times, the due dates and the sequence-dependent setup times for the 6, 7 and 8 jobs problems are given in Table 9, Table 10, Table 11, Table 12, Table 13 and Table 14. Control parameter values are given for the 6 jobs problem in Table 15 and for the 7 and 8 jobs problems in Table 16. The EGOP method, the analytical solution and the GAMS results and the computation times are given in Table 20.

Table 10. Sequence-dependent setup times of the 6 jobs problem

Sequence-dependent setup time	j_1	j_2	j_3	j_4	j_5	j_6
j_0	3	5	4	4	1	2
j_1	0	2	2	5	5	1
j_2	3	0	5	5	2	5
j_3	2	3	0	5	1	3
j_4	5	4	5	0	4	5
j_5	2	2	2	5	0	3
j_6	2	4	3	1	1	0

Table 11. Processing times, arrival times and due dates of the 7 jobs problem

Jobs	Processing time	Arrival time	Due date
j_1	3	3	14
j_2	8	39	63
j_3	1	11	26
j_4	6	8	36
j_5	9	3	18
j_6	4	3	12
j_7	1	14	36

Table 12. Sequence-dependent setup times of the 7 jobs problem

Sequence-dependent setup time	j_1	j_2	j_3	j_4	j_5	j_6	j_7
j_0	5	4	3	2	4	5	5
j_1	0	5	3	2	5	3	3
j_2	5	0	1	3	4	1	1
j_3	1	3	0	3	1	3	5
j_4	1	2	5	0	3	4	2
j_5	4	1	1	1	0	3	3
j_6	1	3	2	1	1	0	1
j_7	1	1	4	4	3	2	0

Table 13. Processing times, arrival times and due dates of the 8 jobs problem

Jobs	Processing time	Arrival time	Due date
j_1	1	40	61
j_2	3	23	40
j_3	5	5	17
j_4	2	47	72
j_5	5	7	34
j_6	8	11	36
j_7	9	48	79
j_8	3	5	18

4.2.1 A case study with 6 jobs problem

All solutions and non-dominated solutions with red dots obtained by the analytical solution for the 6 jobs problem are illustrated in Fig. 7. Non-dominated solutions obtained by the analytical solution for this problem are presented in Table 17. Solution1 is determined as the best solution among the non-dominated solutions in the analytical solution. The total tardiness and the total energy consumption are obtained as (0-320) by the GAMS, respectively. The proposed EGOP method finds the total tardiness and the total energy consumption of the jobs as (0-330), respectively. The EGOP method achieves the same solution obtained by the analytical solution. The EGOP method obtains the same tardiness value as the GAMS, but the total energy consumption obtained by the EGOP method is 3.125% more than the total energy consumption obtained by the GAMS. On the other hand, as seen in Table 20, the EGOP (computation time= 0.524 s) calculates in a shorter time than the GAMS (computation time= 218.297 s) and the analytical solution (computation time= 1.863 s).

Table 14. Sequence-dependent setup times of the 8 jobs problem

Sequence-dependent setup time	j_1	j_2	j_3	j_4	j_5	j_6	j_7	j_8
j_0	4	3	1	2	5	4	4	4
j_1	0	4	2	4	4	1	5	5
j_2	5	0	4	5	3	4	5	5
j_3	5	3	0	5	2	2	5	1
j_4	2	5	5	0	1	4	2	5
j_5	3	5	5	1	0	1	4	1
j_6	5	1	5	5	1	0	1	1
j_7	1	5	4	2	2	5	0	5
j_8	5	5	1	3	5	4	2	0

Table 15. Control parameter values of the 6 jobs problem

Parameter	Value
Population size	15
Crossover rate	1
Mutation rate	0.5
Generation number	20

Table 16. Control parameter values of the 7 and 8 jobs problems

Parameter	Value
Population size	40
Crossover rate	1
Mutation rate	0.5
Generation number	70

Table 17. Non-dominated solutions obtained by analytical solution for the 6 jobs problem

Solution	Total tardiness	Total energy consumption
Solution1	0	330
Solution2	4	310
Solution3	7	300
Solution4	18	290
Solution5	37	250
Solution6	106	240

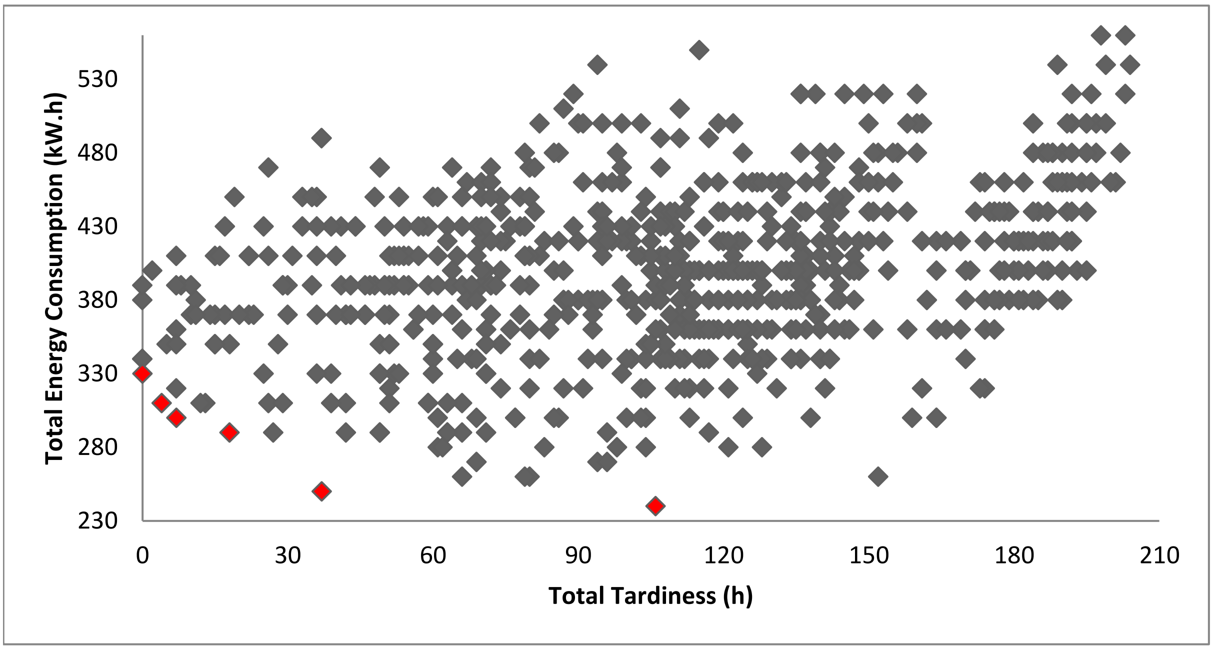

Fig. 7. All solutions obtained by analytical solution for the 6 jobs problem

4.2.2 A case study with 7 jobs problem

All solutions and non-dominated solutions with red dots obtained by the analytical solution for the 7 jobs problem are demonstrated in Fig. 8. Solution2 is obtained as the best solution among the non-dominated solutions in the analytical solution given in Table 18. When solving with GAMS, the total tardiness and the total energy consumption are found as (12-280), respectively. In order to assess the performance of the proposed EGOP method, the same problem is solved by the EGOP method. In Table 20, it is clearly seen that the EGOP achieves the best solution obtained by the analytical solution (computation time= 100.495 s) and the GAMS (computation time= 5437.015 s) solution in a very short computation time of 5.539 s.

Table 18. Non-dominated solutions obtained by analytical solution for the 7 jobs problem

Solution	Total tardiness	Total energy consumption
Solution1	10	290
Solution2	12	280
Solution3	39	240
Solution4	52	220
Solution5	176	210

4.2.3 A case study with 8 jobs problem

In Fig. 9, all solutions and non-dominated solutions with red dots obtained by the analytical solution are shown for the 8 jobs problem. In the first step, by the analytical solution, Solution4 is obtained as the best solution among the non-dominated solutions represented in Table 19. In the second step, to prove that EGOP is a viable solution method, the EGOP method is run. As a result, the EGOP method finds the same feasible solution (5-310) as the analytical solution. In the last step, the total tardiness and the total energy consumption are found by the GAMS as (3-330), one of the pareto solutions, respectively. The total tardiness value obtained by the GAMS is smaller than the total tardiness value obtained by the EGOP method, but the total energy consumption value obtained by the EGOP method is smaller than the total energy consumption value obtained by the GAMS. As seen in Table 20, the EGOP method performs another non-dominated solution, which is not worse than the non-dominated solution obtained by the GAMS (computation time= 18633.677 s), in a remarkably short computation time of 5.944 s. Similarly, the EGOP method solves this problem in an extremely shorter computation time than the analytical solution (computation time= 6162.845 s).

Table 19. Non-dominated solutions obtained by analytical solution for the 8 jobs problem

Solution	Total tardiness	Total energy consumption
Solution1	0	400
Solution2	1	370
Solution3	3	330
Solution4	5	310
Solution5	71	290
Solution6	74	270
Solution7	121	250
Solution8	241	240

Table 20. Comparison of total tardiness and total energy consumption values and computation times obtained by EGOP method, GAMS and analytical solution

	EGOP method			GAMS			Analytical solution		
Jobs	Total tardiness	Total energy consumption	Computation time	Total tardiness	Total energy consumption	Computation time	Total tardiness	Total energy consumption	Computation time
6 jobs	0	330	0.524	0	320	218.297	0	330	1.863
7 jobs	12	280	5.539	12	280	5437.015	12	280	100.495
8 jobs	5	310	5.944	3	330	18633.677	5	310	6162.845

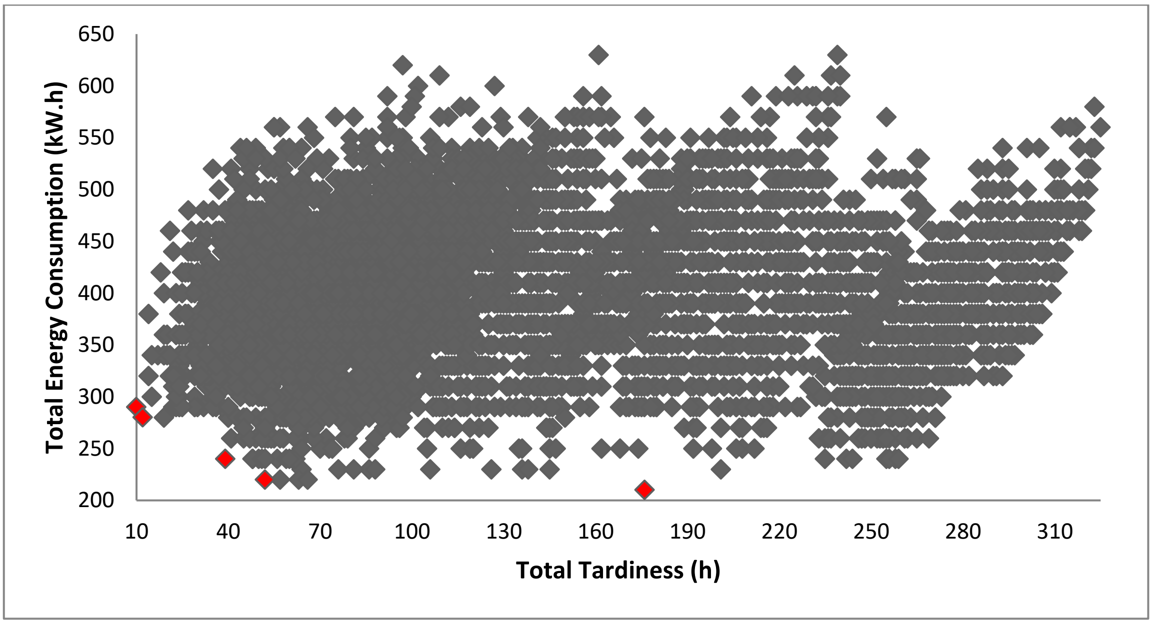

Fig. 8. All solutions obtained by analytical solution for the 7 jobs problem

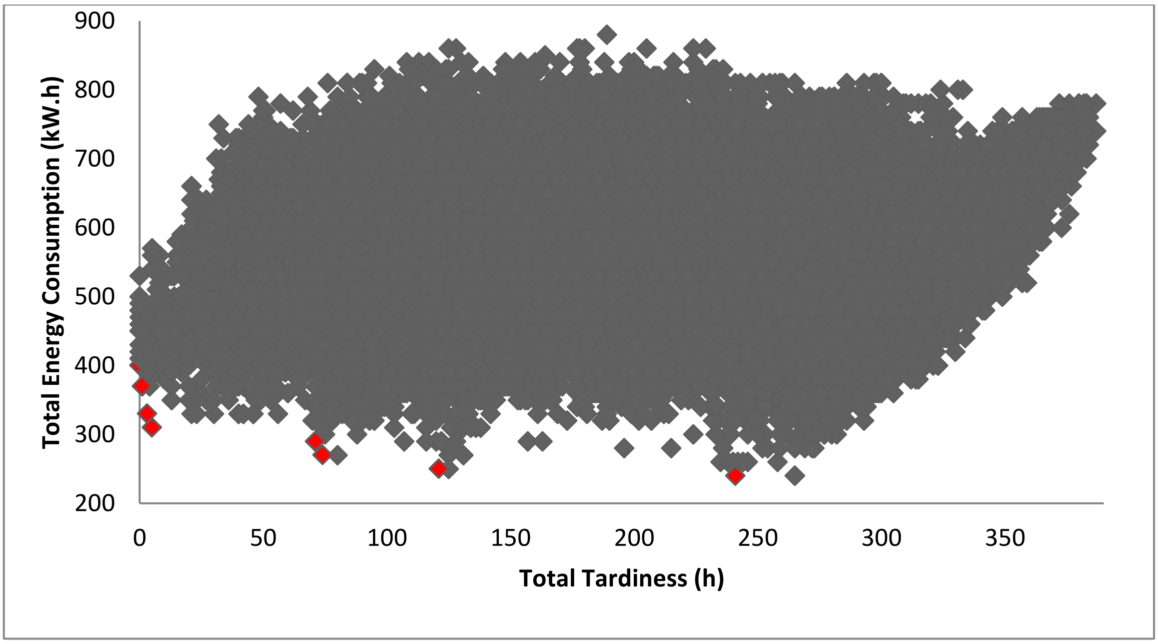

Fig. 9. All solutions obtained by analytical solution for the 8 jobs problem

4.3 Discussion

In scheduling problems, as the complexity level of the problem increases, it is difficult to find an exact solution and takes considerable a long time to solve the problem. For this reason, GA, which is one of the heuristic methods, was preferred to obtain feasible solutions in acceptable time in several scheduling studies [12,26,27,28] in the literature.

Shrouf et al. (2014) developed an analytical solution to obtain the optimal solution. They stated that the analytical solution provided the appropriate solution in an acceptable time for short problems, but GA was preferred because of the much shorter computation time for longer problems [12].

In this study, a comparison of the EGOP method, the analytical solution and the GAMS solution is presented in order to demonstrate the effectiveness of the proposed GA-based EGOP method. The results and computation times presented in Table 20 prove that the proposed GA-based EGOP method obtains feasible solutions in a much shorter time than the analytical solution and the GAMS.

5. CONCLUSION

Setup times can frequently be included in the processing time of jobs in the scheduling problems. As the Schedule of the jobs changes, the total sequence-dependent setup time changes. If energy consumption is to be reduced in a manufacturing system, sequence-dependent setup times should be considered. In this paper, first, a MINLP mathematical model that takes into account the energy consumption is developed for a single machine scheduling problem with sequence-dependent setup times. Furthermore, the model determines whether the machine runs at idle or is turned off/on. Second, this model aims to minimize the total tardiness of jobs that have different arrival times as well as the total energy consumption.

GA-based EGOP method is proposed to solve this NP-hard problem. In order to validate the effectiveness of the EGOP method, the proposed heuristic EGOP method is compared with the GAMS and the analytical solution. The job problems are solved by the proposed EGOP method, the GAMS and the analytical solution. It is generally not possible to obtain a single feasible solution that has the smallest values of the two objectives among the non-dominated solutions on the pareto front in multi-objective problems. Hence, the weighted additive utility function is used to obtain the best solution among the non-dominated solutions.

Computation time is an important criterion for manufacturing systems. At the same time, job scheduling is a key issue so as not to delay the jobs in manufacturing systems. Therefore, various mathematical and heuristic methods are used to solve scheduling problems in manufacturing systems. As in this paper, to obtain a feasible solution, all solutions can be obtained or a program such as the GAMS can be used according to the structure of the problem. However, it may take a long time to obtain a viable solution with these methods. Especially, as the number of jobs in a scheduling problem increases, the computation time can become extremely high. For this reason, an heuristic algorithm that provides a feasible solution in a much shorter time can be preferred for scheduling problems. When the computation times and solutions obtained by the proposed EGOP method, the GAMS and the analytical solution are examined in this paper, it is clearly seen that the EGOP method is an effective method to solve this multi-objective scheduling problem. So, the proposed EGOP method may be preferred to solve larger job problems. The solutions and computation times also verify the effectiveness of the proposed EGOP method.

In the future, job problems targeting energy efficiency can be considered by adding many different features such as machine breakdown and priority of jobs to multi-machine systems. In addition, the studies may include mathematical models that minimize energy consumption when different energy consumption prices occur in separate time periods in manufacturing environments.

DECLARATION OF ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Elif TARAKÇI: Resarching, Conceptualization, Methodology, Coding, Performing the experiments. Analyzing the results. Writing the paper.

Abdül Halim ZAİM: Conceptualization, Methodology. Analyzing the results. Reviewing and editing the paper.

Oğuzhan ÖZTAŞ: Coding. Reviewing and editing the paper.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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