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Multi-objective green flowshop scheduling problem under uncertainty: Estimation of distribution algorithm

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A B S T R A C T

Flowshop scheduling is a well-known NP-hard problem. Sustainable scheduling problem has recently attracted the attention of researchers due to the importance of energy and environmental issues. Moreover, considering uncertainty in the real-world manufacturing environment makes the problem more realistic. Insufficient researches on energy issue under uncertainty were encouraging to conduct this study. In this paper, a mathematical formulation and a scenario-based estimation of distribution algorithm (EDA) are proposed to address the flowshop scheduling problem to optimize makespan and energy consumption under uncertainty. To the best of knowledge, scenario-based EDA has not been used to solve this problem. In this study, it is assumed that the processing times are stochastic and follow the normal distribution with known average and variance. In this problem, the machines have different processing speeds and reducing machine speeds increase makespan and decrease energy consumption and conversely. So, machine speeds affect the objective values which are conflicting. The proposed formulation assigns speeds to machines as well as decides about job sequencing. Different scenarios are used to consider stochastic processing times; so, the E-model approach is used for evaluation of objective functions. At the end, the computational experiment is presented and its results show promising performance of EDA in comparison to another algorithm. The proposed algorithm as practical method gives through insight about the problem and because of the suitable number of solutions in the Pareto set, the decision maker has more choice compared to the competing algorithm.

1. Introduction

Industrial world faces many challenges. Although production criteria is important and have always been considered in decision making, today's world condition requires special attention toward environmental issues as well. Population increase followed by consumption increase and loss of energy put the world at risk of energy crisis (Nabavi-Pelesaraei et al., 2016). Furthermore, pollution is a constant follower of energy consumption which is a serious treat for human being (Nabavi-Pelesaraei et al., 2014). Shortage probability of basic materials and energy sources in the future has attracted public attention (Qasemi-Kordkheili and Nabavi-Pelesaraei, 2014). These are the main reasons why optimum energy consumption becomes one of the most critical issues in the world. Researches in various field are trying to optimum energy consumption (Nabavi-Pelesaraei et al., 2017). Although some researches are concerning renewable energy generator (Bahramia and Amini, 2018), but many manufactories lack sufficient facilities to supply energy from renewable sources and still use fossil-based energy sources. Manufacturing industries are often the biggest consumer of energy and producer of pollution (Le et al., 2012). Therefore, manufacturer are under pressure to consider the environmental issues. This is what has caused the emergence of the concept of sustainable and green manufacturing. In recent years, sustainable manufacturing has attracted many researchers (Gahm et al., 2016). However, in this field the way is too long and needs more studies. So, the existence gap in research along with the importance of optimizing energy consumption in the manufacturing units and the related environmental issues and led to conduct this study. Sustainability means meeting our needs without compromising the ability of the next generation to meet their needs (Kuhlman & Farrington 2013). In green manufacturing, particular attention is paid to consumption of energy and raw materials, in general used resources, as well as process outputs such as waste and loss productions and released gases. It can be

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concluded that green manufacturing controls the environmental impacts. The green scheduling problem considers the scheduling that meets green criteria in other to balance power consumption as well as minimize its environmental impacts. Energy optimization as one of the most important criteria involves green and sustainable manufacturing concepts. In this regard, energy issue is considering at three levels in sustainable manufacturing: product level, machine level and production system level (Miguel et al. 2013). This research focuses on the production system level which tries to reduce energy consumption without re-engineering machines or products. Also, the optimal environmental effect and cost-saving will be achieved.

Flowshop scheduling problem is a well-known scheduling problem. As shown by (Johnson, 1954), although this problem with two machines can be solved in the polynomial time, but, the problem with three machines is strongly NP-hard (Garey et al., 1976). In this study flowshop scheduling with makespan objective function is studied considering energy consumption criterion, because it is a common issue in industry units and it is a base for other investigation (Mansouri et al., 2016). published a paper with both makespan and energy consumption objective function for two-machine flowshop problem. This paper generalizes their work to m-machine flowshop problem and unlike their work not in a deterministic state. There are several methods for solving multi-objective optimization problems. New methods for solving multi-objective problems include the Pareto's optimal, heuristic and metaheuristic methods which yield a set of the Pareto solutions (Asgharpoor, 2013). Since m-machine flowshop problem is NP-hard, metaheuristic algorithms are suitable solutions for this kind of problems. That is because of their speed in solving, good qualification of solutions in the large-size instances and generic usage of them. So, in this study, a metaheuristic algorithm is proposed to solve the problem.

Nowadays, special attention is paid to accurate decision making in which uncertainty is getting entangled with a real-world problem. Due to its particular complexity, it was neglected until recent decades. Whereas deterministic optimization problems are formulated with known parameters, the real-world problems almost invariably include some unknown parameters. In most real optimization problems, used values depend on the environmental condition and are not accurate data. Meanwhile, gathering exact information that does not depend on human recognition and judgment is very difficult or even impossible. Regardless of how accurately the model is formulated, data used in the model determines the reliability of it. Scheduling under uncertainty has been studied with four approaches: Reaction scheduling, stochastic programming, robustness and fuzzy programming. Stochastic programming is a mathematical tool for decision making under uncertainty (Mirhassani and Hoshmand Khaligh, 2014). In stochastic programming, it is assumed that unknown data (parameters) are random variables that have a certain probability distribution (Mirhassani and HoshmandKhaligh, 2014). Since manufacturing units have a high dynamic environment and there are many sources of uncertainty, according to researches on shop floor scheduling problem, uncertainty arises mainly from processing times and due dates (Liefooghe et al., 2007). This paper considers uncertain processing times. Since green scheduling is almost a new field, there are not enough studies on this issue considering uncertainty. So, existence gap motivates to conduct this study. This paper will investigate energy consumption under uncertainty to fill this gap.

Considering above explanations, in this study a Permutation Flowshop Scheduling Problem (PFSP) with two opposing objective functions, minimizing makespan and total energy consumption are considered in a way that the processing times are random and follow a normal probability distribution. Scenario approach is used in this study, which means that different values are considered for the parameters. Scenario method is scalable and natural toward uncertainty (Miguel & Adriana 2013) that it gives complete and good insight about reality and its computational cost is less than simulation in which changing the values of parameter, changes the values of the objective functions, too. Therefore expected values are used as objective functions. To solve this problem, a scenario-based metaheuristic algorithm called Estimation Distribution Algorithm (EDA) is used that its scenario-based version has not been used for solving this problem.

Accordingly, the main contributions of this study can be summarized as follows:

1) In the field of sustainable scheduling, this paper develops a two-machine flowshop scheduling problem with energy consumption criteria to a m-machine flowshop problem using different machine speeds.
2) This study considers sustainable scheduling under uncertainty and achieves a tradeoff between makespan and total energy consumption.
3) Scenario-based Estimation Distribution Algorithm is proposed to solve the problem and the results were promising. The proposed algorithm combines existence methods (metaheuristic algorithms + scenario method) to solve this problem.

This paper is organized as follows. Section 2 focuses on state of art in the energy consumption and stochastic flowshop problem. Section 3 describes the problem and proposes a model for it. Section 4 presents a metaheuristic for solving the problem. Section 5 provides computational results and at the end there is a conclusion.

2. Literature review

Literature review of this study is divided into two main sections: (i) flowshop scheduling with energy consideration, and (ii) stochastic flowshop scheduling problem.

2.1. Energy-efficient flowshop problem

Investigating existent researches show that there are various approaches to deal with the energy issue in production system level. These attitudes can be divided into three classes.

The first class goal is to reduce energy consumption. It should be noted that reducing carbon emissions and its effects are quite proportional to this class and is achievable by decreasing energy consumption. There are three major strategies that researchers have come up to meet the first-class goal. These strategies are explained more below:

a) Division of production time into different parts such as processing, idle and preparation time in order to reduce idle time (Li et al., 2018). presented a compromising heuristic algorithm to solve hybrid flowshop scheduling problem considering makespan and energy consumption objective functions. They divided production time into two parts of processing operations and stand by state. They attempt to reduce makespan which affect energy consumption and mitigate it (Tang et al., 2016). minimized makespan and energy consumption in a dynamic flexible flowshop problem using an improved particle accumulation optimization algorithm. Unlike the most existence researches on energy issue which are static problems, in this research arrival of new jobs and machine failure are considered as dynamic factors. They used dynamic programming strategy based on a predictive-reactive approach. In their paper, they divided energy in three states: processing, start-up and readiness (Liu et al., 2013). tried to minimize total wasted energy consumption in PFSP. In their proposed model energy consumption is divided into two sections: useful part (during operation) and wasted part (over the idle time). They used a branch and bound algorithm to solve this problem (Zeng et al., 2009). presented a study entitled "Dynamic Scheduling of Multi-Task for Hybrid Flow-Shop Based on Energy Consumption". The two most important aspects of this research are: including a time window for machine idle time as a constraint and considering makespan and energy consumption as objective functions. A particle swarm optimization algorithm is used to solve it (Liu et al., 2008). published their research on hybrid flowshop problem considering energy consumption. They provided mixed-integer nonlinear programming model with objective of minimizing energy consumption and product has delivery time. They used an improved genetic algorithm to solve it. Their approach for energy is dividing the production period into process, idle and preparation times. It should mention that reduction of idle times in this strategy is implicitly satisfied with other objective function of the problem such as makespan.

b) Turning on/off devices in order to save energy when machines are idle (Dai et al., 2013). attempted to minimize makespan and energy consumption in a flexible flow shop problem. The energy approach used in this study was interpreted by analyzing the input energy into the loaded and unloaded output energy. Their energy-saving model utilized the shutdown of machines at idle time and a genetic-simulated annealing algorithm was used to solve it. Recently (Meng et al., 2019), considered the energy-aware flexible job shop scheduling problem. In order to minimize total energy consumption based on two different formulations namely idle time variable and idle energy variable, six mixed integer linear programming models with turning Off/On strategy were proposed.

It is obvious that this approach in long-term will have destructive effects on facilities and it seems impractical. Also, it is not possible for some industrial units to turn off machines during idle times.

c) Using different processing speeds to manage energy usage (Fu et al., 2019). proposed new brain storm optimization algorithm to solve a stochastic flowshop scheduling with makespan and energy consumption objective functions. In their study, machines have different speeds but every machine must process at same speed. Furthermore they used chance-constraint approach for considering uncertainty (Lu et al., 2017). presented a mathematical formulation to minimize makespan and energy consumption in the permutation flowshop problem considering sequence dependent set up and controllable transportation time. They used different transmission speeds which have conflicting effect on makespan and energy consumption. Finally they proposed a new algorithm to solve it. In their study the problem was static. To minimize makespan and energy consumption in two-machine flowshop problem (Mansouri et al., 2016) proposed an integer multi-objective mathematical model with sequence-dependent setup time. In order to considering energy, they used different processing speeds and presented a heuristic namely Schedule Development Heuristic (SDH) to solve the problem. They presented two lower bounds for main subproblems of the model. Our paper improves this work by considering m-machine flowshop under uncertainty (Zhang and Chiong, 2015). used a machine speed scaling framework on jobshop scheduling problem in order to optimize total energy consumption and total weighted tardiness. They proposed a multi-objective hybrid genetic algorithm to solve it. In the deterministic environment (Fang et al., 2011), presented a mixed-integer programming (MIP) model for flowshop problem considering energy peak load, energy consumption, carbon-related effects and makespan. Here, speeds of operations are assumed as an independent variable for changing peak load and energy consumption objectives, and for energy consumption, production cycle comprises the unemployed and employed times.

Note that, in some papers such as (Lin et al., 2015) different strategies were employed to optimize the scheduling results. They developed an integrated model for processing parameter optimization and flowshop scheduling. In this study, for minimizing makespan and carbon footprint simultaneously, a multi-objective teaching—learning-based optimization algorithm was proposed.

The second class decrease energy costs by use of Time of Use (ToU) tariffs and changing production time (Zhang et al., 2014). presented a mathematical formulation for minimizing the cost of electricity and carbon effects and flow time using ToU tariffs without compromising production power. This formulation considered the desired production capacity as a constraint. Their approach is changing production time from high peak time to low peak time (Luo et al., 2013). took into account the cost of machines consuming electricity. In this research, ToU tariffs have been used to consider the energy cost and a multi-objective ant colony algorithm has been used to minimize makespan and energy cost. They changed the start time of operations to reduce cost.

The third class is concerned with reducing energy load and its solution is entering idle time or avoiding simultaneous use of machines (Nagasawa et al., 2015). investigated a robust flowshop scheduling problem with random processing times considering makespan and energy peak. In this paper, at the first stage, they provided an initial schedule without considering processing time fluctuations. At the next step, they used simulation approach to find the best scheduling and the best point to enter idle time (Fang et al., 2013). carried out extensive research on the flowshop problem to minimize makespan. In their model, energy peak is considered as a constraint and an upper bound for energy consumption was considered. They provided two mixed-integer programming models, *i.e.,* discrete model and allocation/positioning model. They used valid inequalities and two heuristic algorithms to solve the problem.

Some studies consider the scheduling problems on two different levels. For example (Yan et al., 2016), presented a multi-level method to minimize makespan and energy consumption in the flexible flowshop scheduling problem. They considered energy in two different levels: machine tool and shop floor level. In this paper, grey relational analysis has been used to optimize the cutting parameter of machines at machine tool level. Then, they used a genetic algorithm to optimize makespan and energy consumption at the shop floor level. They broke down the energy consumption of problem into five parts.

Considering the above explanations, it should be pointed out that objective function of the second class (energy cost) is implicitly achieved by optimizing energy consumption and it was not necessary to consider in this paper. Moreover, third class is usually considered in areas that there is peak load constraint, and it was useless for our general point of view. Thus, the first class has been used in this study. Since the first strategy in this class is implicitly considered in the first objective function of the problem; it seems pointless to plan for idle times because they will be minimized due to makespan. Furthermore, the second strategy is not a wise choose because constantly turning on and off the machines led to early breakdown. So, the third strategy is used to consider the energy issue in this work due to the above reasons.

2.2. Stochastic flowshop problem

Pervious part investigates the literature review of the energy issue. In this subsection, another important aspect of the study is considered: uncertainty.

Uncertainty increase complexity of a problem (Ramazan and Dimitrakopoulos, 2007). Yet after more than a decade investigation on these problems, there is no comprehensive solution for them. Solving of each problem is deeply depending on specific circumstance of it. Note that, changing processing time will change the objective function value. Therefore, with different performances, different objective function will be obtained. There are four relationships for objective function of this situation in the literature: Expected objective function, stochastic objective function, objective function with probability and robust function. Expected objective function is mostly used because it is easy to use.

(Gonzalez-Neira et al., 2017) proposed a simheuristic algorithm which integrated biased randomization and simulation techniques in order to minimize expected makespan in distributed assembly permutation flowshop problem. In their research, the processing and assembly times are random variables. Furthermore, they considered a flexible flowshop problem with total weighted tardiness. They used Integral Analysis Method (IAM) to solve this problem (Fu et al., 2017). considered a stochastic flowshop scheduling with deterioration and learning affect. In this research it is assumed that the processing times follow the normal distribution. A MIP model is formulated to minimize expected makespan and total tardiness. They proposed a firework algorithm to solve it. (Framinan and Perez-Gonzalez, 2015) examined basic issues on estimation of expected makespan for a permutation flowshop scheduling problem when processing times follow log-normal distribution and its mean follows uniform distribution. They used a confidence interval based on the T-Student distribution. They provided an approach for estimating expected makespan with a variable number of repetitive which ensures that error rate is limited with a high probability (Wang et al., 2015). presented an effective two-stage hybrid estimation of distribution algorithm for simulation-based scheduling in a stochastic permutation flowshop problem with uncertain processing time. They used level of processing time variation to define uncertainty of processing times. In this paper, actual processing time is generated by the normal distribution. This algorithm makes use of two-stage simulation model to evaluate selected solutions with makespan objective function. This model firstly used a regression base meta-model to determine the number of selected solutions at a lower computational cost. Then, more accurate but timely simulator is used for evaluating performance of these points (Juan et al., 2014). presented a simulation-optimization algorithm to solve the permutation flowshop problems with uncertain processing time. Their algorithm was combination of Monte Carlo simulation and iterated local search metaheuristic algorithm to minimize expected makespan. In their research, there is no specific assumption about the probability distribution function and it is also possible to consider situation that the processing time of one machine has different probabilistic distribution from another. In summary, their approach is in a way that they firstly attempt to transform the stochastic problem into its deterministic equivalent then use effective metaheuristic algorithm for deterministic problem with makespan criteria. (Elyasi and Salmasi, 2013) attempted to minimize expected number of delays in a dynamic flowshop problem. In this case, it is assumed that the processing times and delivery deadline are random and follow the normal distribution. They applied dynamic approach to solving m machine stochastic flowshop by split it into m randomized single-machine subproblems. Then, each of these m subproblems was solved using mathematical model. In this study, as dynamic problem, it is assumed the availability time of jobs at the beginning of planning horizon is unclear. (Baker and Altheimer, 2012) considered m machine problem and general distribution of processing time. Processing times have specified average and variance and follow probabilistic distribution family independently. In this paper, three constructive heuristics with the least computational requirements are presented. These procedures are in fact followed by CDS, NEH heuristics and Johnson & Talwar laws (Jiao et al., 2009). studied flowshop problem with random processing times which follow normal probability distribution. This algorithm is combination of particle algorithm and differential evolution algorithm. They used “large fish eat small fish” theorem for population growth and the mutation and crossover operators of differential evolution algorithm (Liefooghe et al., 2007). were pioneer in surveying multi-objective stochastic scheduling problem and used a predictive-probabilistic approach. In their research, the processing times were random and follow normal, lognormal, uniform, exponential probability distributions and the distribution of each machine is different from another. Two objectives were considered: makespan and total delay. They presented three different procedures which were inspired by multi-objective evolutionary algorithm designed for a definite state called evolutionary indicator base algorithm. In the first procedure each solution is evaluated only once, but in the second procedure mean value of each solutions are consider and in the third procedure estimation of solutions are possible in stochastic way. In (Gourgand et al., 2005) study, it is assumed the processing time had exponential distribution. They provided recursive scheme using Chapman-Kalmogrov relations and Markov chain to calculate expected makespan. The performance evaluation terms for two-machine flowshop with limited and unlimited intermediate storage was given. Then, m-machine flowshop with unlimited and limited intermediate storages are discussed and solved them with simulation annealing heuristic (Gourgand et al., 2003). examined a flowshop scheduling problem with unlimited intermediate storage and exponential processing time to minimize expected makespan. They proposed a recursive algorithm based on the Markov chain to solve the problem and used a discrete-event simulation model to evaluate the objective function. Using standard test problems, they examined the performance of their proposed algorithm and could find the optimal solutions for two machines modes and valid solutions for m-machine modes. (Balasubramanian and Grossmann, 2002) presented a stochastic multi-period flowshop scheduling model. In this paper, a mixed integer model for no-wait flowshop problem was presented for minimizing expected makespan. They compared two models and presented a branch and bound algorithm to solve problem optimally. Also, they used this algorithm for flowshop problem with unlimited intermediate storage.

As it is obvious in literature review, there are so many ways to consider uncertainty. The scenario is barely used among all solution in this problem and is used in the current study. In addition, there are very few studies on sustainable scheduling problem under uncertainty.

3. Problem statement

Previous two sections show the importance of the problem and literature review. In this section problem is surveyed and a mathematical formulation is proposed. In a PFSP, there is a set of n jobs that must be processed through a set of m machines. The problem is determining the sequence of jobs considering of some criteria. If each job passes through the same sequence of all machines, this is call permutation flowshop scheduling. There are two major criteria considered in this problem: maximum completion time and total energy consumption. Each machine can operate at different speeds and each job can be processed at slow, normal or fast speed on each machine and consequently, the processing times can change at different speeds. Makespan and energy consumption are related to processing time and change as speeds change. These two objectives are in contrast with each other. If jobs process at a fast speed, their processing times and subsequently makespan decreases but energy consumption increases because machines use more energy at higher speed and vice versa. Operators are responsible for processing jobs and each operator at any times has different speed. Here it is assumed that the processing times are uncertain and follow the normal distribution with known mean and variance. Normal function is better for showing this kind of uncertainty among other functions because each operator has his/her skill and there is not much deviation from his/her average performance and one significant feature of normal function is that data near the mean are more frequent in occurrence than data far from the mean. To simplify the problem, three skills are considered for operators: low, normal, high, which limit uncertainty of processing times into these three states. Each operator's skill can be one of them with same probability. Each of these skills is like a scenario and that's why the scenario approach is used to handle uncertainty in this paper. Expected values of objectives are used to report objective values under each scenario. The problem is indicated by *Fm | perm | E(Cmax), E(TEC)* symbol. This problem is NP-hard.

3.1. Hypothesis

There is a different variety of assumption for flowshop scheduling problem. The assumptions of this research are as follows:

1 Machines cannot operate more than one job at the moment.
2 Any job at the moment can be processed only by one machine.
3 Every job is processed only once per machine.
4 Operations cannot stop
5 Jobs can wait between machines (unlimited storage between machines).
6 There is only one machine of any type at each production level.
7 All jobs are available at zero time (not a dynamic problem).
8 Each job consists of a set of operations that must be performed by different machines.
9 There is no switching time between machines.
10 Processing times are probabilistic and follow the normal distribution with known mean and variance.
11 Preparation times are included in the processing times.
12 The unit of processing time is minute and energy consumption is kilowatt-hour.
13 Except for processing time, there is no other kind of uncertainty in the problem.

14- Machines have a certain set of speeds (slow, normal, fast).

3.1. Formulation

In this section, mathematical model for flowshop scheduling problem concerning sustainable criterion and under defined scenarios is proposed. It should be noted that the symbols used in the notation are case-sensitive. Table 1 introduces indexes, parameters and variables used in this model.

3.2. Model

$$\min\ Z1 = \sum_{l=1}^{L} pr^l Cmax^l \tag{1}$$

$$\min\ Z2 = \sum_{l=1}^{L} pr^l TEC^l \tag{2}$$

Subject to:

$$c_{11}^l \geq \sum_{j=1}^{n}\sum_{s=1}^{3} \frac{p_{1j}^l}{v_s} x_{1j1s},\ \forall l \tag{3}$$

$$c_{ik}^l \geq c_{i-1,k}^l + \sum_{j=1}^{n}\sum_{s=1}^{3} \frac{p_{ij}^l}{v_s} x_{ijks},\ i\in\{2,\ldots,m\} k\in\{1,\ldots,n\} \forall l \tag{4}$$

$$c_{ik}^l \geq c_{i,k-1}^l + \sum_{j=1}^{n}\sum_{s=1}^{3} \frac{p_{ij}^l}{v_s} x_{ijks},\ i\in\{1,\ldots,m\} k\in\{2,\ldots,n\} \forall l \tag{5}$$

$$c_{ik}^l = s_{ik}^l + \sum_{j=1}^{n}\sum_{s=1}^{3} \frac{p_{ij}^l}{v_s} x_{ijks},\ \forall i\ \forall k \forall l \tag{6}$$

$$\sum_{k=1}^{n}\sum_{s=1}^{3} x_{ijks} = 1,\ \forall i\ \ \forall j \tag{7}$$

$$\sum_{j=1}^{n}\sum_{s=1}^{3} x_{ijks} = 1,\ \forall i\ \ \forall k \tag{8}$$

$$\sum_{s=1}^{3} x_{ijks} = \sum_{s=1}^{3} x_{hjks},\ \ \forall i\ \forall h\ \forall j\ \forall k \tag{9}$$

$$cmax^l \geq c_{mn}^l,\ \ \forall l \tag{10}$$

$$\theta_i^l = cmax^l - \sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{s=1}^{3} \frac{p_{ij}^l}{v_s} x_{ijks},\ \ \forall i\ \forall l \tag{11}$$

$$TEC^l = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{s=1}^{3} \frac{\pi_i p_{ij}^l x_{ijks} \lambda_s}{60 v_s} + \sum_{i=1}^{m} \frac{\varphi_i \pi_i \theta_i^l}{60},\ \ \forall l \tag{12}$$

$$\theta_i^l \geq 0, c_{ik}^l \geq 0, s_{ik}^l \geq 0, TEC^l \geq 0, cmax^l \geq 0, z_1^l \geq 0, z_2^l \geq 0, x_{ijks} \in \{0,1\} \tag{13}$$

The first and second phrases indicates objective functions of the problem which calculate the expected value of maximum completion time and total energy consumption considering scenarios. The third constraint calculates completion time of the first job processed by the first machine. The fourth and fifth constraints calculate completion time of other jobs processed by remaining machines. The sixth constraint ensures that jobs are processed without interruption. The seventh and eighth constraint ensures that each position of sequence is assigned to a job and each job is assigned to a sequence position. The ninth constraint ensures that

Table 1
Notations of mathematical formulation.

i, h	index of the machines i, $h = 1, \ldots, m$
J	index of the jobs $j = 1, \ldots, n$
K	indicator of the position of a point in the sequence $k = 1, \ldots, n$
S	index of speed $s = 1,2,3$
L	indicator of scenarios $l = 1, \ldots, L$
Parameters	
M	number of machines
N	number of jobs
L	number of scenarios
v_s	processing speed (which for $s = 1, 2, 3$ respectively, indicates slow, normal and fast speeds)
λ_s	conversion factor for processing speed *s*
φ_i	conversion factor for idle time on machine *i*
π_i	power of the machine *i*
pr^l	occurrence probability of scenario *l*
Random variable	
p_{ij}^l	processing time of job *j* on machine *i* under scenario *l*
➢ The only random variable is processing time and follows a normal distribution.	
Positive variables	
θ_i^l	idle time of machine *i* under scenario *l*
c_{ik}^l	completion time of *k*th job, processed by machine *i* under scenario *l*
s_{ik}^l	start time of *k*th job, processed by machine i under scenario *l*
$Cmax^l$	completion time of the last job on the last machine under scenario *l*
TEC^l	total energy consumption under scenario *l*
*Z*1	mean value of the first objective function (expected makespan)
Z2	mean value of the second objective function (expected total energy consumption)
➢ $Cmax^l$ and TEC^l are functions of random variable p_{ij}^l.	
Binary variable (decision variable)	
X_{ijks}	1 if the job *j* is the *k*th job that is processed on the machine *i* at speed *s*, otherwise it is zero.

any job on any machine is processed at one speed. The tenth constraint calculates completion of the last job by the last machine which is one of the objective functions (makespan). The 11th constraint calculates idle time on each machine. The 12th constraint calculates total energy consumption which is a green metric and our goal is to minimize this value. The last phrase determines the type of problem variables.

This formulation has been solved by GAMS (win64−24.1.3) for a different small and medium-size instances in a reasonable time.

4. Estimation distribution algorithm

In this section a metaheuristic algorithm is proposed to solve aforementioned problem. As mentioned before m-machine flowshop problem is NP-hard and exact methods cannot solve it in the polynomial time. So, metaheuristic algorithms are used to solve these hard problems to give a good solutions in the reasonable time. Genetic algorithm (GA) is the famous metaheuristic algorithm. Classical genetic algorithm is a class of optimization algorithms inspired by natural selection and genetic recombination theory. This algorithm attempts to find a better solution for the problem by select and recombine the promising solutions. GA works well on a variety of problems, but sometimes it is not easy to get good solution by genetic algorithm. This is due to the lack of effective maintenance of the important structure of individuals. Searching for techniques which protect important structures led to the emergence of a new class of an algorithm called Estimation Distributed Algorithms (EDA). Estimation distribution algorithm is a new concept in the field of evolutionary computing that it constructs a probabilistic model from the population to preserve valuable structures in the successive generation of algorithm. The probabilistic model describes statistical information of elite individuals from previous generations and therefore can predict the most promising search area. This algorithm does not so much rely on genetic algorithm concept. The model-sample step in this algorithm can be thought of crossover with multiple parents. Strength or weakness of this algorithm is mainly determined by the probabilistic model. In this algorithm, the parent's role is diminishing in the creation of next generation, since it does not directly create a child.

As mentioned, EDA is almost new metaheuristic which has been successfully used for solving the flowshop problem; however, this algorithm needs more investigation. This algorithm indirectly protects the characteristics of elite solutions by constructing a probabilistic model of elite solution and transforming good structures to the next generation to improve the quality of solutions in the successive generation of the algorithm. This mechanism focuses

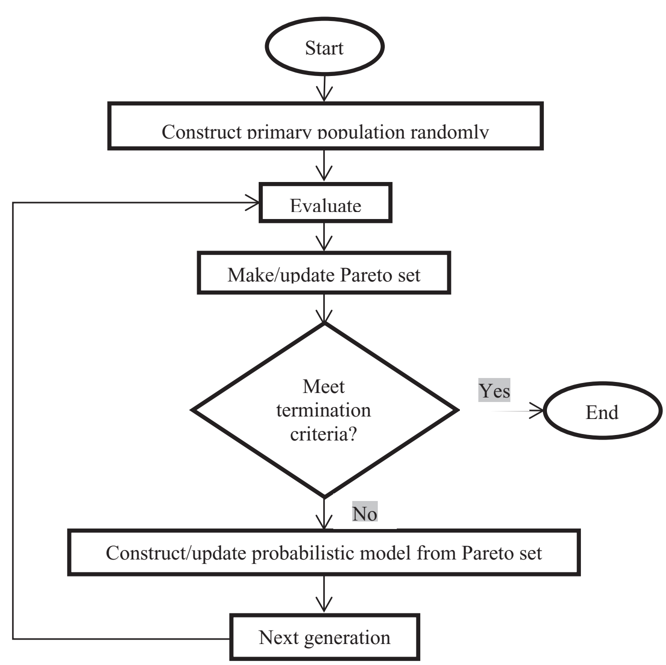

Fig. 1. Estimation distribution algorithm flowchart.

on good solutions and its general trend is like a genetic algorithm. As an iterative procedure, EDA includes the following steps (1) Randomly generate an initial population; (2) Choose some good individuals to construct elite set; (3) Establish probabilistic model from the elite set; (4) Generate new individuals from the estimated probabilistic model; and (5) Repeat Steps 2–4 until stopping criterion is satisfied. A termination criterion for this research is a specific number of repetitions. Pseudo code and flowchart of the algorithm is shown in Algorithm 1 and Fig. 1, respectively.

4.1. Algorithm 1:Pseudo code of estimation distribution algorithm

1. Convert problem to a searchable solution using encoding scheme (x_{ijks})
2. Determine parameter of the problem including m, n, π_i, φi, λ_s, v_s
3. Determine parameters of the algorithm including the number of iteration and population size
4. Generate a primary population randomly
5. Evaluating primary population Z_1, Z_2 (the first generation)
6. The specific number of repetition of generation evolution process includes:
   a. Determine elite individuals
   b. Construct a probabilistic model with respect to elites
   c. Generate next generation using the probabilistic model
   d. Evaluate the population
7. Repeat Step 6 until meet the termination criteria

4.2. Encoding scheme

As described in previous sections, the decision variable determines positions of jobs and assigns speeds. Each solution of the algorithm is called chromosome. Each chromosome refers to one individual in the population which represents a solution in the space of solutions. Chromosome should design in a way that the problem constraints such as job sequencing and speed allocating constraints in the encoding scheme are satisfied. For encoding a solution with m-machines and n-jobs a matrix is considered with n columns (number of jobs) and m+1 rows (one more than number of machines). The first line of this encoding scheme represents the sequence of jobs and other rows indicate the speed of each job on each machine. As an example, Table 2 shows a chromosome for a problem with five jobs and two machines. The first line shows the sequence of jobs which means the third job will operate first of all on machines and then the first job and …. Other rows show speed assignment: the third job on the first machine will operate by fast speed (1) and on the second machine with normal speed (2).

4.3. Cost function regarding scenarios

In the optimization problems, each solution corresponds to a certain value of the objective function. In the proposed algorithm, each chromosome (solution) represents a point in solution space. The objective value of a solution relies on model, constraints and parameters of the problem. This value is determined by a function known as fitness for maximization problems and cost for minimization problems. In this study, there is a multi-objective problem and both objectives are minimization. Some constraints of problem were satisfied by encoding scheme and other constraints are satisfied through cost function. Unlike single-objective problems which have an optimal solution, multi-objective problems have a set of solutions called dominant or the Pareto solutions. In this study processing times are uncertain and follow the normal distribution. There are various approaches for this type of problems such as transform to deterministic equivalent, sensitivity analysis, scenarios and so on. Here scenario approach has been used to solve and address problem in order to consider uncertainty effects. As mentioned in the previous section for this parameter three scenarios are defined and problem is solved under each of them and ultimately, the expected value is calculated.

Table 2
Encoding scheme.

3	1	4	2	5
1	3	1	2	2
2	1	2	3	1

4.4. Pareto set

As explained earlier, this research seeks for the Pareto set. At the end of each iteration of this algorithm as population-based algorithm, a set of solutions using examining the current generation and eliminating non-dominant solutions are obtained. In this research, the procedure of algorithm is modified and to find the Pareto set, another technique has been used. In this technique, considering the first objective function value, the solutions are arranged from small to large (lower values of the objective functions are preferred). Then the second objective function value of latter order (the second order) is compared with the second objective function value of its prior order (the first order); if this value is superior to its previous solution, it will stay in the set, otherwise it will eliminate. This process will be followed for solutions until the last one. Thus there is a set of dominant solutions that the first row has the best value for the first objective function and the last row has the best value for the second one and the intermediate elements are distributed between these solutions.

4.5. Probabilistic model

Probabilistic model in EDA is used to guide the process of exploring solution space and determines the performance of the algorithm. The probabilistic model is constructed from the Pareto set with conserving the structure of good solutions. In this paper, an effective probabilistic model presented by (Wang et al., 2016) is used to solve flowshop problem. Their proposed model calculates the probability of choosing job j in kth position as follows:

$$\pi_{jk} = \begin{cases} \dfrac{\eta_{jk}}{\sum\limits_{l\in\Omega_k} \eta_{lk}}, & k = 1 \\ \dfrac{\eta_{jk} \times \mu_{j[k-1]}}{\sum\limits_{l\in\Omega_k} (\eta_{lk} \times \mu_{l[k-1]})}, & k = 2, 3, \ldots n \end{cases} \tag{14}$$

Table 3
Scenarios of the problem.

Scenarios	Parameter value of normal distribution	Occurrence probability
1	Mean = 15 variance = 5	0.333
2	Mean = 35 variance = 5	0.333
3	Mean = 55 variance = 5	0.333

in which η_{jk} shows the number of times that job j is in position k or before it, μ_{jk} shows the number of times that job j is exactly in position k and Ω_k shows set of jobs that are not scheduled until position k.

4.6. Generate next generation

After constructing probabilistic model, for each offspring of the next generation, the cumulative probability of a position based on different jobs is obtained for allocating jobs to positions. Then a random number is generated between zero and one. The number of intervals which this random number is in it, will be considered as job's position. Same approach is used for allocating speed.

5. Computational experiment

In previous sections the problem was investigated and a meta-heuristic algorithm was introduced to solve it. In this section we will compare our proposed algorithm with a competing algorithm. Since there is no benchmark for stochastic flowshop problem, for these comparisons nine random instances were used in the small, medium and large-size instances. Processing time of each instance under each scenario has been generated by normal function in EXCEL 2010. Experiments are conducted by a PC (610 M, 2 GB). Parameters of problem are set based on (Mansouri et al., 2016) research and two parameters of the algorithm are set based on its competitor algorithm (Karimi and Dvoudpour, 2014). The Pareto layers obtained from two algorithms for each of instances are characterized by dominant solutions.

$v_1 = 1.2, v_2 = 1, v_3 = 0.8$
$\lambda_1 = 1.5, \lambda_2 = 1, \lambda_3 = 0.6$
$\pi_i = 60$ kw $\forall i$, $\varphi_i = 0.5 \ \forall i$.
$npop = 100$, $maxit = 100$.

As mentioned before and shown in Table 3, there are three scenarios for the random parameter (the processing time). Processing times are stochastic and follow the normal distribution. Each scenario specifies mean and variance of normal distribution in three different situations. It is logical to consider these scenarios because the processing speed of each operator is different. In a general view operators' speeds can be categorized into three groups of beginner, normal and skilled. There are several methods for handling scenarios. This research used Here and Now approach. Eventually, the expected value of scenarios is used to report the objective function.

5.1. Competing algorithm

Considering the mentioned assumptions, as a competing algorithm, the most related study to this research is (Karimi and Dvoudpour, 2014) in which a high-performance GA is proposed for multi-objective flowshop scheduling problem. The flowchart of their algorithm as is shown in Fig. 2.

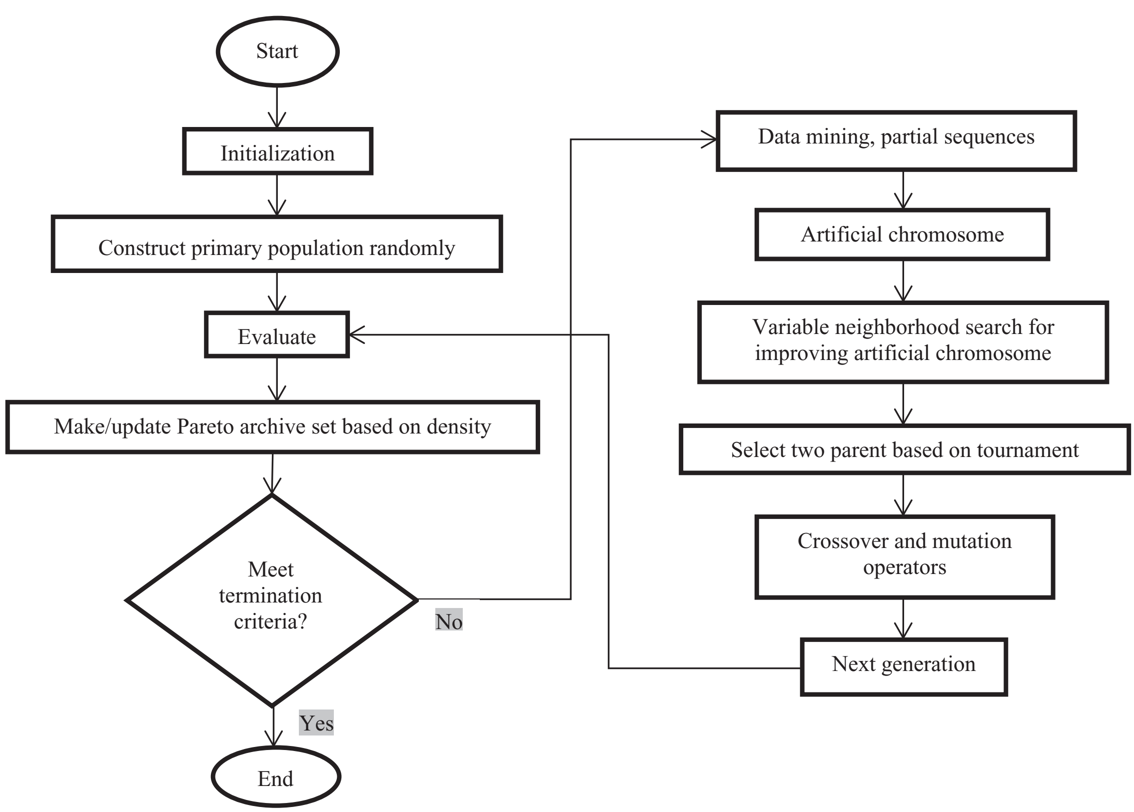

Fig. 2. Competetive algorithm flowchart

Table 4
Results of algorithms.

Instances			MID		SNS		RAS		NPS		TIME	
Size	Machine	Jobs	EDA	GA	EDA	GA	EDA	GA	EDA	GA	EDA	GA
Small	2	10	907.73	857.97	50.05	17.76	1.27	0.90	35	12	8.91	63.81
	2	20	1754.04	1619.89	82.63	31.84	1.32	0.86	52	16	43.96	185.76
	2	30	2657.55	2413.39	129.24	41.02	1.48	0.87	61	24	114.92	494.63
	5	10	2394.45	2236.6	103.75	63.98	4.03	3.28	24	8	14.32	67.86
	5	20	4577.18	4127.62	238.35	18.86	4.68	3.34	37	8	47.69	158.8
	5	30	6516.39	5926.98	366.26	87.75	4.54	3.5	45	9	65.86	448.87
	7	10	3680.06	3453.24	124.18	50.37	5.65	4.6	31	5	18.03	67.62
	7	20	6543.54	6060.6	306.44	111.75	6.19	4.95	26	9	37.02	155.88
	7	30	9473.27	8529.27	425.66	118.82	6.69	5.05	40	4	79.83	329.35
Medium	8	30	10926.19	9940.24	507.1	122.84	7.6	5.83	52	8	93.38	308.27
	8	50	17499.55	15711.45	904.72	244.25	7.98	6.14	47	9	171.69	1869.78
	8	100	33758.97	29565.29	1961.9	109.22	8.42	6.17	71	6	407.13	9199.34
	10	30	13970.42	12807.85	574.71	149.81	9.16	7.3	47	4	97.13	275
	10	50	22210.47	19996.69	1023.89	215.69	9.96	7.79	57	8	158.23	946.42
	10	100	42429.37	37878.01	2556.06	193.5	10.51	8.03	86	6	516.31	9651.98
	15	30	22342.13	20856.05	767.18	238.86	12.84	10.8	45	2	87.49	80.93
	15	50	34733.05	31802.97	1505.66	87.79	14.52	11.5	45	5	116.71	293.83
	15	100	64401.74	59592.86	3046.2	281.97	14.93	12.2	66	11	348.46	2955.26
Large	20	100	89823.04	81564.22	4063.06	352.84	20.20	16.3	77	3	449.98	3958.78
	20	300	228102.41	226027.05	1926.43	1036.99	17.52	17.22	13	14	665.19	92820.44
	20	500	385963.84	369176.11	10030.7	776.92	19.18	17.6	45	6	1609.13	237073.57
	40	100	188774,01	182058.07	4075.51	558.88	33.59	30.88	40	4	379.78	3215.77
	40	300	476691.6	474708.46	2121.61	843.3	34.26	34.11	7	4	964.71	46550.1
	40	500	763664.62	764063.72	950.95	1081.98	35.1	35.06	4	4	3520.29	168771.41
	60	100	306398.4	300574.41	2225.51	261.8	46.04	44.51	18	3	1011.12	1537.26
	60	300	753566.63	743287.03	5505.15	1122.92	50.73	49.87	17	3	3009.77	63617.53
	60	500	1189043.6	1181775.6	3573.65	752.7	52.22	51.8	13	5	4932.03	63617.53

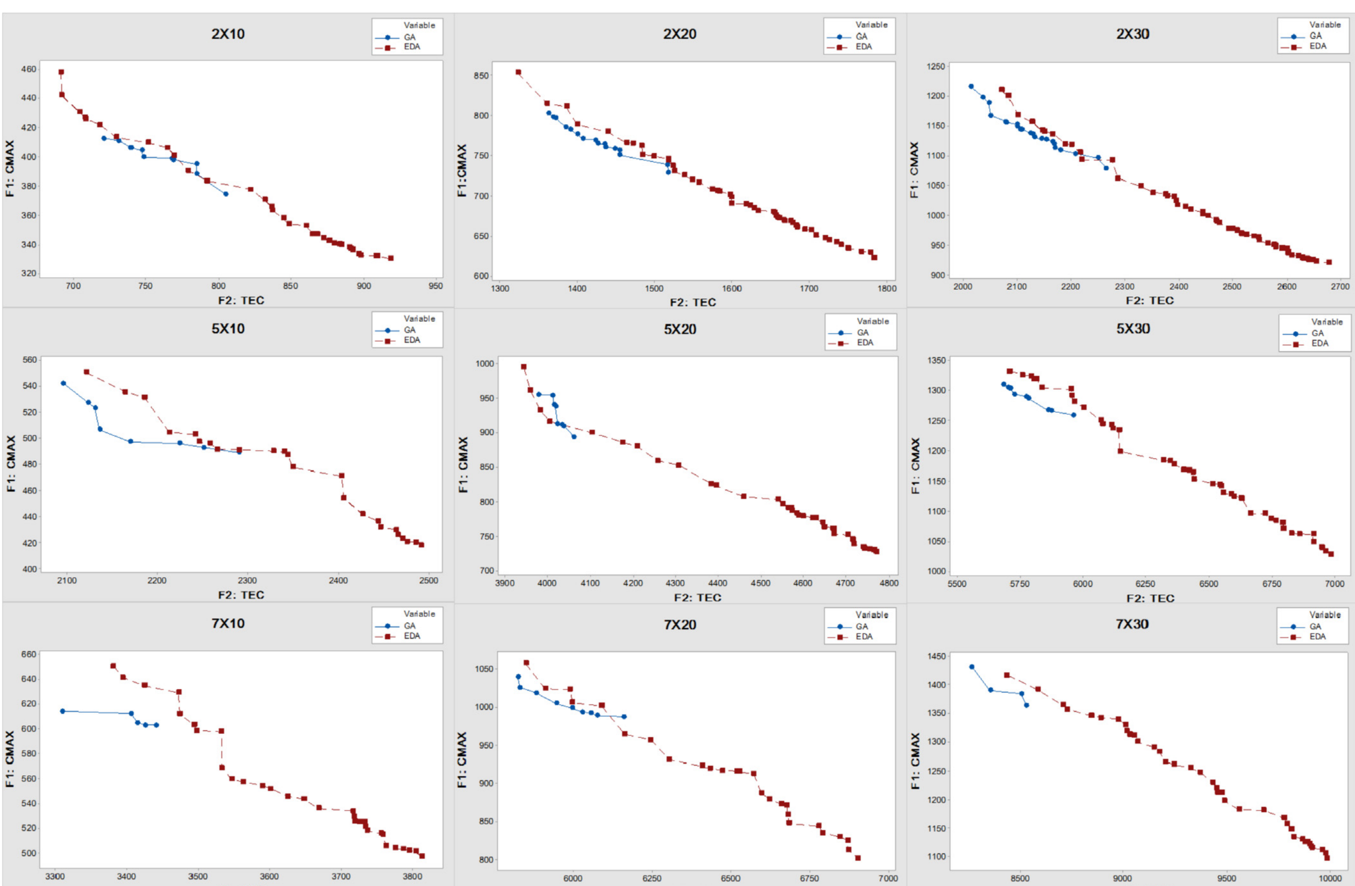

Fig. 3. Comparison in small-size instances.

5.2. Evaluation metrics

In section 4 an algorithm was proposed to solve the problem. Multi-objective optimization methods create a Pareto layer by the number of dominant solutions. Now, the main issue is assessment of quality of solutions. Also, comparison of two approximate Pareto layer's solutions obtained from several algorithms is not easily possible. Therefore, quantitative criteria for evaluating solutions are needed. In this research five criteria as described in the following are used.

MID: calculates the proximity of the Pareto solution and ideal point (0, 0). Lower value of MID indicates better performance of algorithm. If n represents number of dominant solutions, the following equation will measure this criterion:

$$MID = \frac{\sum_{i=1}^{n} c_i}{n} \tag{15}$$

$$c_i = \sqrt{f_{1i}^2 + f_{2i}^2} \tag{16}$$

in which i is indicator for n, n is number of solutions in the Pareto layer, f_{1i} is the first objective function of the ith solution of set, f_{2i} is the second objective function of the ith solution of set.

SNS: shows spread of dominant solutions. Higher amount of this criterion shows better performance of the algorithm.

$$SNS = \sqrt{\frac{\sum_{i=1}^{n} (MID - c_i)^2}{n-1}} \tag{17}$$

RAS: shows simultaneous access rate of two objective functions. Lower amount of this criterion represents the better quality of the algorithm.

$$RAS = \frac{\sum_{i=1}^{n} \left(\frac{f_{i1} - F_i}{F_i}\right) + \left(\frac{f_{i2} - F_i}{F_i}\right)}{n} \tag{18}$$

$$F_i = \min\{f_{1i}, f_{2i}\} \tag{19}$$

NPS: is number of solutions in the Pareto set. High amount of this criterion is better because it increases number of options for the decision maker.

TIME: is time that is spent for the algorithm running. The lowness of this criterion is better and indicates efficiency of the algorithm. In this research, time is in seconds.

Table 4 shows the experimental results of two algorithms. The results indicate that proposed algorithm has proper functionality. EDA searches space of solutions properly and finds wide the Pareto set in reasonable time while the quality of solutions is good too. As seen in Table 4, SNS and NPS and TIME metrics show superiority of EDA, however MID and RAS show that competitor is slightly better. In our opinion, the competing algorithm used a data mining mechanism to find better solutions and that is why MID and RAS criteria are better in this regard. Above figures illustrate the Pareto layers of two algorithms, which is dispersion of dominant solutions can give a better insight about the performance of them. According to the problem size, the results are drawn separately in Figs. 3–5. It is obvious from figures that EDA explores solution space better than the competing algorithm. The number of solutions in the Pareto set

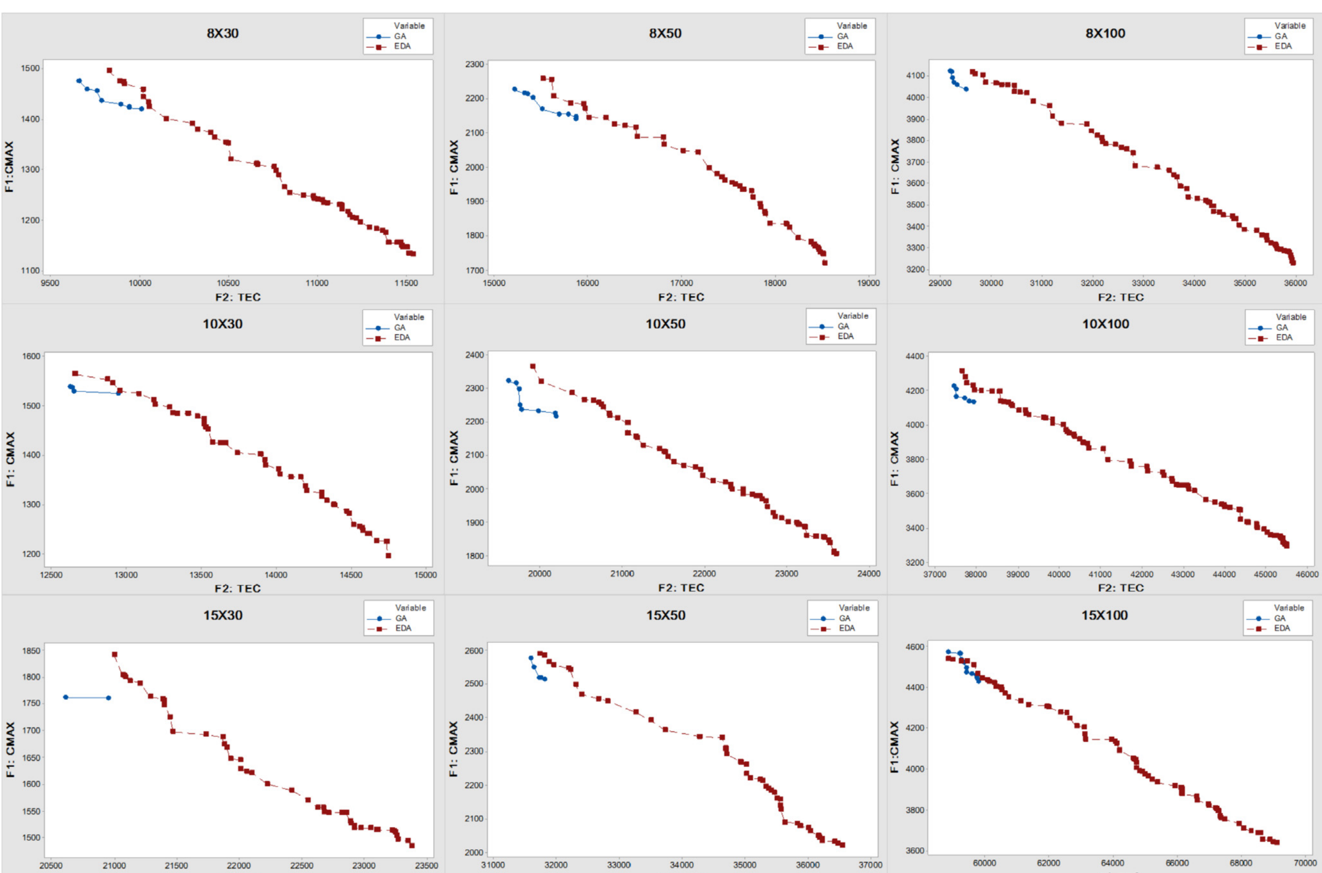

Fig. 4. Comparison in medium-size instances.

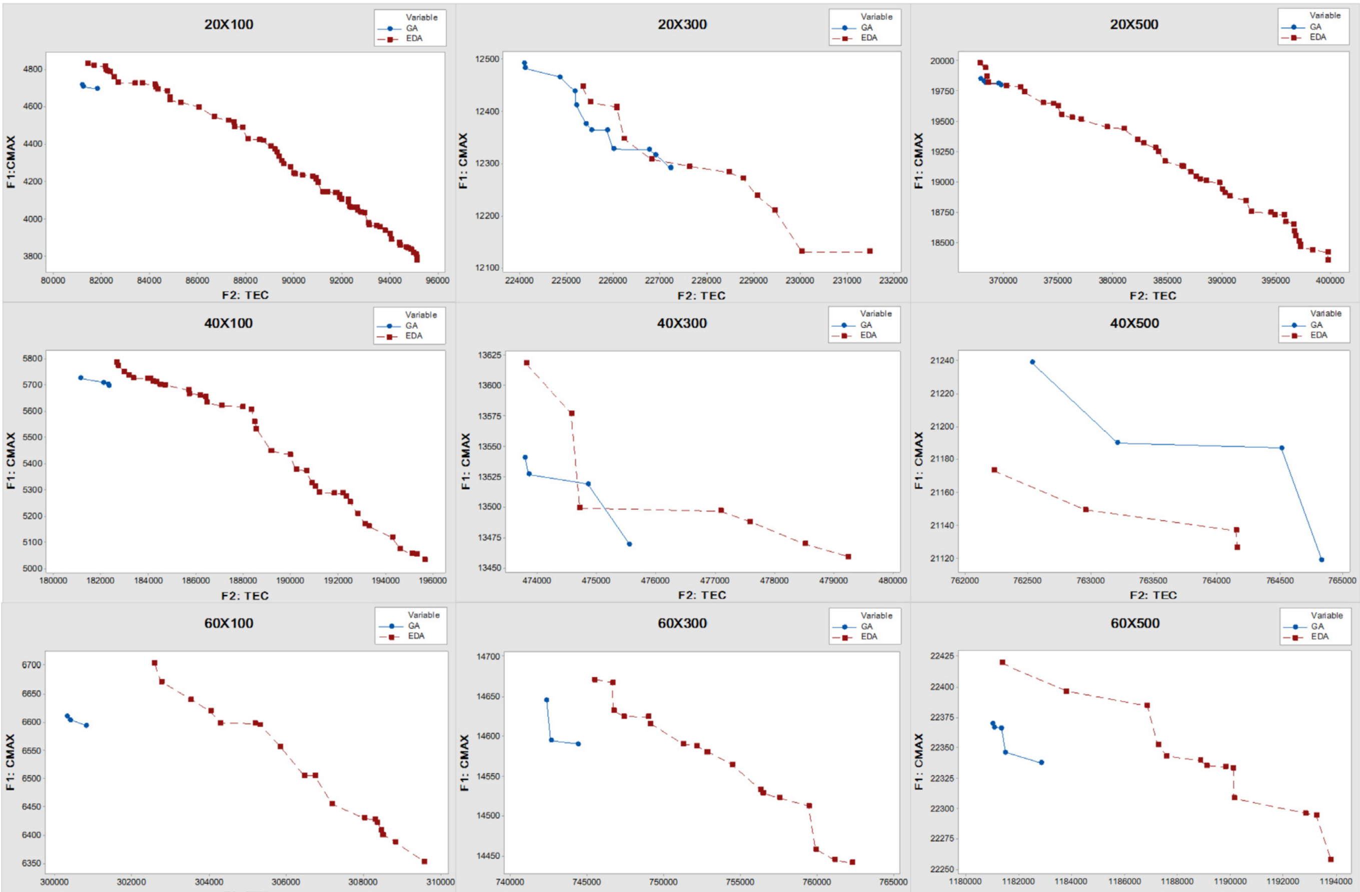

Fig. 5. Comparison in large-size instances.

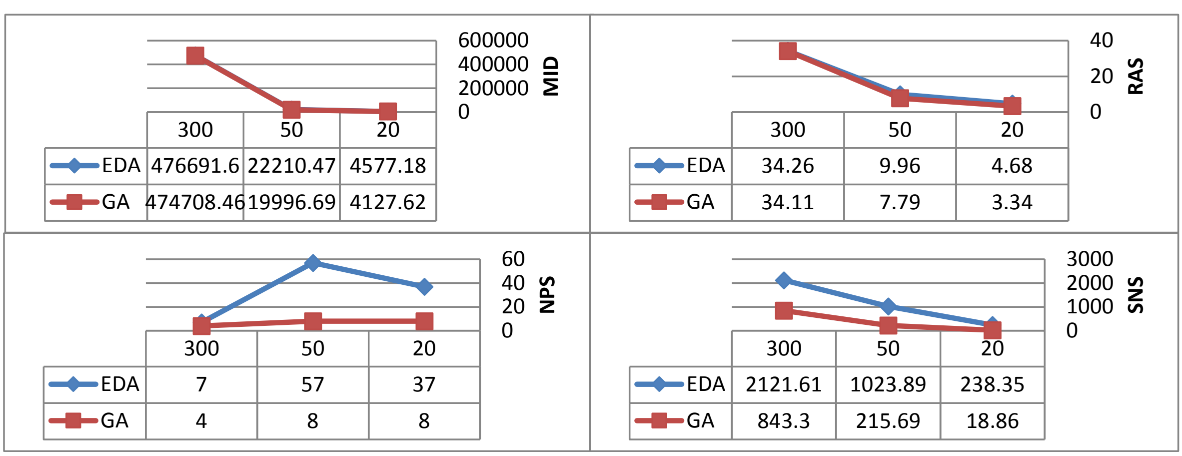

Fig. 6. Evaluation metric value.

of EDA is more than the competing algorithm which means more choices are available for decision maker.

Fig. 6 is drawn to clarify difference in the performance of two algorithms and it shows that the difference between MID and RAS metrics are so little and almost negligible. Actually, it can be said that these two algorithms have same performance from the MID view point because of their close results. So, the superiority of the competing algorithm in these metrics is not significant. As it is obvious, the competing algorithm spends a lot of time in the large-size instance to get a few solutions.

Fig. 7 shows the comparison between the running times in two algorithms. As it is obvious, the competitor's algorithm spends a lot of time in the large-size instances to get a few solutions. Thus, the running time in EDA is its benefit and makes it applicable (as this is the mission of metaheuristic algorithms). It is obvious that we have limited time to get the Pareto set and that is why time is considered as an important criterion.

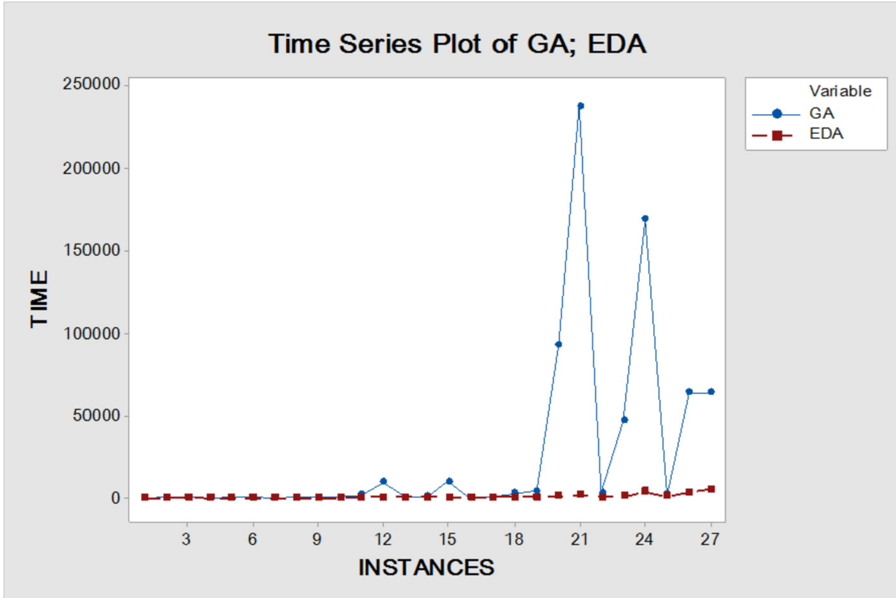

Fig. 7. Running time of algorithms.

6. Conclusion

Nowadays, energy is one of the most important issues in the world. Since the industry is among the largest consumer of energy, the production units pay attention to sustainable production. The necessity of considering uncertainty in problems and moreover existing research gap has inspired this research. In this research a mathematical model is presented for sustainable flowshop scheduling with uncertainty to minimize makespan and total energy consumption. Energy consumption is directly related to the cost of energy and environmental impact, so by optimizing it, the energy costs and environmental impact will decrease too. In the considered problem, machines can operate at three speeds. Each of these speeds will result in different and conflicting values of objective functions. Processing times are also uncertain and follow the normal distribution. This study attempted to minimize energy consumption and makespan under uncertainty and gives a good insight about the energy issue.

This research approach dealt with uncertainty with a scenario approach. A mathematical model for the problem with the finite number of scenarios is presented. In order to report objective functions, expected value of scenarios has been used. The proposed model has been validated in the small-size instances using GAMS solver. Since this problem is NP-hard, a Scenario-based Estimation Distribution Algorithm (EDA) as a metaheuristic algorithm is used to solve it. Main idea of this algorithm is to maintain valuable structures of good solutions.

In order to evaluate and validate EDA, experimental design and analysis have been carried out. Results show that this algorithm is capable of obtaining optimal solution in reasonable time. Also, the number of small, medium and large-size instances is also used to measure the performance of EDA compared to the genetic algorithm. According to the results, it can be claimed in general the both of objective functions have been optimized and good solutions are achieved and in particular, we can conclude SNS, NPS and TIME metrics are impressively better in EDA and in other metrics, the difference between algorithms is not significant. Furthermore, the results show that EDA has less time to solve as well as perfectly explores the space of solution and provides a broader Pareto layer and offers more options to decision maker in the practical environments for industrial units which need quick actions. The major benefit of this study is that energy consumption which is one of the most current important issues is considered under uncertainty which makes it more precise and practical. Among other procedures for solving stochastic problems scenario has little computational cost which is favorable, especially in the large-size instances and gives a through insight about problem.

Energy consumption in industrial units is an important research direction that needs more survey. Not all the aspect of this problem is investigated. This field needs more studies considering different production models and situations. In order to complete this research following topics are suggested:

✓ Other probability distributions
✓ Use another approach of energy consumption to find more accurate model
✓ Considering other production models such as job shop and so on
✓ Determine exact model parameters based on case studies
✓ Use other metaheuristic algorithm
✓ Use other methods for solving problem

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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