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DESIGN OF A GENETIC ALGORITHMIC APPROACH FOR REDUCING ENERGY CONSUMPTION IN SINGLE MACHINE PRODUCTION SYSTEMS

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Abstract:

In traditional production systems, production is generally based on performance criteria such as total completion time, price and quality. Energy consumption or environmental impacts of production systems are not often considered. This article deals with a scheduling problem aiming to increase energy efficiency, which has been noticed by companies in recent years. A mathematical model is set up to minimize the total energy consumption in a single machine production system. Genetic algorithm method is used to solve this problem. To prove the efficiency of our model and algorithm, we use the sample problems in the reference paper. According to the test results, our model and algorithm have been shown to reduce energy consumption by 50% compared to the algorithm in the reference paper.

Keywords:

Energy Consumption, Single Machine, Genetic Algorithm

1. Introduction

Nowadays, competition for energy sources is becoming more intense than previous decade because of the increase in energy prices and non-renewable resources. Including production, the industrial sector consumes about half of the total energy produced in the World (Zhang et al., 2016).

Global climate change, limited energy sources, reduction of dependence on fossil fuels and CO2 emissions require that energy management in production systems be integrated into decision-making processes (Mikhaylidi et al., 2015). In addition, changes in customer behavior towards greener products and new environmental regulations contribute to the key role of the energy management strategy in production organizations (Shrouf et al., 2017).

Briefly, various approaches and solutions for energy efficiency in production systems have been started to be developed in recent years. Measures have been taken to increase efficiency factor components or to avoid inefficient components. Generally, energy efficiency studies in the literature can be classified under two categories. The first, studies are aimed at reducing energy consumption through technological advances in production processes (Neugebauer et al., 2011). The second is the efforts to reduce energy consumption by adjusting the managerial parameters of the production process called energy efficient production planning. In comparison to technological infrastructure investments to increase energy efficiency in manufacturing systems, energy efficient production planning studies are becoming increasingly popular in practice. Because production planning studies usually do not require large investments. Especially, there has been an increase in the number of scientific publications in this field in the last decade (Biel and Glock, 2016).

In this study, it is aimed to develop an efficient mathematical model considering energy efficiency for production systems. A suitable genetic algorithm is proposed for the energy efficient scheduling model.

The outline of this study is as follows. In section 1, literature review is presented. In section 2, a single-objective problem is proposed in a production system. In addition, an energy efficient model has been developed that minimizes energy consumption in the single machine scheduling problem. In section 3 inproves genetic algorithm to solve the model. In section 4, various problems were used to measure the computational performance of the model. Finally in section 5, the results are discussed.

2. Literature Review

The first systematic approach to scheduling problems was introduced in the mid-1950s. From past to present, thousands of articles have been published in the literature on different scheduling problems. (Allahverdi et al., 2008). In the past, operational and planning decisions in production systems were primarily based on traditional measures such as cost, quality, flexibility. (Vijayaraghavana and Dornfeld, 2010). The research on energy scheduling is limited. (Zhang et al., 2016).

Mouzon et al. (2007) is based on the principle that energy consumption is performed by idle-running non-bottleneck machines. For this purpose, they have developed operational methods that minimize the energy consumption of production equipment. In other words, they aimed to reduce total energy consumption together with other production planning targets. In addition, they have proposed a multi-objective mathematical programming model to reduce the energy consumption and total completion time in the single CNC machine. As a result, when there is non-bottleneck in the machine, turning on/off operation of the machine can be decreased the idle energy consumption of the machine.

Mouzon and Yildirim (2008) proposed an NP-hard problem to minimize total energy consumption and total tardiness. They developed a new greedy randomized meta-heuristic to solve the single machine problem. They used analytic Hierarchical Process to find the feasible solution from non dominated solutions.

Fang et al. (2011) proposed a multi objective mixed-integer mathematical model with flow-shop scheduling problem that minimizes makespan, carbon emissions and peak total power consumption.

Dai et al. (2013) have developed an energy-efficient scheduling model for flexible flow shop. A genetic-simulated annealing algorithm is used to obtain the appropriate solution in the model. Experimental results have shown that there is a conflicting between makespan and energy consumption.

Liu et al. (2014) have developed a model that aims to reduce total electricity consumption and total weighted tardiness. The study focuses on the classical job shops in the manufacturing industry. Non-dominated sorting genetic algorithm method is used to solve 10 * 10 job shop scheduling case study.

Lu et al. (2017) have developed a multi-objective scheduling problem of permutation flow shop that minimizes makespan and total energy consumption. They used a hybrid multi objective backtracking search algorithm to solve the problem. For this problem, a new energy saving scenario is presented extending the life of the machines. Backtracking search algorithm is compared is the two well-known NSGA-II and MOEA/D methods. The results show that the performance of the backtracking search algorithm method in the study was better.

3. Problem Definition and Mathematical Model

3.1. Problem Definition

Generally, when the first product arrives, the machines are opened and not closed until completion of the last product in the manufacturing industry . If there is a long time between two consecutive jobs' arrival times, the machine runs idle (Liu et al., 2014). If the time between two consecutive jobs is longer than the break even duration, closing the machine between the two jobs can provide significant energy savings. Thus, energy consumption can be reduced by controlling the machine (Mouzon et al., 2007).

Assume that the energy consumption per unit time is PI when the machine stays idle. The energy consumption for turning on and turning off machine is Eon-off. The time for turning on and turning off machine is Ton-off. TBED is defined as the minimum time of required for turning on/off machine.
Mathematically,

$$TBED = \max (Eon\text{-}off / PI , Ton\text{-}off). \quad (1)$$

There are two important key factors in this problem. First, the job scheduling and start times of jobs (or completion times) should be determined. Second, it is essential to decide whether to turn on and off the machine between two consecutive jobs.

2.2. Assumptions in The Model

The following assumptions are accepted in the model.

i. Arrival time and processing time of each job are known.
ii. The machine can only process one job at a time.
iii. Preemption is not allowed. When an operation is started, it must be completed without interruption.
iv. Jobs are independent each other.
v. The machine is always available during the job scheduling.
vi. The total turning on/off energy consumption of the machine per unit time is fixed.
vii. The idle energy consumption per unit time is fixed when the machine stays idle.
viii. The objective function is the turning on/off and idle energy consumption of the machine. A job can only be processed once on the machine.
ix. Setup time of each job includes in processing time.

<u>Parameters</u>

n = The number of jobs
i = The index of job (i= 1,2,…,n)
j = The index of job (j= 1,2,…,n)
Pj = The processing time of job j
Cj = The completion time of job j
rj = The arrival time for job j
PI = The idle energy consumption per unit time when machine stays idle.
Eon-off = The total energy consumption for turning on/off the machine at a time.
Ton-off = The time required for turning on/off the machine
ET = The total energy consumption for producing all jobs
TBED = Minimum time of used for turning on/off machine. (It means that when both the time and the energy consumption of turning on/off machine is less than the idle time and the energy consumption of the idle machine, we should turn on/off the machine to consume less time and energy)

<u>Decision variables</u>

Sj = The starting time of job j
Yij = The state of the machine in the time between job i and job j
Xij = Processing state of j after job I

3.3. Mathematical Model

Mathematical model of a single machine scheduling problem that minimizes total energy consumption is presented the following.

$$E_T = \min \left(P_I \sum_{i=1}^{n} \sum_{j=1\neq i}^{n} (S_j - C_i)) (1 - Y_{ij}) X_{ij} + \sum_{i=1}^{n} \sum_{j=1\neq i}^{n} (E_{on-off}) Y_{ij} X_{ij} \right) \quad (2)$$

$$Y_{ij} = \begin{cases} 0, \ (S_j - C_i) \leq T_{BED} \quad \text{(if the machine is idle)} \end{cases} \quad (3)$$

$1,\ (S_j - C_i) > T_{BED}$ (if the machine is turned off)

$$X_{ij} = \begin{cases} 1, \text{ job i and job j are consecutive jobs} \\ 0, \text{ otherwise} \end{cases} \quad (4)$$

$$S_j \geq r_j \qquad \forall j = 1,2,\ldots,n \quad (5)$$

$$S_j \geq C_i \qquad \forall j = 1,2,\ldots,n\,; \qquad \forall i = 0,1,2,\ldots,n \neq j \quad (6)$$

$$\sum_{i=0}^{n} X_{ij} = 1 \qquad \forall j = 1,2,\ldots,n \neq i \quad (7)$$

$$C_j = S_j + P_j \qquad \forall j = 1,2,\ldots,n \quad (8)$$

$$S_j \geq 0 \qquad \forall j = 1,2,\ldots,n \quad (9)$$

In this model;
Equation (2) aims to minimize the total energy consumption of the machine. Equation (3) indicates that the machine runs idle if the time between two consecutive jobs is smaller than TBED, otherwise the machine shuts down. Equation (4) identifies that the sequence of consecutively processed jobs. Equality (5) implies that a job can not start to be processed in the machine without coming to the production system. Equation (6) imposes that the starting time of a job must be equal and greater to completion time of a preceding job. Equation (7) ensures that each job is processed once on the machine. Equation (8) shows that the completion time of a job is equal to the sum of the processing time and starting time. Equation (9) indicates that the starting time of each job is greater than zero.

4. Solution Method: Genetic Algorithm

Genetic algorithms have been extensively researched in the literature (Shrouf et al., 2014). The genetic algorithm originally proposed by John Holland (1975) in the 1960s and later developed by Goldberg (1989) is the heuristic search algorithm that simulates the natural selection and evolutionary process. In order to reach successful solution values, it is important to determine gen structure , chromosomes structure, population size and genetic operators used in algorithm construction well (Elmas, 2016).

The steps of the genetic algorithm are as follows:
Step 1: Generate initial population of solutions.
Step 2: Calculate the fitness value of each solution in the population.
Step 3: Apply the selection operation (solutions with better fitness values are represented more in the new population).
Step 4: Perform the crossover operation (two new childs are produced from the two available solutions).
Step 5: Perform the mutation operation
Step 6: Calculate the fitness values of the individuals in the new population.
Step 7: Perform the elitism operation
Step 8: Run the algorithm until the stopping criterion
Step 9: Output the best solution

Chromosome structure, generation of the initial population, selection strategy, genetic operators and stopping criterion affecting the performance of the genetic algorithm are explained below.

4.1. Coding

Alphanumeric or real digital coding rather than binary coding is prefered in scheduling problems (Elmas, 2016). In this problem, each job is represented by an integer. Consecutive integers from 1 to N are generated for N jobs. Each gene identifies a job. Each chromosome contains genes as the number of jobs. Each chromosome in the search space gives a solution point.

4.2. Generation of The Initial Population

Population is a community of chromosomes. An each chromosome that consists job scheduling represents a solution point. Under some constraints, some random solutions (chromosomes) is created for the initial population.

4.3. Fitness Function

The fitness function is used to determine the quality of solutions in the current population. The value of the objective function for each individual (chromosome) in the population is calculated. The calculation value is as follows:

$$\text{Function value} = P_I \sum_{i=1}^{n} \sum_{j=1 \neq i}^{n} (S_j - C_i))\,(1 - Y_{ij})\,X_{ij} + \sum_{i=1}^{n} \sum_{j=1 \neq i}^{n} (E_{on-off})\,Y_{ij}\,X_{ij} \qquad (10)$$

Equality (10) represents the total energy consumption of the machine for processing of all jobs. This value consists of two parts. The first section shows the energy consumption when the machine is idle. The second part calculates the energy consumption for turning on/off of the machine.

4.4. Selection Operator

The selection operation is a method used for the selection of feasible individuals and the elimination of infeasible individuals in the population. The selection mechanism ensures the best survival. Chromosomes, which generally have feasible fitness values, are more likely to be found in future generations. There are many selection operators, such as tournament method, fitness proportional selection, and local selection (Liu et al., 2014). Stochastic universal sampling operation is used in this study. Stochastic universal sampling operation is similar to the roulette wheel selection operation. The most important difference is that the outer part of the circle is divided into equal parts. The number of these parts equals the number of individuals in the population. When the selection is made, the circle is rotated only once. Thus, all of new individuals are selected. Not only the selecting of the best individuals but also the disappearance of the bad ones is prevented with this method. it prevents the algorithm from sticking to a local point.

4.5. Crossover Operator

Crossover is a genetic operator that the displacement of the reciprocal genes of two individuals. There are many methods such as one-point crossover, two-point crossover, position-based or order-based crossover. In this study, an order-based crossover operation is used (Elmas, 2016). The steps of the method are shown below.

Step 1: Two individuals are randomly selected from the population.
Step 2: Generate 0 and 1 numbers as the number of genes. The genes are determined for the crossover process according to more numbers of 0 or 1. These genes are replaced with the genes on the other chromosome respectively. The same process is applied on the other chromosome.
Step 3. This crossover procedure is applied for all chromosomes.

4.6. Mutation Operator

The mutation operator is the modification of several gene values of individuals in the population. In addition, this operator makes to increase diversity of the target population and speed up the comprehensive search. Various mutation operators such as adjacent two-job change, arbitrary two-job change, arbitrary three-job change, Shift change are used in the genetic algorithm (Murata et al., 1996).

Arbitrary two-job change operators are used in this paper. Two genes are randomly selected according to determining mutation rate and these genes displace. In this way, new chromosomes are obtained.

4.7. Elitism

Elitism is a strategy for preserving the elite solutions in the evolutionary process. This operator can usually help to speed up the convergence of genetic algorithms (Zhang and Chiong, 2015). The used elitism strategy is explained below.

Step 1: Sk is determined as the best solution in the Pk population.
Step 2: Run the algorithm for the Pk population. Sk+1 is determined as the best solution in the solutions of new Pk+1 population.
Step 3: Sk and Sk+1 solutions are compared. The highest fitness-valued solution is updated in the Pk+1 population. In other words, the worst fitness-valued chromosome is eliminated from the current population. The best fitness-valued chromosome is added to the new population. (Rajkumar and Shahabudeen, 2009).

4.8. Stopping Criteria

The stopping criterion is the number of generations specified. When the algorithm reaches this stage, it stops. The best fitness-valued chromosome in the population is the optimal solution of problem (Yildirim and Mouzon, 2012).

5. Computational Performance

In the literature, Liu et al. (2014) tried to minimize the total carbon dioxide emissions and the total completion time with First Come First Served rule in a single machine manufacturing system. They achieved some feasible solutions with NSGA-II method. We used data sets of three-jobs and five-jobs problems in the paper of Liu et al (2014) to verify our proposed algorithm. We have created job sequences. We evaluated the performance of our model. We compared solution results of our genetic algorithm and their NSGA-II outcomes. In addition, we considered the delivery time of all jobs in this paper. Liu et al (2014) used the Ctcf = λ.Etec (λ=0.785 kgCO2/kwh) formula to convert energy values to total carbon dioxide emission values. We used same formula to convert total carbon dioxide emission values to energy values.
Below is a comparative analysis based on the obtained solutions for these problems.

5.1. A Problem With Three Jobs

Jobs have processing times of 10 h, 10 h and 20 h, respectively. The arrival times of the jobs are 0 h, 40 h and 60 h, respectively. Delivery time of all jobs is 100 h. Kilowatt (kW) is used as a unit of measure for energy consumption. Processing energy consumption and idle energy consumption are 3 kW and 0.4 kW respectively. The total energy consumption for turning on/off the machine at a time. is 4 kW hours and the turning on/off on time is 12 hours. According to the above datas, we find the TBED value in the equation below (Liu et al., 2014).

$$T_{BED} = \max (E_{on\text{-}off}/ P_I , T_{on\text{-}off})= \max (10,12)= 12 \quad (11)$$

The machine must be switched off when both the on-off energy consumption and the on-off time of the machine are less than the idle energy consumption and time between the consecutive two jobs. Otherwise, the machine should not be turned off. According to the data, some feasible solutions were obtained as shown in Table 1.

Table 1. Some feasible solutions of the three-job by different algorithms

GA (Proposed in this paper)

	S_1	S_2	S_3	Y_{12}	Y_{23}	E_T

Solutions (1)	0	40	60	1	0	8
	S_2	**S_1**	**S_3**	**Y_{21}**	**Y_{13}**	**E_T**
Solutions (2)	40	50	60	0	0	0
	S_3	**S_1**	**S_2**	**Y_{31}**	**Y_{12}**	**E_T**
Solutions (3)	60	80	90	0	0	0
	S_2	**S_3**	**S_1**	**Y_{23}**	**Y_{31}**	**E_T**
Solutions (4)	40	60	80	0	0	4
NSGA-II (Liu et al., 2014)						
	S_1	**S_2**	**S_3**	**Y_{12}**	**Y_{23}**	**E_T**
Solutions (1)	10	40	60	0	0	16
	S_1	**S_2**	**S_3**	**Y_{12}**	**Y_{23}**	**E_T**
Solutions (2)	10	40	60	1	0	12
	S_1	**S_2**	**S_3**	**Y_{12}**	**Y_{23}**	**E_T**
Solutions (3)	10	50	60	1	0	8
	S_1	**S_2**	**S_3**	**Y_{12}**	**Y_{23}**	**E_T**
Solutions (4)	40	50	60	0	0	0

Table 1 shows that; Solution (1) of the genetic algorithm and Solution (3) of NSGA-II (Liu et al., 2014) gives same result value for same job scheduling. This result shows the success of our model and algorithm. In addition, We achieved zero energy consumption values with different job sequences except First Come First Served rule in Solution (2) and Solution (3).

5.2. A problem With Five Jobs

The proccessing time, arrival time and the delivery time of each job are given in Table 2. Table 3 shows the genetic parameters used in this problem. These parameter values are taken from Liu et al. (2014). The other parameter values are the same with three jobs problem above. This problem is solved with the MATLAB program. Some feasible solutions are presented in Table 4.

Table 2. Basic input data of each product

Jobs	**1**	**2**	**3**	**4**	**5**
Arrival time	0	30	50	80	150
Processing time	10	20	20	30	10
Time for delivery	200	200	200	200	200

Source: Liu et al., 2014

Table 3. The parameter values

Parameter	**Value**

Population size	300
Maximal number of generations	100
Crossover probability	0,98
Mutation probability	0,5

Source: Liu et al., 2014

Table 4. Some feasible solutions of the five-job by different algorithms

GA (Proposed in this paper)

	S_3	S_2	S_1	S_4	S_5	Y_{32}	Y_{21}	Y_{14}	Y_{45}	E_T
Solutions (1)	50	70	90	100	150	0	0	0	1	4
	S_4	S_3	S_2	S_1	S_5	Y_{43}	Y_{32}	Y_{21}	Y_{15}	E_T
Solutions (2)	80	110	130	150	160	0	0	0	0	0
	S_3	S_4	S_2	S_1	S_5	Y_{34}	Y_{42}	Y_{21}	Y_{15}	E_T
Solutions (3)	50	80	110	130	150	0	0	0	0	8
	S_1	S_2	S_3	S_4	S_5	Y_{12}	Y_{23}	Y_{34}	Y_{45}	E_T
Solutions (4)	0	80	100	120	150	1	0	0	0	4

NSGA-II (Liu et al., 2014)

	S_1	S_2	S_3	S_4	S_5	Y_{12}	Y_{23}	Y_{34}	Y_{45}	E_T
Solutions (1)	10	30	55	119	165	0	0	1	1	14
	S_1	S_2	S_3	S_4	S_5	Y_{12}	Y_{23}	Y_{34}	Y_{45}	E_T
Solutions (2)	10	45	65	100	150	0	0	1	0	26,93
	S_1	S_2	S_3	S_4	S_5	Y_{12}	Y_{23}	Y_{34}	Y_{45}	E_T
Solutions (3)	10	66	105	130	162	1	1	0	0	10,8
	S_1	S_2	S_3	S_4	S_5	Y_{12}	Y_{23}	Y_{34}	Y_{45}	E_T
Solutions (4)	10	84	129	152	183	1	1	0	0	9,61
	S_1	S_2	S_3	S_4	S_5	Y_{12}	Y_{23}	Y_{34}	Y_{45}	E_T
Solutions (5)	10	106	128	154	186	1	0	0	0	8
	S_1	S_2	S_3	S_4	S_5	Y_{12}	Y_{23}	Y_{34}	Y_{45}	E_T
Solutions (6)	10	76	137	157	188	1	1	0	0	8,4

In Table 4, we presented some feasible solutions of our algorithm. Solution (4) in our algorithm and Solution (5) in NSGA-II (Liu et al., 2014) have with same job sequence. The value of solution (4) in our algorithm is better than solution value Solution (5) in NSGA-II (Liu et al., 2014). We were able to reduce energy consumption by 50%. As a result, it proves that our model can find much better solutions. Besides, we have created with various job sequences except First Come First Served rule and found zero energy consumption in Solution (2). The our algorithm succeeded to achieve a zero energy consumption value by creating an appropriate job sequence with different job sequences except First Come First Served rule.

6. Conclusion and Future Work

The machines consume waste energy while idling or switching on and off. In single-machine systems, keeping the machine idle running instead of turning it on and off or vise versa would reduce the waste of energy. Therefore it is important from the point of energy consumption to decide on when to turn the machine on/off and keep it idle. In this paper, we have developed a model and algorithm that minimize energy consumption in a single machine production system. We aimed to reduce energy consumption with decision whether the machine should be idle or switched on or off between consecutive jobs.

Liu et al. (2014) set up a model that reduces the total carbon dioxide emissions and the total completion time. They used NSGA-II method to solve three-jobs and five-jobs problems with First Come First Served rule in a single machine menufacturing system. They obtained some feasible solutions. We used data sets of three-jobs and five-jobs problems in the paper of Liu et al (2014) to verify our proposed algorithm. We generated a simulation environment on MATLAB and obtained some feasible results. We have achived job sequences. We evaluated the performance of our model. We compared solution results of our genetic algorithm and their NSGA-II outcomes. we considered the delivery time of all jobs in this paper. We used Ctcf = λ.Etec (λ=0.785 kgCO2/kwh) formula to convert total carbon dioxide emission values to energy values (Liu et al., 2014). Solutions of the problem with three jobs was presented in Table 1. Solution (1) of the genetic algorithm has same value and same job scheduling as Solution (3) of NSGA-II (Liu et al., 2014). It seems that our solutions in three jobs problem were not worse than the solutions provided by Liu et al. (2014). In addition, We reached zero energy consumption values with different job sequences except First Come First Served rule in Solution (2) and Solution (3) thanks to our genetic algorithm. We presented some feaseble solutions for the problem with five jobs in Table 4. Solution (4) in our algorithm and Solution (5) in NSGA-II (Liu et al., 2014) have same job sequence. While Solution (5) energy value is 8 in NSGA-II (Liu et al., 2014), solution (4) energy value is 4 in our algorithm. We succeeded to decrease energy consumption rate 50% with our genetic algorithm. Besides, we generated various job scheduling except First Come First Served rule in this problem. Energy consumption value of Solution (2) was calculated zero. As a result, that proves our genetic algorithm generating much better solutions than NSGA-II of Liu et al. (2014).

In this article, a scheduling problem with single objective was studied in a single machine system. There are in the real world that a lot of target need to be optimized together for companies. Therefore, multi-objective mathematical models can be established in future resarch. In addition, an enegy efficient model can be developed with sequence-dependent setup times.

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