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ENERGY EFFICIENT SCHEDULING IN MANUFACTURING INDUSTRY

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Abstract - *The global economy, dominated by the industrialized world, already consumes more natural resources than ecologically bearable, it is about 33% of the total consumption. Production scheduling is the key for the energy efficiency improvement. By improve scheduling approach manufacturing firms can achieve sustainable manufacturing processes, reduce emissions and minimizing total energy consumption and makespan in production. The practice of considering energy consumption in the production schedule is not commonly followed by many industries. This project proposes an optimised methodology for production schedule where in energy consumption is focused. The methodology is developed using the data collected from a steel furniture manufacturing company where the cost of electrical power was found to be very high. The methodology has two components, namely makespan time reduction and plant simulation. The former was done using genetic algorithm implemented in Microsoft visual studio and the later by using a commercial plant simulation package. The present project is to identify the techniques used to optimize the energy efficiency through production scheduling in a manufacturing industry. An optimized schedule and energy demand output is obtained. Demand is also considered during the reduction of makespan and energy consumption.*

Key Words: **Energy efficient scheduling, Manufacturing system, Sustainable manufacturing, Genetic algorithm, Makespan, Energy Consumption.**

1.INTRODUCTION

Energy consumption is an important issue in current society. In last 40 years, the energy demand of the world has doubled and will double again in next 10 years [1]. In general, the industry is one of the primary consumers of energy. In 2018, industry accounted for approximately 25% of energy consumption by end use in the European Union [2]. The energy consumption of industrial fields is about 26.3% of estimated U.S. energy consumption of 2018 [3]. As energy-intensive fields, manufacturing industries consumed nearly a third of the global energy consumption of the world. In China, more than 56% of the total energy consumption is occupied in manufacturing sector attributed and in India it is about 41.16%. It is essential to reduce the manufacturing industry's energy consumption and demand. The manufacturing industries play a key role to satisfy continuously growing of various goods as living standards increasing. Hence, how to improve energy efficiency or to reduce energy demands for the same output becomes a critical approach to achieve the purpose of reducing energy consumption and developing sustainably. In actual machining processes, machine tools stay in an idle state for the most of the time and consume about 80% energy with the idle state .In general, scheduling problem is an assignment problem, which can be defined as the assigning of available resources (machines) to the activities (operations) in such a manner that maximizes the profitability, flexibility, productivity, and performance of a production system. Production scheduling has been proven as an NP-hard problem; hence, energy-efficiency scheduling is no exception. The motivation of this review work is the green manufacturing and energy-saving awareness in production scheduling area. The design of intelligent scheduling strategies should consider reducing energy consumption which is an important scheduling objective in current production scheduling area.

2. LITERATURE SURVEY

The main objective of work reported in [4] is to present heuristic methods based on genetic algorithms. This paper proposes how genetic algorithms can be applied in the optimization of manufacturing scheduling problems. Representation scheme of a feasible solution to the considered problem is a key aspect of evolutionary algorithms. A new approach to the distributed scheduling in industrial clusters which uses a modified genetic algorithm. Therefore, in this study, the focus is brought on the coding problems. It is common knowledge that in solving large-size problems, genetic algorithms show much better performance Despite many advantages in solving scheduling problems presented in the existing literature, many applications of genetic algorithms are questionable. Researchers still study small-scale problems or only flow shop problems, where there are many constraints. It is possible that equally important and stimulating research unknown to the authors was unintentionally omitted. The previous approach often ignores dividing jobs and interactions between the various firms within supply networks at operations management level in order to improve manufacturing processes. But, in the era of supply network, decisions on the use of resources should concern both internal and external capacities; the internal flow of materials should be synchronized with the incoming and outgoing flows. For this purpose, a system for scheduling must take into consideration the possibility of dividing jobs into factories, loops, and a long transport. The proposed modified genetic algorithm (MGA), which take into account loops in supply networks. Additionally, the proposed modified genetic algorithm enables dividing jobs between factories, and transport orders planning in the industrial cluster. Summarizing, advances in genetic algorithms create new prospects for inter-organizational cooperation. As mentioned above, But, it is noted that another group of researchers proposed an ant colony optimization (ACO) for solving advanced scheduling problem. Ant algorithms are optimization algorithms inspired by the foraging behavior of real ants in the wild. Within the Artificial Intelligence (AI) community, ant algorithms are considered under the category of swarm intelligence. Swarm intelligence encompasses the implementation of intelligent multi-agent systems that are based on the behavior of real world insect swarms, as a problem solving tool. Future research can also investigate the possibility of incorporating the proposed ACO for solving scheduling problems in the industry.

The objective of this paper[5] is of minimizing the makespan and scheduling in FMS. Two types of scheduling algorithm such as priority scheduling (TMFR and STPT) and evolutionary algorithm (Genetic Algorithm) are suggested in this paper. These algorithms are implemented in MATLAB. Performances of these algorithms are compared with each other FMS is a highly automated manufacturing system which provides various types of flexibilities like machine flexibility, routing flexibility, product flexibility etc. The various types of flexibilities in FMS provide a lot of benefits in terms of reduction in inventory, idle time, mean flow time and increase in the utilization of machines. The present works deals with scheduling of 4 jobs on 4 machines. Each of the job have certain operations and some of the operations can be performed on more than one machine. So, two different loading cases are being discussed to process the job. There are 4 jobs which are to process on the four machines. The processing time information for each of the operations on various machines are collected. The processing time information and priority rule act as input for generating the schedule which minimizes the makespan. The parameters like makespan, idle time, flow time and utilization of machines are calculated for each of case from the schedule obtained from TMFR, STPT and genetic algorithm. The results obtained from these algorithms are compared with each other to measure the various performance measures of FMS. It has been found that genetic algorithm minimizes the makespan as compare to the TMFR and STPT algorithm. This work contains 2 priority algorithm (TMFR and STPT) and genetic algorithm for minimizing the makespan. TMFR (Two Machine Fictitious Rule) algorithm is used for scheduling of n jobs and m machines. Genetic algorithm and two priority rule (TMFR and STPT) are used for determining the sequences of jobs which minimizes the value of makespan. These algorithms are implemented in MATLAB. Further, the optimized value of average idle time, average flow time and average machine utilizations are calculated corresponding to the minimum value of makespan for two different loading conditions. For two cases comparisons are made by using each of the algorithms and then both cases are compared with each other to find out the operation allocation which minimizes the makespan. genetic algorithm gives the minimum value of makespan. Genetic algorithm not only minimizes the makespan but also optimizes the value of average idle time and average machine utilization. Further, the comparison between TMFR and STPT priority rule depicts that TMFR priority rule is better approach for minimizing makespan as compare to STPT rule. However, it can be seen that STPT priority rule perform better for minimizing average flow time. From the comparison of results genetic algorithm is a better approach to tackle scheduling problem in FMS. The present work deals with scheduling in FMS with the objective of minimizing the makespan under the assumption that a loading plan is given for operation allocation. Results show that the genetic algorithm perform better than the priority scheduling for minimizing the makespan. It minimizes the makespan and maximizes the machine utilization. Genetic algorithm gives minimum value of makespan in reasonable amount of computation time. Further, the presence of machine and operational flexibility improve the performance of FMS. It was found that the TMFR rule minimizes the value of makespan while STPT priority rule can be effectively used for minimizing average flow time.

This paper [6] aims to optimize the weighted sum of two criteria: the minimization of the makespan of production and the minimization of time-dependent electricity costs. a hybrid genetic algorithm with our blank job insertion algorithm and demonstrate its performance in simulation experiments. To save energy or reduce energy costs is important not only for manufacturing companies but for our environment. This method allows the decision maker to seek a compromise solution using the weighted sum objective of production scheduling and electricity usage. Reliability models are used to consider the energy cost aspect of the problem. Therefore, each manufacturing company and each country should establish a method to reduce energy use or energy costs. Hence, the DR of manufacturing companies is important, and it will become more important in a smart grid environment. new production scheduling scheme enables companies to minimize their production costs, defined as the weighted sum of time dependent electricity costs and completion time-related costs of production. Mathematical modelling can be solved in a mixed integer linear programming solver such as CPLEX. However, given that the problem is NP-hard, we cannot solve the problem efficiently in a short time. Therefore, a modified genetic algorithm is proposed ie, Hybrid inserted genetic algorithm In time-dependent electricity costs, it is necessary to consider the idling time or blank job insertion to avoid a high electricity cost. They can solve our unrelated parallel machine scheduling problem by using the inserted GA (IGA) with a modified gene structure. Our new blank job insertion (BJI) algorithm was developed to obtain an improved solution. In addition, our hybrid inserted genetic algorithm (HIGA) with the BJI algorithm was applied to the scheduling problem to improve its solution Our problem sets consisted of five jobs and two machines and six jobs and three machines for two scenarios. The jobs had different processing times for each machine with different power consumption levels. The current hourly electricity price for the peak-load, the mid-load, and the off-peak-load were used as the input data. The data of industrial electricity price were from the Korea Electric Power Corporation in South Korea. UI application Was developed to test our algorithms and show our simulation result in C#. This was executed on a Pentium 2.4 GHz PC. Scenario no. 1 there is 5-job and 2-machine problem. The power consumptions for each machine were 100 and 250 kWh, respectively. Result of scenario no. 1 shows the screen of configuration data input and resulting Gantt charts for scenario no. 1. It also shows the makespan and the total cost for each method. while comparing graph four methods. SGA reduced the total cost by 5 % compared to that of the simple GA. HIGA reduced the total cost by 13 % compared to that of the simple GA. In Scenario no. 2 there is 6-job and 3-machine problem The power consumptions for each machine are 100, 250, and 120 kWh, respectively. Result of scenario no. 2 shows the screen of configuration data input and resulting Gantt charts for scenario no. 2. It also shows the makespan and total cost for each method. While comparing the graph for 4 methods. SGA reduced the total cost by 15 % compared to that of the simple GA. HIGA reduced the total cost by 22 % compared to that of the simple GA. In addition, In next study, is tested on flexible job shop scheduling problem. With many operations, these problems have much larger applicability than parallel machine problems and are therefore more realistic and complex. Adoption of finer time slots for the processing time.

3.METHODOLOGY

Energy conservation opportunities are identified at equipment level based on the power consumption. The product specific data from the process plans of each product are fed to the makespan minimization module. The minimum makespan for each product is fed to the manufacturing system simulation module. The process data, equipment data and power consumption are also fed to the manufacturing simulation module and two stage multi objective optimised solutions are obtained as output. The makespan minimization program was executed in Microsoft visual studio and the manufacturing simulation was implemented in a commercial package.

3.1 Problem definition

The steel furniture manufacturing industry is in the MSME sector, equipped with advanced machines and having good market share. However, the company resorted to cost reduction efforts in order to remain competitive in the sector. The company has identified that the cost of electrical power is the major component of the total product cost.

Like any industry in SME sector, the production plan of the company is prepared based on the delivery agreement with customers wherein the use of resources like electrical power is not effectively taken care of. The fluctuation of demand leads to unbalance in production flows and non-productive idle times. In order to solve the problem objectives and set and are discussed in the proceeding section.

In this problem, we use 9 different machines for manufacturing 5 products. Table 1 shows job sequence and processing time got from the simulation output of current model. Here a genetic algorithm is proposed for scheduling of the manufacturing processes.

Table -1: Processing time and Sequence of products

	Processing time, Sequence of operation								
Job	M1	M2	M3	M4	M5	M6	M7	M8	M9
J1	_	_	_	_	_	6,1	_	_	1,2
J2	10, 1	5,3	2,2	_	1,5	5,4	_	_	_
J3	3,1	5,2	_	2,5	4,4	7,3	-	_	-
J4	_	_	_	_	8,4	5,2	3,3	1,1	-
J5	_	_	_	_	_	10, 1	5,2	1,3	_

3.2 Genetic Algorithm

Optimization problems rise in various fields of production scheduling like minimization of the
cost of electricity, minimization of cost of production, maximization of profit etc.

There are different types of optimization techniques,

1. Classical optimization
2. Heuristic optimization

The classical optimization techniques are very useful to obtain the optimal solution of problems involving continuous and differentiable functions. Some challenges of classical optimization techniques

1. Consider only small scale problems
2. Local search
3. Need to be updated continuously
4. Not used for handling real time and dynamic optimization problem. In order to overcome the limitations of classical optimization methods, another branch of the optimization is developed, i.e. the heuristic optimization. Heuristic optimization techniques perform stochastic search in the problem spaces and it has global search and robustness.

Here we propose a new meta heuristic algorithm ie called Genetic Algorithm (GA).It has strong search capability, robustness and applied to broad range of problems compared to heuristic techniques.

Genetic algorithm inspired by Charles Darwin's theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation.

Phases including GA

- Initial population: The process begins with a set of individuals which is called a Population. Each individual is a solution to the problem.

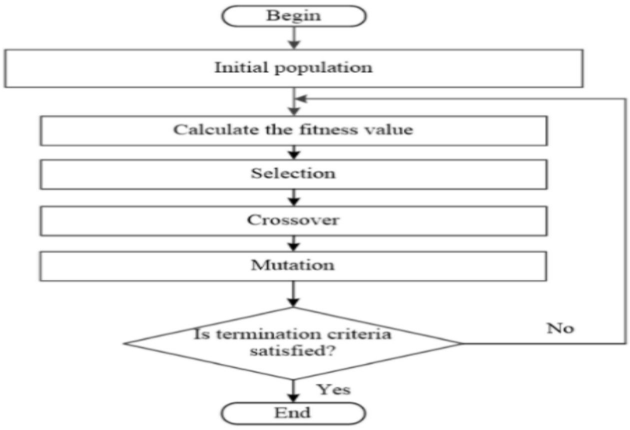

Fig -1: Flow chart of GA

- Fitness function: The fitness function determines the ability of an individual to compete with other individuals. The probability that an individual will be selected for reproduction is based on its fitness.
- Selection: selection phase is to select the fittest individuals and let them pass their genes to the next generation.
- Crossover: Crossover is the most significant phase in a genetic algorithm. For each pair of parents to be mated, a crossover point is chosen at random from within the genes.
- Mutation: In certain new offspring formed, some of their genes can be subjected to a mutation with a low random probability.

4.RESULT

Makespan of each product from current and optimized model is shown in the figure 2. object1 and object3 represents the products produced from the current and optimized model respectively. Product arrival and exit time from each assigned machine is taken from the data generated from the plant simulation software to calculate the makespan of each product. The makespan of current and optimized model is calculated and the difference between the current and optimized model is calculated. A reduction of 4.308514% in makespan is obtained.

object1	arrivaltim	exitime1	makespan1	object3	arrivaltim	exitime3	makespan3			
Chair:1	0	1598.509	1598.509181	Chair:1	0	1478.509	1478.509181			
Chair:2	626.7659	2861.654	2234.887895	RoundTable:1	0	2081.042	2081.042235			
RoundTable:1	626.7659	3551.482	2924.71593	Chair:2	525.1191	2961.882	2436.763208			
Podium:1	626.7659	4698.16	4071.393874	Tables:1	0	3418.388	3418.388284			
Tables:1	0	5212.64	5212.639663	RoundTable:2	1456.87	3780.998	2324.12786			
RoundTable:2	1870.747	5216.611	3345.864198	WashBasin:1	0	5108.952	5108.951728			
Podium:2	1870.747	7026.74	5155.992745	Podium:1	206.7659	5252.868	5046.102324	makespan mode1	311616.2	14:33:36
WashBasin:1	0	7275.768	7275.768108	RoundTable:3	3168.406	5477.183	2308.777171	makespan mode2	298190.2	10:49:50
Chair:3	2606.296	7641.741	5035.445735	Chair:3	2225.576	5806.968	3581.392254			
RoundTable:3	4963.386	7845.452	2882.066425	Tables:2	1456.87	6241.97	4785.099439	model1-model2	13426.03	03:43:46
Tables:2	1237.08	8143.258	6906.178042	RoundTable:4	4924.88	7194.674	2269.793977			4.308514
WashBasin:2	1237.08	9383.348	8146.267369	WashBasin:2	1456.87	7249.771	5792.900468			
RoundTable:4	6225.166	9607.295	3382.129348	Podium:2	1712.904	8063.487	6350.582534			
Podium:3	4963.386	9956.982	4993.596621	Chair:4	3984.928	8617.211	4632.283351			
Chair:4	4963.386	10597.05	5633.666622	RoundTable:5	6675.075	9009.132	2334.056256			
Tables:3	4344.04	11125.5	6781.463043	Tables:3	3168.406	9077.281	5908.875026			
WashBasin:3	4344.04	11672.99	7328.954713	WashBasin:3	3168.406	9384.243	6215.837101			
RoundTable:5	9331.379	12238.07	2906.694965	RoundTable:6	8425.039	10740.55	2315.514518			
Podium:4	6225.166	12951.12	6725.959001	Podium:3	3452.079	10925.73	7473.652749			
Chair:5	6960.803	13583.37	6622.567909	Chair:5	5683.716	11491.35	5807.637277			
WashBasin:4	5585.214	13793.46	8208.247817	WashBasin:4	4924.88	11535.53	6610.653814			

Fig -2: Makespan calculated

Figure 3 and 4 show the energy consumption of current and optimized model. Using energy analyser tool in plant simulation data related to energy consumption for each individual machines is obtained. Energy consumption of bundle cutting is higher comparing to other machines. Total energy consumption for both model is obtained and compared. Energy consumption of current model is 343.5335kWh and energy consumption of optimized model is 293.9586kWh and difference between the energy consumption between the current and optimized model is 49.57488kWh. reduction in energy consumption 14.43087% is achieved.

Energy Consumption points	Energy Consumption [kWh]
LaserCutting	22.79272488
Bending	88.30671762
LaserMarking	0.44
Notching_HoleCutting	29.18332907
PowerPress	4.766666667
BundleCutting	148.5031476
HolePunch	46.80615293
Notching	0
DegreeCutting	0
PipeBending	0.733333333
PipeRolling	2.001388889
Total	343.533461

Fig -3: Energy consumption in current model

Energy Consumption	Energy consumption [kWh]				
LaserCutting	23.20829793				
Bending	74.81715874			Model1 energy consumption	343.5335
LaserMarking	0.446666667			Model2 energy consumption	293.9586
Notching_HoleCutting	22.11513182				
PowerPress	4.766666667			model1-model2	49.57488
BundleCutting	130.6039291				14.43087
HolePunch	35.23545221				
Notching	0				
DegreeCutting	0				
PipeBending	0.733333333				
PipeRolling	2.031944444				
Total	293.9585809				

Fig -4: Energy consumption in optimized model

Figure 5 and 6 show the quantity of products entering and leaving the particular machine. A total of only 131 products are processed in laser cutting machine for current model., but in the case of optimized model 135 products are processed. There is increase in number of products produced in optimized model. Similarly, in the case of pipe rolling machine 130 and 131 products are produced respectively in current and optimized model.

Object	Number of Entries	Number of Exits	M C
Source	331	330	
Store	309	0	
LaserCutting	132	131	
Bending	130	129	
LaserMarking	66	65	
Notching_HoleCutting	195	195	
PowerPress	65	64	
BundleCutting	327	326	
HolePunch	130	130	
Notching	0	0	
DegreeCutting	0	0	
PipeBending	66	66	
PipeRolling	131	130	

Fig -5: Quantinty of products entering and leaving in current model

Object	Number of Entries	Number of Exits
Source	338	337
Store	309	0
LaserCutting	135	135
Bending	135	135
LaserMarking	67	67
Notching_HoleCutting	196	196
PowerPress	65	64
BundleCutting	337	336
HolePunch	131	131
Notching	0	0
DegreeCutting	0	0
PipeBending	66	65
PipeRolling	133	132

Fig -6: Quantinty of products entering and leaving in optimized model

Summary of the result obtained, total makespan and energy consumption is shown in table 2, a total reduction of 4.3085% is achieved in makespan and 14.4308% reduction in energy consumption.

Table -2: Result

	Present Model	**Optimized model**	**% Reduction**
Makespan	14:33:36	10:49:50	4.308514235
Electricity consumption	343.533461kWh	293.9585809 kWh	14.43087375

5. CONCLUSIONS

The growing awareness of energy efficiency and sustainable development has led to persistent attention to energy efficiency in production scheduling. This paper describes how the genetic algorithms have been applied to the optimization of manufacturing scheduling problems. Representation scheme of a feasible solution to the considered problem is a key aspect of evolutionary algorithms. Therefore, in this study, the focus is brought on the coding problems. It is common knowledge that in solving large-size problems, genetic algorithms show much better performance. In this paper Genetic algorithm gives minimum value of makespan in reasonable amount of computation time. Further, the presence of machine and operational flexibility improve the performance. In this paper Simulated model of the company has been optimized using GA. Then the proposed models and the existing model are compared. Makespan has been reduced by 4.3% and energy consumption has been reduced by 14.4% in optimized model. The computational result shows that GA can obtain better solution. In future, study related to smart grid environments, in which electricity usage and costs have many diverse options, including distributed energy resources and renewables such as solar and wind power.

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