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Procedia CIRP 57 (2016) 728 – 733

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49th CIRP Conference on Manufacturing Systems (CIRP-CMS 2016)

Dynamic Agent-based Bi-objective Robustness for Tardiness and Energy in a Dynamic Flexible Job Shop

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Abstract

Nowadays, manufacturing systems are shifting rapidly with the significant change in technology, business, and industry to become more complex and involved in more difficult issues, customised products, variant services and products, unavailable machines, and rush jobs. In the current practices, there are limited models or approaches that are dealing with these complexities. Most of the scheduling models in literature are proposed as centralised approaches. Researchers recently started to pay attention to reduce energy consumption in manufacturing due to the rising cost and the environmental impact. The energy consumption factor has been lately introduced into scheduling research among other traditional objectives such as time, cost and quality. Although reducing energy in manufacturing systems is very important, few researchers have considered energy consumption factor into scheduling in dynamic flexible manufacturing systems. This paper proposes an agent-based dynamic bio-objective robustness for energy and time in a job shop. Two types of agent are introduced which are machine agent and product agent. A new decision making and negotiation model for multi-agent systems is developed. Two types of dynamic unexpected events in the shop floor are introduced: dynamic job arrival and machines breakdown. A case study is provided in order to verify the result.

Peer-review under responsibility of the scientific committee of the 49th CIRP Conference on Manufacturing Systems

Keywords: Dynamic scheduling; Multi-agent system; Flexible job Shops; Energy saving; Robustness; Random disruptions.

1. Introduction

In the manufacturing process, energy is the key to running of the plants and consumption of energy is evident in different levels of the manufacturing process. Evans found that the manufacturing activities are major users of energy in the world accounting for over one-third of the world's usage of energy [1]. It is factual that the world population is on the increase and there is significant rise in living standards which translates to increased demand of manufactured goods. The challenge facing the manufacturing sectors is the energy consumption. As the populations grow, more manufactured products are required and subsequently a lot of energy is used to manufacture the products. Therefore, manufacturing systems and processes that are energy efficient should be incorporated in the production process [2].
There are many research efforts that have been carried out to provide knowledge on the ways energy consumption can be reduced at various levels of manufacturing system [3]. These levels are the process level [4], equipment level [5], systems level [6] and the factory level [7]. This paper focuses on the system level where energy can be reduced through scheduling and planning.

Scheduling is a process of allocating or assigning appropriate resources to a job [8]. A good scheduling can help in reducing the effort, time or cost in manufacturing. The classical scheduling or static scheduling approaches may achieve this and help in solving the problem. However, real manufacturing systems are complex and dynamic with a large number of products and processes, involving many production levels, and subject to accidental disturbances. Examples of these disturbances include: arrivals of new orders, cancellation of jobs in queues, changes in urgency of some jobs, failure of

Peer-review under responsibility of the scientific committee of the 49th CIRP Conference on Manufacturing Systems
doi:10.1016/j.procir.2016.11.126

technological equipment or temporary unavailability of some resources. Therefore, in real life conditions, classical scheduling or static scheduling approaches turns out to be impractical due to their mostly unrealistic assumptions [9]. So, such dynamic entity requires dynamic scheduling. Therefore, dynamic scheduling can play a very important role for the successful implementation of real-world scheduling systems.

Since the scheduling problem is complex and considered to be NP-hard, the researchers apply different types of artificial intelligent techniques to optimise the production scheduling. These techniques are including genetic algorithms, fuzzy logics, neural networks, and Tabu search. However, such methods are likely to encounter difficulties when applied to real-world situations as they are essentially centralised and based on simplified theoretical models. Multi-agent systems (MAS) have been applied in decentralised manufacturing planning and scheduling as well as for shop floor control where they have been demonstrated to good results especially for dynamically changing situations [10]. Hence, they provide a very promising framework for more dynamic and adaptive scheduling.

This paper focuses on investigating the robustness of flexible job shops controlled by multi-agent system with dual optimisation objectives; tardiness and total energy consumption. In order to measure the robustness, the system should be analysed to assess how quickly it responds to possible natural errors that can occur and the impacts of these disruptions. In this study, two types of dynamic uncertainties were considered to benchmark the robustness of the proposed multi-agent scheduling system. These are the dynamic arrival of jobs and random machine breakdowns.

2. Literature review

Research on scheduling to minimise energy consumption is limited but increasing. One of the significant studies was carried out by Mouzon et al. who minimised energy consumption and total completion time by turning off the non-bottleneck machines until needed. Up to 80% of energy saving was achieved [11]. Liu et al. focused on the reduction of energy consumption and total weighted tardiness using Genetic Algorithms in a classical job shop [12]. Fang et al. considered the carbon footprint, peak load and productivity during a job shop scheduling [13]. Chen et al. investigated the reduction of energy consumption by an effective scheduling of machine start up and shutdown. Machines were assumed to have Bernoulli reliability model [14]. Moreover, Mashaei et al. reduced energy consumption in idle machines by using the control strategy for closed-loop flow shop [15].
In a flexible manufacturing system, Diaz et al. optimised the performance of the system in terms of cost and environmental impact using discrete-event simulation [16]. Guerrero et al. also proposed an optimal scheduling procedure to select the appropriate batch and sequence policies to improve the paint quality and decrease repaints, resulting in reduction of energy and material consumption in an automotive paint shop [17]. He Y et al. used mixed integer programming and nested partition to optimise energy through the machine selection and operation sequence [18].

All of these energy reduction researches focused on heuristic and meta-heuristic approaches. These methods are all centralised approaches. There is a lack on reducing energy consumption on a dynamic decentralised approach. The multi-agent systems are among the promising approaches to developing robust, cost-effective, and complex manufacturing scheduling systems for the next generation because of their autonomy, distribution, and dynamic form, and their strength against failures [19]. Multi-agent systems are significant in dynamic scheduling in manufacturing systems as a means for energy consumption reduction. This research characterises the multi-agent system for this purpose. Due to the complexity, uncertainty and dynamics in the modern manufacturing environment, flexible and adaptive scheduling is essential to achieve production objectives that include not only high delivery performance and low production costs, but generic system properties like the ability to develop flexible behaviour, guaranteeing fault tolerance. The centralised approaches limit the expandability, re-configurability and fault tolerance of manufacturing systems. The multi-agent system is the methodology able to design and support efficient distributed intelligent manufacturing systems. Several researches have applied the agent methodology to develop industrial distributed systems.

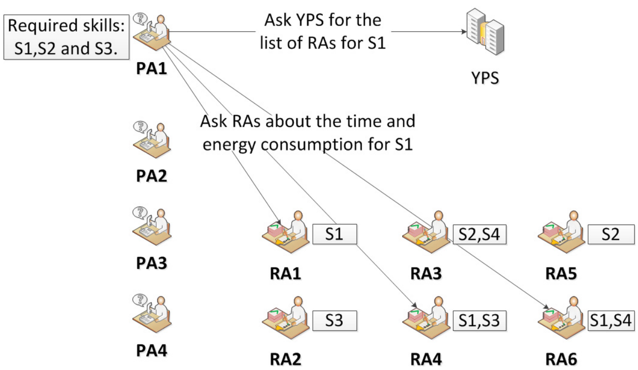

Figure 1: Multi-agent system approach

The MAS is a realisation of a distributed artificial intelligence (DAI) system that consists of a group of autonomous agents [20]. The agents in the MAS interact and collaborate to achieve collective goals while each agent simultaneously seeks individual objectives [21]. Manufacturing scheduling and control systems can be developed using MAS technology if the requirements of reconfigurable and agile manufacturing are met. Multi-agent methods are promising approaches that can increase productivity and profitability through enhancing shop floor flexibility [22]. Due to their flexibility, reconfigurability, and scalability, MASs have been extensively applied in manufacturing applications [23]. The essential aim of the agents in these systems is to fulfill global objectives from local agent solutions. Using the agents in dynamic manufacturing systems can enrich the reliability and flexibility of planning and scheduling functions, as the agent structure facilitates reconfigurability in response to changes. The agents also provide a fault tolerance feature to the manufacturing environment, which can be achieved through resource reallocation. Previous research on this topic have mainly focused on altering traditional centralised system forms and integrating multiple decision makers that can be organised via different coordination systems [24].

3. Methodology and implementation:

In order to investigate the robustness of flexible job shops, we use MAS to implement a decentralised flexible manufacturing system. With MAS, it is easier conduct experiments comparing with a real-life system, and we can control which of dynamic factors to be introduced into the system. Figure 1 describes the structure of the system. It consists of many machines and products. Each machine can perform one or more services and has different time and energy consumption. And each product requires a sequence of services to be performed on it. Since a service can be performed by several machines, a product can be processed by different machines depend on decision-making policies in the negotiation protocol. There is also a yellow page service (YPS), which has the set of services provided by machines. The transpiration is not considered in this study.

The MAS is implemented using JADE platform (Java Agent Development Environment) [25]. In the proposed system, agents represent the manufacturing system components. Two types of agents are involved: the resource agent (RA) representing a machine and the product agent (PA) representing a product. Agents communicate and interact with each other by using a common shared communication protocol, ACL messages [26].

Agent structure:

A resource agent represents a machine:

- Each machine agent can perform a several predefined tasks.
- For each task, a machine also has information on the time and energy required to perform that task.
- When a machine is idle, it also consumes a predefine amount of idle energy.
- Machines breakdown occur randomly with a random duration between 15 and 20 minutes.

A product agent represents a product:

- Each product agent has a list of tasks to be performed and a due time.
- Products arrive dynamically at the shop floor as per probability.
- When starting up, a product agent calculates the total minimum processing time by summing all the minimum time required to do each task on the list. The product is defined as urgent if the slack time is less than 30% of total minimum processing time.

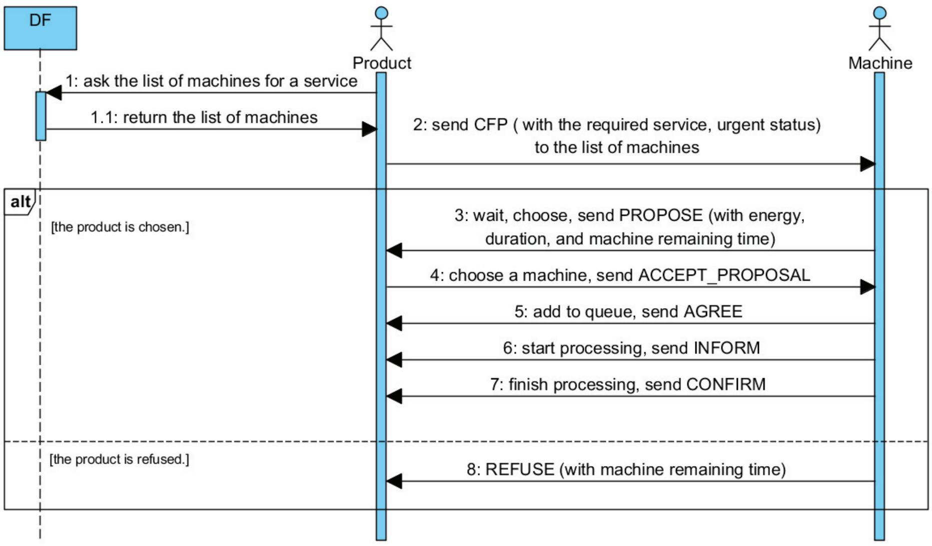

Figure 2: Sequence diagram

Table 1: Decision making policies

Agent	Policy	Full name	Explanation
RA	U&FIFO	Urgent & First In First Out	Choose the first urgent product, prioritizing urgent over non-urgent products.
	U&SPT	Urgent & Shortest Processing Time	Choose the product with the shortest processing time, prioritizing urgent over non-urgent products.
	LPT	Longest Processing Time	Choose the product which requires longest processing time
	LE	Least Energy	Choose the product which requires least energy
PA	FIFO	First In First Out	Choose the first machine
	SPT	Shortest Processing Time	Choose the machine with shortest processing time
	LPT	Longest Processing Time	Choose the machine with longest processing time
	OT&SE	On Time & Save Energy	Create a list of machines that will process the product on time. If there is no machine, create a list with all approved machine. Choose the machine with the least energy from created list.

Table 2: Results for all scenarios

Scenario	Idle energy (Wh)	Processing energy (Wh)	Total energy (Wh)	Tardiness (minute)	Idle time (minute)	Makespan (minute)
0% breakdown, 0 arrival	565.57	2014.81	2580.38	-24.75	27.90	41.35
50% breakdown, 0 arrival	705.52	1997.01	2702.53	47.45	33.95	59.80
0% breakdown, 30m arrival	1069.43	1932.89	3002.32	-34.75	52.65	55.80
50% breakdown, 30m arrival	1314.14	1978.93	3293.07	24.50	63.00	76.85

Agent behaviours:

Figure 2 is a sequence diagram that illustrates the interaction between products and machines. When the system starts up, the product agent looks up the current task on the list and gets the list of machines that are able to perform the task from Directory Facilitator (DF), which manages the YPS. Once the product agent receives the reply list of machines, it will send a call-for-proposal (CFP) message to the all machines in the list. In the CFP, the product also informs machines its urgent status. When receiving CFP, the machine waits for a predefined period before choosing one product based on its decision-making policy. After that, machine can send a PROPOSAL message which includes the energy and time for the required task, as well as the remaining time of the machine, and REFUSE messages to other products (or when the machine breaks down, or cannot perform the task the product is required). If there is no PROPOSAL message, the product will look for another machine. After receiving all PROPOSAL messages from all the machines that can perform the current task, the product agent chooses which machine to perform the task using following decision-making policy of the product. After choosing a machine, the product will send an ACCEPT_PROPOSAL message to that machine. Upon receiving the ACCEPT_PROPOSAL message, the machine will put the product on the queue, and send an AGREE message to inform the product agent. The queue of the machine is FIFO (First In First Out) which means the earlies the product goes into the queue, the earliest it will be processed. When starting processing a product, the machine agent sends an INFORM message to the product. When the machine is done with a product, it will send a CONFIRM message to the product. The decision making policies of RA and PA are listed and reviewed in Table 1.

4. Experiment:

The present study looks at a dynamic flexible job shop under the presence of uncertainty. The proposed system parameters, which include number of machines, number of products, setup time, cutting time, idling energy and cutting energy was obtained from [18]. The system was modified and the due dates were implemented in order to show the effectiveness of the system in terms of tardiness. In addition, the current system is subject to dynamic uncertainty. These uncertainties are arriving of products and the breaking down of machines, which both occur randomly. The fixing time rate for machine is from 15 to 20 minutes.

Table 3: both dynamic jobs arrival and machine breaking down scenarios results

RA	PA	Total Energy (Wh)	Tardiness (minute)	Makespan (minute)
1-U+FIFO	FIFO	3407.29	48.55	84.90
2-U+SPT	SPT	3107.54	18.30	76.80
3-LPT	LPT	3866.43	93.05	95.40
4-LE	OT&SE	3122.05	34.80	81.00
5-U+FIFO	SPT	3293.07	24.50	76.85
6-U+FIFO	OT&SE	3240.67	39.20	80.95

The policies used in this paper are described in table 1. PA and RA have their own individual decision making policy. In this experiment, we have investigated the effect of applying different decision making policies where the arriving of jobs and the breaking down of machine occur randomly.

The experiment is divided into three sections. The first section compares fixed system with dynamic system scenarios. The second section compares different decision making policies in dynamic jobs arrival and machine breakdown scenarios. The third compares the effect of the different decision making policies on the robustness of the proposed system when it is subject to disruptions.

5. Result and discussion

5.1: Comparing between fix vs dynamic scenarios

In this experiment, we experimented by comparing the scenarios without and with different dynamic factors. Due to the limit space in this paper, only one policy will be discussed. The policy is the same for all scenarios: “Urgent+FIFO” for RA and “Least remaining time” for PA. Table 2 shows the results of scenarios with different dynamic factors. The total energy as well as the makespan increases more when there are more dynamic factors in the systems. This is because the two dynamic factors we introduced are breakdown and arrival time, which will delay the makespan and consume more energy. In term of energy, the processing energy is similar between four scenarios but there are differences in idle energy consumption which cause the differences in total energy. Interestingly, the tardiness is increasing when only breakdown is included (47.75), but decreasing when only dynamic arrival is included (-34.75). It can be explained that the breakdown causes the product to be processed late; while the dynamic arrival helps spread out the jobs, thus more products will be processed on time. The energy consumption profile of this study is shown in figure 3.

5.2: Comparing between decision making policies in dynamic jobs arrival and machine breakdown

In this experiment, we included both breakdown and dynamic arrival in the system, and experiment on 6 different combinations of policies for machine and product agents. Table 3 shows the average results for each combination. The combination 2 (urgent+SPT & SPT) gives us the best result in terms of minimizing total energy, total tardiness, and makespan. Combination 4 also gives a good result, just second best after combination 2. Both combinations have PA use SPT. Combination 2 performs better by having A also use SPT policy.

5.3: The effect of using different decision making policies on the robustness of the proposed system when it is subject to disruption.

The last section of the experiment focused on the effect of using different decision making policies on the robustness, stability, and resilience in the scenario where the machines breakdown. In this experiment, the profiles of energy consumption over the time of a fixed system using all policies are created and compared with the scenario of machine breakdown. It was found that some policies resulted in more energy consumption and required longer time to recover. There was a remarkable variation in the energy consumption when compared to fixed system scenario. On the other hand, other policies performed well and were able to minimise the impact of the disturbances faster in terms of energy consumption. Figure 4 shows the energy consumption profile of policy 4 used in static system and machine breakdown system. It can be seen that there were slightly different variation in energy consumption when compared to the fixed system. Figure 5 shows the energy consumption profile of policy 3 used in fixed system and machine breakdown. When comparing both scenarios, it is clear that the proposed policy is not resilient since it does not respond well when disruption occurs.

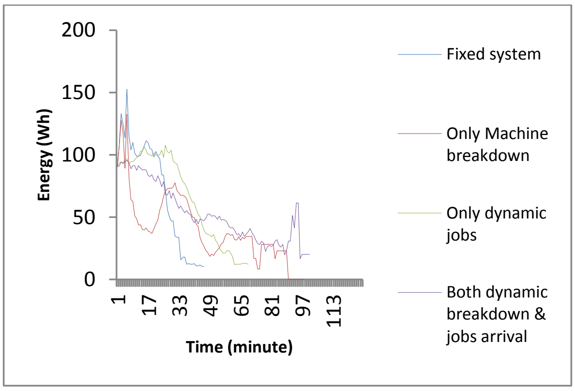

Figure 3: result for fixed and other dynamic system scenarios

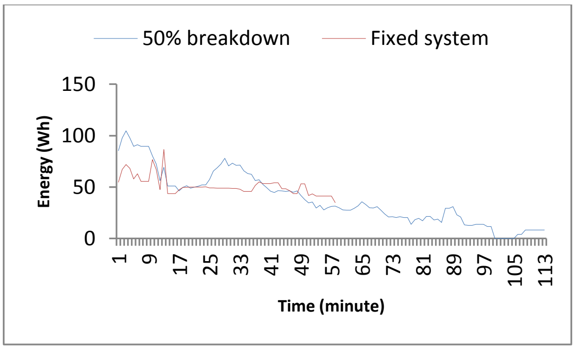

Figure 4: result for Policy 4 in fixed and machine breakdown scenarios

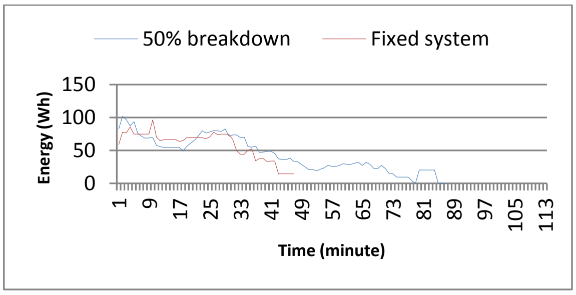

Figure 5: Result for policy 3 in fixed and machine breakdown system scenario

6. Conclusion

The paper investigated the effect of testing different decision making policies using MAS. Dynamic disturbances such as machine breakdown and dynamic jobs arrival were introduced in the system. The system consists of two agents: machine agent and product agent. We compared one policy in different system scenarios. We also compared six different decision making policies in a dynamic system which includes machine breakdown and dynamic arrival jobs. We examined how different combinations of decision making policies affect the system. This can be very hard and expensive to perform in the real system. Thus, our approach in using simulation with dynamic factors can be used to explore the decision making policies and later make informed decisions on the real job shops.

It was found that the resilience of the system changes significantly as a result of using different decision making policy. In the scenarios where machines breakdown, it is noticeable that the energy consumption decreases. This is due to the times of broken machine and not consuming energy. This result suggests a new strategy that can be used in further research for energy optimisation through setting machines on a sleep mode when they are not operating. In addition, considering the transportation agent in the future research will have a major impact on the dynamic scheduling.

Acknowledgement

The reported work has been partially funded by the EPSRC Centre for Innovated Manufacturing in Intelligent Automation (EP/IO33467/1). The support of which is gratefully acknowledged.

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