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The Scientific Field of Production Economics

Production Economics focuses on scientific topics treating the interface between engineering and management. All aspects of the subject in relation to manufacturing and process industries, as well as production in general are covered. The subject is interdisciplinary in nature, considering whole cycles of activities, such as the product life cycle - research, design, development, test, launch, disposal - and the material flow cycle - supply, production, distribution, recycling and remanufacturing.

The ultimate objective is to create and develop knowledge for improving industrial practice and to strengthen the theoretical base necessary for supporting sound decision making. It provides a forum for the exchange of ideas and the presentation of new developments in theory and application, wherever engineering and technology meet the managerial and economic environment in which industry operates.

Tracing economic and financial consequences in the analysis of the problem and solution reported, belongs to the central theme.

♦

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The purpose of the ***International Working Seminars on Production Economics*** is to provide an opportunity for research scientists and practitioners to meet, present and develop their ideas on subjects within the field of Production Economics. A ***Discussant*** is appointed for each paper. The intention is that models and methods presented, and the discussion of them, will result in concrete ideas for future research and developments in this area. These seminars are ***working seminars***, indicating that their main aim is to initiate and improve research results and to provide ample opportunities for interaction between Authors, Discussants, Chairmen and Audience, rather than to publish results. The purpose of these ***PrePrints*** is to have background working material for the discussion.

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Pre-Prints

Twentieth International Working Seminar on Production Economics, Innsbruck, Austria, February 19-23, 2018

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Order Acceptance and Scheduling in Metal Additive Manufacturing: An Optimal Foraging Approach

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Abstract

Metal Additive Manufacturing (MAM), as an advanced direct digital manufacturing method with shortened lead time and increased performance, has been increasingly applied in industrial sectors, in particular those characterised by small production batches but high level of demand customization. In a manufacturing company, the first baffling problem faced is how to properly respond to the price and due date inquiries from customers, i.e., the problem of Order Acceptance and Scheduling (OAS). OAS problem has been proved as NP-hard problem and studied extensively by academic scholars and industrial practitioners in the past decades. However, the nature of MAM process, e.g. serial-batching scheduling and inconclusive production time, makes the OAS problem in MAM environment become more challenging.

This paper introduces the OAS problem faced by MAM companies for the first time in the literature and proposes a novel decision model inspired by Optimal Foraging Theory (OFT) for solving this problem. The proposed model combines scheduling optimization and order acceptance decision-making for the cases where the MAM machines, following various optimal foraging strategies, compete for orders by providing attractive offers to maximize the utilization of machine and optimize the payoff from an order acceptance decision as well.

Keywords: Metal Additive Manufacturing, Order Acceptance and Scheduling, Decision Making, Serial Batching, Optimal Foraging Theory.

1. Introduction

Metal Additive Manufacturing (MAM), as an advanced direct rapid manufacturing method with shorter lead time and higher flexibility, is rising particularly in industrial sectors with small batch sizes and a high level of customization (Li et al., 2017; Schmidt et al., 2017). This development will put practical problems regarding production planning and scheduling on to the table. Typically, the order acceptance and scheduling (OAS) problem is one of the trickiest challenges which must be faced by MAM service providers. The problem of OAS is defined as a joint decision of which orders to accept for processing and how to schedule them (Slotnick, 2011). Over the last decades, the different versions of OAS problems have been studied with different objective functions under different sets of manufacturing assumptions (Jiang et al., 2017; Oguz et al., 2010; Slotnick, 2011; Zwier and Wits, 2016). Although the topic of OAS has attracted considerable attention from those who study scheduling and those who practice it, the OAS problems in MAM is barely discovered.

Traditionally, the OAS problem is motivated by practical situations in make-to-order (MTO) production systems to optimize the use of the limited capacity through determining whether to accept or reject orders from customers (Oguz et al., 2010). However, the nature of MAM makes it more challenging for decision making in OAS problems due to high level of uncertainties in production cost and lead time caused by different combinations of parts into a job. The production planning and scheduling problem in MAM was defined for the first time in the literature by (Kucukkoc et al., 2016; Li et al., 2017)and a mathematical model was proposed for the optimization of parts regrouping and allocating jobs to minimize average production cost per volume of material while satisfying certain constrains. According to our research, for a specific part, the difference of production cost per volume of material could be more than 40% by scheduled into different jobs. In powder-bed based MAM, the machine can handle one job at a time and the job consists of a batch of parts which will be started and completed simultaneously. For each job, a specific machine set-up/clean-up time is required. However, the time as well as the costs to produce parts included in the job is dynamic which depends on the total material volume and maximum height of these parts. In other words, the production time and costs are unknown before all the parts assigned to this job are confirmed. This will make it hard to answer the questions from customers: when will a part can be delivered and how much does it cost to produce this part?

This paper will introduce the OAS problem faced by MAM companies for the first time in the literature and propose a novel decision model inspired by Optimal Foraging Theory (OFT). The OFT is one of the major predictive theories of animal foraging behaviour (Pyke, 1984; Pyke et al., 1977) and has inspired researches in decision making and optimization area (Hayden, 2018; Sulikowski, 2017; Zhu and Zhang, 2017). Foraging decisions are accept-reject decisions just like the decisions on order acceptance. The reminder of the paper is organized as follows: Section 2 introduces the nature of OAS problem in MAM filed; Section 3 presents the proposed decision model inspired by OFT; Section 4 discusses the simulation results based on the proposed decision model and Section 5 concludes the paper.

2. The OAS problem in MAM

2.1 The nature of production with MAM

As one of the dominant applications of MAM processes, Selective Laser Melting (SLM) also known as Direct Metal Laser Sintering (DMLS) has been widely adopted in a variety of industries (Calignano et al., 2017; Schmidt et al., 2017). The general production process of SLM/DMLS, as well as powder-bed based MAM technology, is illustrated in *Figure 1*.

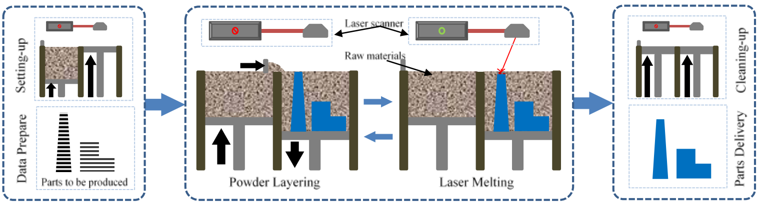

Figure 1. The production process of SLM/DMLS.

The production with powder-bed based MAM is job-based and a batch of parts can be produced simultaneously in one job. The MAM machine can handle one job at a time and, once the job starts, any of the parts included in this job cannot be taken out before the job finishing. Normally, a relative fixed time needs to be spent on setting up a new job and collecting the produced parts from the machine. However, the time of powder laying and melting to produce the parts is dynamic which depends on the total material volume and the maximum height of the parts included in the job. Also, the average production cost of per volume of material is dynamic due to all the parts in a job will share some of the fixed costs, such as the costs caused by job setting up and powder laying, which is not related with their volume of materials. Compared with traditional manufacturing processes, the major distinction of production with a powder-bed based MAM process is that the production cost and lead time are dynamically impacted by the combination of parts included in the same job. The cost and time of a job may vary when a part with a particular height, production area, and material volume is added. The dynamics of production time and costs make it more challenging for the planning and scheduling of MAM production jobs when considering the constraints of dynamic release time and due date of orders.

2.2 OAS problem statement

This paper studies the OAS problem faced by MAM companies where the orders are dynamically released on the market and the MAM companies compete for orders to maximize their profits based on applied strategy. In a period of time T, a set of distinct orders ($i = 1, \ldots, i_n$) are released on the market one by one in time sequence and a set of MAM machines ($m = 1, \ldots, m_n$) with different specifications, including operation cost, production efficiency and maximum supported production area and height, are available at the beginning. The orders in this paper will be dispersed on a part by part basis using specific height h_i, width w_i, length l_i, material volume v_i, release time r_i, expected due date d_i, expected production price p_i, and sale price s_i. The MAM machines monitor the orders released on the market and provide offers to the selected orders based on their situation and applied strategy. Meanwhile, the orders will compare the received offers from different MAM machines and make choice based on applied strategy. Once an offer is accepted, the order who accepted this offer will be assigned to the MAM machine within one of its jobs.

Index/Parameters /Variables	Descriptions
i	Order index ($i = 1, \ldots, i_n$ and $i \in I$)
j	Job index ($j = 1, \ldots, j_n$ and $j \in J$)
m	Machine index ($m = 1, \ldots, m_n$ and $m \in M$)
h_i, l_i, w_i, v_i	Height, length, width, and material volume of part i
r_i, d_i	Release date and expected due date of part i
p_i, s_i	Expected profit and sale price of part i
MC	Cost per unit volume of material
TC_m	Operation cost per unit time for machine m
VT_m	Time for forming per unit volume of material for machine m
HT_m	Accumulated interval time per unit height for machine m
HC_m	Cost of human work per unit time for machine m
ST_m	Set-up time needed for machine m
P_m	Production price per unit volume of material for machine m
H_m, W_m, L_m	Maximum height, width, and length of part that machine m can process
op_{mi}, od_{mi}	Price and due date offered to part i by machine m
δ_m	Profitability expected by machine m
JPC_{mj}	Production cost of job j on machine m
JPP_{mj}	Profit of job j on machine m
JPT_{mj}	Production time of job j on machine m
JST_{mj}	Start time of job j on machine m

Table 1. Index, parameters and variables used for OAS problem.

Each MAM machine ($m \in M$) aims to win as many as possible orders to maximize its total profit within a time duration. To do this, the machine must carefully considere the decisions on the price and due date of the offer as well as the selection of target order who will receive the offer. The index, parameters and variables used for describing the above model are shown in *Table 1*.

In terms of the notations given in *Table 1,* the profit of job j on machine m, represented by JPP_{mj}, can be formulated as follows:

$$JPP_{mj} = P_m \cdot \sum_{i \in I_{mj}} v_i - JPC_{mj}, \quad (1)$$

where I_{mj} is the set of parts assigned to job j ($j \in J$) on machine m ($m \in M$), and JPC_{mj} is the production cost of job j which can be formulated as follows:

$$JPC_{mj} = (TC_m \cdot VT_m + MC) \cdot \sum_{i \in I_{mj}} v_i + TC_m \cdot HT_m \cdot \max_{i \in I_{mj}}\{h_i\} + ST_m \cdot HC_m. \quad (2)$$

The production time of job j on machine m, represented by JPT_{mj}, can be formulated as follows:

$$JPT_{mj} = VT_m \cdot \sum_{i \in I_{mj}} v_i + HT_m \cdot \max_{i \in I_{mj}}\{h_i\} + ST_m. \quad (3)$$

Therefore, the objective function of machine m can be formulated as follows:

$$\max P = \frac{\sum_{j \in J_m} JPP_{mj}}{\sum_{j \in J_m} JPT_{mj}}, \quad (4)$$

where J_m is the set of jobs processed on machine m.

With the objective function given above, the MAM machine would be able to make decision on order selection and offer generation. The details of decision model will be described in Section 3.

3. Decision Model Inspired by OFT

3.1 Foraging decision-making

Animals forage and feed to obtain energy for survival and successful reproduction. However, foraging and processing of the food require both energy and time. To maximize the benefit (energy) with the lowest cost, the animal needs to make decision on whether to pursue or ignore a prey item during foraging. OFT addresses the kinds of decisions faced by animals. The animals (predators) make decisions under the constraints of the environment and take optimal decision rule, or the best foraging strategy, to maximize a variable known as the currency, such as the value of an item by taking into account the cost and time to acquire the item (Sinervo, 1997), which can be presented as follows:

$$Profitability\ of\ prey = \frac{Energy\ per\ prey\ item - Costs\ to\ acquire\ prey\ item}{Time\ taken\ to\ acquire\ prey\ item} \quad (5)$$

The profitability of a prey provides decision-making basis for a predator on the chosen of prey item. Generally, the predator will gain more energy by eating large prey provided that the prey is not too large so that the predator runs into processing constraints, while the handling time, or the time taken to catch, subdue, and consume prey, will increase with prey size and prey armour (Sinervo, 1997). The handling time will be more crucial for some species, such as snakes, due to mobility impairment during feeding. Once a snake swallowed a prey, it will be not able to attack another prey before the prey was digested, and the other preys may have escaped or been captured by other predators. Therefore, in a competitive environment with limited food source, a snake must be more careful on the selection of preys to capture by considering the total potential benefits it will obtain over a period.

Given that a snake with intelligence, a possible smart way to maximize the total benefits from foraging is to trap preys and consume the captured preys in packaged form based on snake's maximum size threshold. A prey with ability of activity will not stay there to be captured. The prey will be captured only when it has chosen and eaten a bait. A concept of trap-based foraging is illustrated in *Figure 2*. The predator releases a bait to attract a prey and capture it if it eaten the bait. The captured preys will be packaged, when their total size reached the expected goal, and stored as food packages which will be consumed on schedule. However, the value of a prey has timeliness which means the prey, if dead or decayed, may become valueless even harmful to the predator. Therefore, the crucial decision a snake needs to make is how to set a competitive bait to attract target preys and how to determine the boundary conditions of a food package to meet the maximum size threshold?

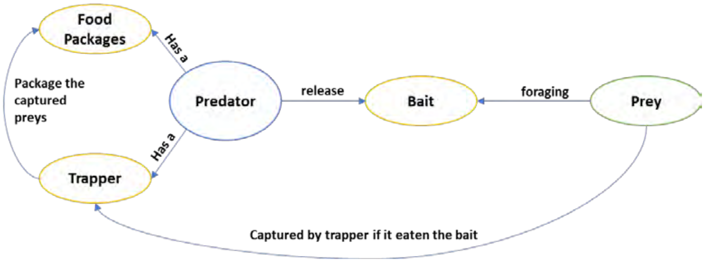

Figure 2. The illustration of trap-based foraging concept.

3.2 Decision model for OAS in MAM

The nature of order competition and production scheduling in MAM is extremely similar to the trap-based foraging behaviour of snakes. For the OAS problem stated in Section 2.2, a MAM machine monitors the orders appeared on the market and competes for an order by providing an offer. The customer determines whether to accept an offer through comparing the price and due date of the offers provided by different MAM machines. Once the MAM machine obtains (or wins) enough orders, the orders will be grouped as a MAM production job which will be processed on a schedule. The MAM machine aims to compete orders as many as possible to maximize the utilization as well as the total profit obtained within a given period.

To achieve this objective, the MAM machine needs to make optimal decision rules. The most important decision faced by MAM machine is to determine the price and due date of the offer and which order it should provide to? As mentioned previously, the parts included within one MAM production job will be produced simultaneously with same due date (completion time). However, the due date of a job is dynamic which depends on the combination of parts assigned to this job. At the time of making an offer, the MAM machine does not know if the offer would be accepted and does not know what orders it can obtain from the market in the future. Therefore, the MAM machine has to estimate the due date as well as the start time of the job based on its expected profitability. For machine m, its expected profitability δ'_{mj} of job j can be formulated as follows:

$$\delta'_{mj} = \frac{JPP'_{mj}}{JPT'_{mj}} = \frac{(P_m - TC_m \cdot VT_m - MC) \cdot V'_{mj} - TC_m \cdot HT_m \cdot h'_{mj} - ST_m \cdot HC_m}{VT_m \cdot V'_{mj} + HT_m \cdot h'_{mj} + ST_m}, \tag{6}$$

where V'_{mj} and h'_{mj} are the estimated total material volume and maximum height, respectively, for job j on machine m. The value of V'_{mj} can be calculated as follows:

$$V'_{mj} = V_{mj} \cdot \frac{\rho_m \cdot W_m \cdot L_m}{\sum_{i \in I_{mj}}(w_i \cdot l_i)}, \tag{7}$$

where V_{mj} is the total material volume already assigned to job j and ρ_m is the expected utilization of the total production area of machine m.

Given the value of expected profitability δ'_{mj}, the allowed maximum height h''_{mj}, which will not lower the expected profitability, can be calculated based on formulation (6) as follows:

$$h''_{mj} = \frac{\left(P_m - TC_m \cdot VT_m - \delta'_{mj} \cdot VT_m - MC\right) \cdot V'_{mj} - (HC_m - \delta'_{mj}) \cdot ST_m}{(\delta'_{mj} + TC_m) \cdot HT_m}. \tag{8}$$

However, the currently real maximum height h_{mj} of job j based on already assigned parts is presented as follows:

$$h_{mj} = \max_{i \in I_{mj}} \{h_i\}. \tag{9}$$

It can be mentioned that a part is profitable to job j if $h''_{mj} \geq h_{mj}$ after including this part into the job. Therefore, the value of $(h''_{mj} - h_{mj})/h''_{mj}$ as a function of part i, termed as the profitability of part i to job j (marked as δ^i_{mj}), can be a decision variable for the selection of part to be offered. The estimated due date of job j on machine m, also the due date offered to the parts which will be included in this job, will be determined based on the first part i who accepted the offer. The offered due date od_{mi} for a new job j by machine m can be calculated based on the first part i as follows:

$$od_{mi} = JST_{mj} + VT_m \cdot V'_{mj} + HT_m \cdot h'_{mj} + ST_m, \tag{10}$$

where JST_{mj} is the start time of a new job j, $V'_{mj} = v_i \cdot (\rho_m \cdot W_m \cdot L_m)/(w_i \cdot l_i)$ is the estimated total material volume based on part i, and $h'_{mj} = \min\{H_m, h''_{mj}\}$ is the estimated maximum height.

For the price offered to a part, the MAM machine can determine it with various strategies. One of practical strategy, termed as "*FIX_PRICE"*, is pricing based on the material volume of the part where the price is fixed relative to per unit volume of material. Alternatively, the MAM machine can adopt a "*FLEX_PRICE"* strategy where the price offered to each part can be flexible by considering the material volume and the profitability of the part together. Given a reference price per unit volume of material P_m, the flexible price op_{mi} offered to part i can be calculated as follows:

$$op_{mi} = P_m \cdot \left(1 - \omega^i_{mj} \cdot \delta^i_{mj}\right), \tag{11}$$

where $\omega^i_{mj} \in [0, 1]$ is the weight factor related to the profitability of part i. The offered price will be cheaper than P_m if a part has a positive profitability so that the offer will be more competitive.

On the customer side, the offers provided by different MAM machines will be compared and selected to accept based on the customer's strategy. The customers aim to produce their parts through buying MAM service and make profit through selling the parts. The profit obtained from part i produced with machine m can be calculated as follows:

$$p_i = (s_i - op_{mi}) \cdot v_i. \tag{12}$$

In the case of existing multiple offers which make positive profit, the customer may prefer the offer either with the lowest price (“*PRICE”* strategy) or with the shortest due date (“*TIME”* strategy). However, a “*BLANCE”* strategy, by considering the price and due date together, may be more practical if the sale price is highly time-sensitive which means the sale price will be higher if the part can be available earlier.

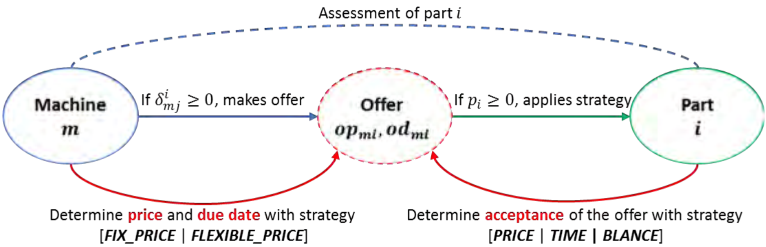

Figure 3. The principle of decision-making in OAS problem of MAM.

By now, the principle of decision-making in OAS problem of MAM can be illustrated as *Figure 3*. The MAM machine will make an offer to the part with positive profitability to current job of scheduling and determine the price and due date to be offered to the part based on applied strategy. Meanwhile, the part who received the offer will consider whether to accept the offer if it can make positive profit. The decision of acceptance or rejection depends on the strategy applied by the customer. The part who accepted the offer will be assigned to a job of the machine who made the offer. However, the machine will withdraw the offer if it is rejected, and make a new offer to another available part on the market. The due date offered by the machine will be updated based on a new job to be scheduled if the obtained parts have reached expected level or the moment for starting the job has come.

4. Simulation of OAS in MAM

4.1 OAS simulation system

The method of simulation-based optimization becomes more and more important because of its flexibility and the capability to represent complex real world systems (Frantzé N et al., 2011; Klemmt et al., 2009). According to the decision model proposed in Section 3, a simulation system was developed using SimPy which is a process-based discrete-event simulation framework based on standard Python (“SimPy,” n.d.). Also, a graphic user interface was developed using Kivy which is an open source Python library for creating GUIs (“Kivy,” n.d.). An example of result generated with developed OAS simulation system is shown in *Figure 4*.

Figure 4. An example of result generated with OAS simulation system.

With the developed OAS simulation system, various MAM machines with different strategies can be generated at the beginning and the parts with selected strategy will be generated randomly in sequence during the simulation. The MAM machines monitoring the arrived parts (coloured in green) provide offers based on their strategies for competition. A part is coloured in red if it has accepted an offer or in blue if it has rejected all the offers. The scheduled jobs are displayed as rectangles with different size and colours based on their start time, due date, and status (red for completed, green for in printing, and blue for in scheduling).

4.2 Application of the OAS simulation system

The potential applications of the developed OAS simulation system are various. It can be used for the investigation of the competitivity of different pricing strategies and the analysis of sensitivities of various influencing factors including waiting time to start a new job, estimated due date, priority of orders, etc. To demonstrate the basic application of this system, a scene where 2 MAM machines with different strategies to compete 100 parts dynamically released on the market within 30 days was simulated. The 2 MAM machines with the same specifications as shown in Table 2 and the 100 parts are generated randomly with different size, material volume, sale price, release data and expected due date (details of the first 10 parts are shown in Table 3).

Parameters	M1	M2
VT_m, (hour/cm^3)	0.030864	0.030864
HT_m, (hour/cm)	0.7	0.7
ST_m, (hour)	2	2
TC_m, HC_m, (GBP/hour)	60, 30	60, 30
H_m, W_m, L_m, (cm)	32.5, 25, 25	32.5, 25, 25
P_m, (GBP/cm^3)	5	5

Table 2. The specifications and parameters of the MAM machines.

With the test data given above, the situations where the 2 MAM machines applied with different strategies were simulated. The parts were applied with "*PRICE_TIME*" strategy for the acceptance of offers, where the offer with lowest price and satisfied due date will be accepted. The simulated results as shown in Table 4.

Part	Size $h_i * w_i * l_i$ (cm)	Volume v_i (cm^3)	Arrive r_i	Due date d_i	Price s_i (GBP/cm^3)
P1	15.4*3*15.2	229.21	512	9602	16.41
P2	11.2*24.8*20.3	3559.27	895	30885	15.17
P3	7.9*17.3*10.8	476.61	944	20439	20.15
P4	25.7*8.6*18.3	2456.64	980	18182	15.9
P5	28*23.5*15.4	7681.96	1356	34689	17.68
P6	17.6*5.2*6.1	360.00	1615	25688	21.05
P7	28*20*11.2	3689.05	1640	36063	21.99
P8	2.8*8.6*24.5	469.36	2258	12749	24.9
P9	19.9*12.3*11	1734.38	2912	20199	23.66
P10	31.6*11*5	791.85	3339	16825	23.47

Table 3. Sample data related to parts.

	Applied strategy	**Number of parts**	**Volume (cm^3)**	**Makespan (hours)**	**Profit (GBP)**	**Profit/volume (GBP/cm^3)**	**Profit/time (GBP/hour)**
M1	FIX_PRICE	15	30756.47	1123.48	58229.45	1.89	51.83
M2	FIX_PRICE	5	27960.74	970.78	56233.82	2.01	57.93
M1	FIX_PRICE	15	29011.10	1081.58	54320.14	1.87	50.22
M2	FLEX_PRICE	8	32713.52	1148.33	31679.97	0.97	27.59
M1	RANDOM	12	29080.08	1029.37	57051.65	1.96	55.42
M2	RANDOM	14	29237.34	1058.82	56472.80	1.93	53.34

Table 4. Simulation settings and results.

The machine M1 and M2 obtained 15 and 5 parts from the market respectively although they were applied with the same strategy of "*FIX_PRICE"* – the part with best profitability will be selected to provide offer. However, they obtained 12 and 14 parts respectively when applied with strategy of "*RANDOM"* – available parts will be randomly selected to provide offer. For the former situation, M1 and M2, with the same specifications, are likely to compete for the same part on the same price and due date. The winner will gain superiority in the follow-on competition. While for the latter situation, the competition on the same part is likely avoided due to randomly selection of parts to offer. Although the total profit and makes pane are different, M1 and M2 achieved similar profitability when applied with the same strategy. The results indicated that the selection of the first part to be assigned to a new job will affect the final competition results.

Another factor which will affect the competition results is the price offered to a part. As shown in Table 4, M1 and M2 obtained 15 and 8 parts by applying strategy of "*FIX_PRICE*" and "*FLEX_PRICE*", respectively. For the same part, M2 will provide an offer with lower price than M1 and this will give M2 more compactivity. As the result, the total profit achieved by M2 increased about 17% although the profitability decreased about 50%. The strategy of "*FLEX_PRICE*" will be useful when the manufacturers want to improve the utilization of their machines.

5. Conclusions

In this paper, the OAS problem faced by MAM companies was introduced and a novel decision model inspired by OFT was proposed for the first time. The nature of production with MAM, particularly the dynamism in the cost and time of a production job, makes it hard to determine on which order should be accepted and how to schedule the accepted order to maximize profit within a competitive market environment. The authors inspired by the trap-based foraging behaviour of animals, proposed a competition behaviour mechanism of MAM machines which aim to obtain as many orders as possible from the market to maximize their profit through providing competitive offers. Further, a simulation system based on the proposed competition mechanism was developed and the application for the investigation of different strategies was demonstrated.

As a first attempt to handle the OAS problem in MAM, this study provided a principle decision making model as well as a novel simulation tool for the future studies in this emerging research field. A lot of efforts need to be undertaken to perfect the optimal decision rules for MAM machines to generate competitive offers based on their business strategy and objectives. Further, advanced theories such as the game theory will be considered in future for the study of cooperation and competition behaviours of MAM machines, while the machine learning theory will be considered to help the MAM machines to make more accurate estimations for decision making.

6. References

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