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Agent-Based Simulation Model for Profit Maximization

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Abstract- This study considers a single-machine scheduling problem where the objective is to maximize total profit (Pr_{max}). The problem is identified as 1 ││ Pr_{max}. The aim of this study is to develop a profit-based scheduling model using agent-based architecture in order to increase profitability of a single machine manufacturing systems. All objective functions in the literature are based on manufacturing cost. This study shows a new profit based approach to solve single machine scheduling problems. The model is simulated on the hypothetical data and simulation results show that performance of the proposed model is highly acceptable.

Keywords- Scheduling, Agent Based Systems, Profit Based Scheduling, Single Machine

1. Introduction

The single machine scheduling problem has been studied by many researchers. Most of them are complex when arrivals of the orders are dynamic. A branch of artificial intelligence, multi-agent architecture provides the ability to respond quickly to dynamic changes. Agent-based technology has recently been used to solve this problem to produce complex collective behavioral patterns. An agent is a hardware or software that can autonomously perform its tasks with a degree of intelligence (Huang and Liao, 2012).

According to Madejski (2007), the agent-based model can be designed in two way, ‘‘physical’’ or a ‘‘functional’’ decomposition scheme. In the first case, agents represent physical entities (e.g., machine tools, resources, workers) and in the second case, agents represent the functional decomposition approach. In the functional decomposition approach, agents are assigned to some functions (for instance, scheduling, sequencing, material handling) based on some rules aimed at reproducing optimizing behaviors.

In this study, functional decomposition is used to solve single machine scheduling problem and belief-desire-intention architecture (Meirina et al., 2003) is used to define rules of the decision making process depending on the manipulation of data structures.

Scheduling is defined as the allocation of limited resources. Manufacturing scheduling is a difficult problem, especially when it takes place in a dynamic environment. Most scheduling problems are considered to be NP-hard since computation time increases exponentially with problem size.

This paper considers the single machine scheduling problem with a new objective function (Pr_{max}). Aim of this objective is to maximize the total profit. The difference between cost-based approach and profit-based approach could be summarized as instead of minimizing the cost, a profit is maximized by a schedule for the manufacturing orders. Well known objective functions and the proposed Pr_{max} are given in Table 1.

The proposed multi-agent based approach works under a real-time environment and generates feasible and the most profitable schedules using negotiation/bidding mechanisms between agents.

Table1. Well known objective functions (Adapted from Ross and Corne, 2005)

Performance measure	*Symbol*	*Based On*
Maximum total profit	Pr_{max}	***Proposed Profit based approach***
Maximum complete time	C_{max}	Cost based approaches in the literature
Mean complete time	$\bar{C}$	
Maximum flow time	F_{max}	
Mean flow time	$\bar{F}$	
Maximum lateness	L_{max}	
Mean lateness	$\bar{L}$	
Maximum tardiness	T_{max}	
Mean tardiness	$\bar{T}$	
Number of tardy jobs	NT	
Maximum earliness	E_{max}	

This paper is organized as follows: In Section 2, a brief review of the previous research on agent-based architecture and the single machine scheduling problem is given. In Section 3, the problem is introduced and formulated. In Section 4, test results of the problems are shown. And the last section includes conclusions and future research of the study.

2. Literature Review

The first use of agents in manufacturing scheduling and factory control was studied by Shaw (1983). He proposed that a manufacturing cell can subcontract work to other cells through a bidding mechanism. According to Wooldridge and Jennings (1995) an agent interacts with its environment depending on features listed below;

Independence: Agent has ability to act without direct human beings or another device

Social ability: Agents use a communication language to satisfy communication and coordination between agents.

Re-activeness: Agents answer to perceived actions in a precise way

Pro-activeness: Agents decides itself for the necessary activities.

Sousa and Ramos (1999) propose an advance model which is involve also job agents. In this study resource agent has an ability to send fault messages to job agents. Cowling, Ouelhadj, and Petrovic (2004) presented an adaptation of agent-based scheduling to dynamic scheduling in steel production process, Liao and Chen (2003) considered single-machine scheduling under periodic maintenance and non-reusable jobs. Walker et al. (2005) studied on dynamic and responsive scheduler using multi agent architecture for the holonic manufacturing system.

Single machine total weighted number of tardy jobs problem was considered by Cheng et al. (2006). In their study each agent considered the same objective function. Mosheiov and Yovel. (2006) studied a generalized version of minimizing the total earliness tardiness problem. The objective is defined as minimizing the total cost.

Agnetis and Pacciarelli (2007) presented single machine scheduling problems where the objective functions are total weighted completion, maximum of regular functions. The single-machine minimize makespan problem is considered with periodic maintenance by Ji et al (2007).

Janiak and Rudek (2008) considered minimizing the number of late jobs with a positional learning. They proved that the problem is strongly NP-hard. Eren (2009) showed that minimizing the total weighted completion time problem and developed a non-linear mathematical programming model. Zhang et al. (2009) presented the single-machine scheduling problems under release dates constraint.

Single machine minimize the total cost problem is studied Nong et al. (2011), two-agent architecture is used in their study. Yinet al. (2012) considered single machine scheduling problem with two agents under release dates constraint. The objective is to minimize the tardiness.

Wu, et al. (2013) considered two-agent single-machine scheduling problem under ready time constraint. Their objective was minimizing total completion time. Single-machine scheduling with two synergetic agents was studied under non-preemptive jobs by Yu et al. (2013). Their study seeks to minimize a regular objective function that depends on the completion times of its own jobs only.

A new scheduling model was proposed by Cheng (2014) that considered both two-agents; minimizing total (weighted) earliness cost of one agent, under an upper bound on the maximum earliness cost of the other agent.

There are numerous studies on single machine scheduling problem. A brief summary is stated in this section. As a result of this section total profit maximization was not observed, which define the agent’s decision making processes. The next section provides detail information about the proposed model.

3. Profit Based Scheduling Model

The single machine scheduling problem is consists of a single machine to process n jobs. In this study, the objective function is defined as the maximization of the profit of processing these n jobs. Model parameters, sets, and variables are;

J : set of scheduled operations,

J^d : candidate jobs to be scheduled at time t,

J^c : set of unscheduled jobs at time t

t : scheduling time

P_j : unit processing time of job j

d_j : due date of job j

C_j : completion time of job j

Pr_j : unit profit of job j

Dm_j: amount of demand of job j

PR_i : profit of job j

The problem is identified as $1 \mid\mid Pr_{max}$. The jobs may not be preempted and each job j is characterized by its processing time P_j, its due date d_j and its profit value Pr_j.

The model was constructed with n independent job to be processed on a single machine under the time constraint. The proposed model is included a set of three integrated agent based modules; Order Analysis Agent (OAA), Profit Analysis Agent (PAA), and Reporting and Scheduling Agent (RSA). Figure 1 shows the relationship of these agents where the arcs are indicating the work flow.

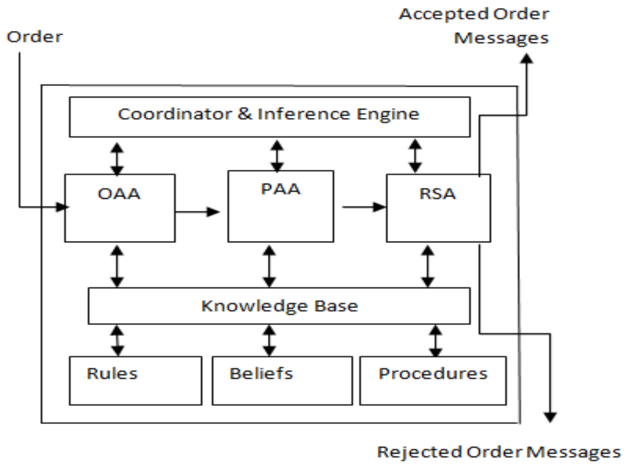

Fig.1. Component of PBSM

Agent architectures of the proposed model are detailed in each respective section

3.1. Order Analysis Agent (OAA)

The primary task of OAA is to identify predefined set of order and support the assessment with respect to the decision of whether those orders are acceptable or not.

In this study, customer orders are generated from a discrete uniform distribution. After random number generation process, OAA uses three analysis methods for decision of accepting or rejecting of an order and related production sequence of the orders. The first analysis technique is “Model-1: Unit Profit Model (UPM)” which is defined as the most profitable product is produced first.

The business rules of UPM are;

- Prepare a list of orders with respective order quantity;
- Compute the needed production time of each order;
- Elaborate unit profits of each order;
- Define most profitable order list from top to bottom; and
- Generate a production sequence to report.

The second analysis technique is “Model 2: Daily Profit Model (DPM)” which considers that the most daily profitable job is selected to schedule first.

The business rules of DPM are;

- Prepare a list of orders with respective order quantity;
- Compute the needed production time of each order;
- Elaborate daily profits of each order depends on machine capacity;
- Define most profitable order list from top to bottom; and
- Generate a production sequence to report.

And the last analysis technique is “Model 3: Total Profit Model (TPM)” where the most profitable order is processed.

The business rules of DPM are;

- Prepare a list of orders with respective order quantity;
- Compute the needed production time of each order;
- Elaborate total profits of each order depends on order quantity;
- Define most profitable order list from top to bottom; and
- Generate a production sequence to report.

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Figure 2 shows OAA components where each model represents a different analysis approach.

OAA engine defines the 3 different production sequence of orders depends on 3 different models explained above. This information is transmitted to Profit Analysis Agent to make profit analysis.

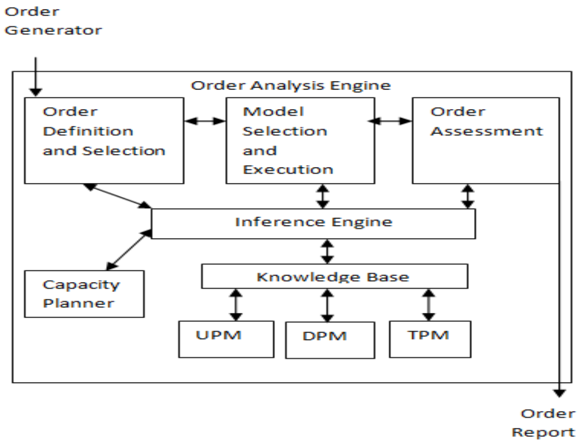

Fig.2. Order Analysis Agent Architecture

3.2. Profit Analysis Agent (PAA)

The PAA is responsible for the selection of most profitable sequence of three different models. After an order report is prepared by OAA, this information is transmitted to PAA. Negotiation is a key function of PAA which satisfies interaction in groups of agents that enables mutual agreement including belief, goal, or plan. In this study, the simplest case of negotiation is used which could be define as the structure and contents of the agreement are fixed. For that purpose the calculation of the accepted order' profits for three sequence was elaborated by PAA. The agents' reasoning models provide the decision making which model attempt to achieve objectives.

The business Rules of PAA are;

- Calculate total profits of 3 types order sequence (UPM, DPM and TPM);
- Select the most profitable sequence to schedule manufacturing;
- If total profits of the three models are equal send this information to order elaborator ;
- The order elaborator selects the technique that has the maximum number of orders in it to satisfy more customers and sends the selected profit model schedule to scheduler; and
- When all total profit values and number of accepted orders are same for each 3 models. Select the model randomly.

After the analysis is complete, PAA sends related information (selected model and related production schedule) to Scheduling Agent for the preparation of a job order and sends it to the Reporting Agent for prepare a form to inform customers. Figure 3 shows its components where each component represents model selection and amount determination.

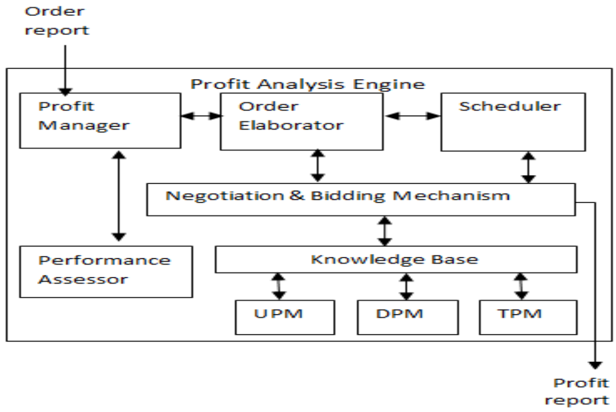

Fig.3. Profit Analysis Agent Architecture

3.3. Reporting and Scheduling Agent (RSA)

The RSA is responsible to prepare preparing a form indicating the status of order acceptation or rejection messages as well as due dates for accepted orders to inform customers. Scheduling engine of RSA prepares a job order form including accepted jobs, jobs' schedule and related due dates.

The business rules of RSA are;

- Prepare job order list for accepted orders;
- Check scheduled delivery date of orders and provide an approval form;
- If there is a late job send this information to Coordinator & Inference Engine to start new scheduling process; and
- Prepare an order acceptance report to send customers including delivery date or rejection of given order.

Figure 4 shows the architecture of RSA

This section introduced a prototype profit based scheduling model based on agent based architecture. The model execution of the proposed model is outlined in the next section.

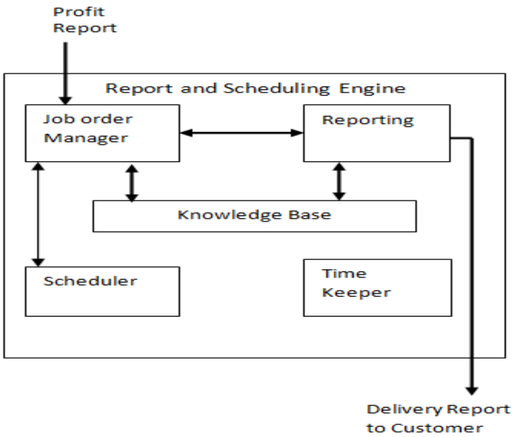

Fig.4. Reporting and scheduling agent architecture

4. Test Results

Computational example and simulation test results are explained below.

4.1. Algorithm Test Results

In this section, implementation of the proposed model is presented. Simulation technique is used to see effectiveness of the proposed model.

Model assumptions are;

1. In order to measure the capability of reference model a hypothetic database is constructed which is explained in section 3.1
2. Simulation parameters are; The problem considers n independent jobs (j=1,2,…,n) on a single machine to maximize total profit. There are no precedence constraints between jobs and each job has a nonnegative due date d_j ($d_j \geq 0$). The machine is continuously available and can process one job at a time.
   a. P_j is generated from a discrete uniform distribution between 5 and 250 (in terms of minutes)
   b. d_j is generated from a discrete uniform distribution between 1 and 9 (in terms of days)
   c. Dm_j is generated from a discrete uniform distribution between 5 and 900 units
   d. Pr_j is is generated from a discrete uniform distribution between 5 and 90
3. The experimental study is conducted in MS Excel
4. Number of job sets is restricted to 9 due to the macro capacity limitations of MS Excel
5. There could be more than one order which includes same type of job
6. An order must include only one type of job

A hypothetical example including the Unit Profit Model, Daily Profit Model, Total Profit Model and Opportunity Cost values calculated after 20 simulation runs (Table 2). As can be seen from the Table 2, results of each trial are different than others depending on random orders and random due dates. As a result of 20 trials, it can be said that $126.008 will be lost that is the opportunity cost (if comparison of the three models is not used and if the lowest profit techniques were selected, the company will lose this amount of money) of the manufacturing company.

The reference model was run 100 times and the results were recorded. The success frequency of each profit model is summarized in Figure 5.

Table 2. Results of the first 20 trials

TRIALS	UPM	DPM	TPM	Opportunity Cost
1	48456	48456	39456	9000(*)
2	42853	42853	42853	0
3	45463	45463	44983	480
4	37690	43225	37690	5535
5	42380	51292	46572	8912
6	52260	52260	52260	0
7	30438	30438	30438	0
8	39805	47151	39805	7346
9	31926	31926	31926	0
10	29340	29340	43405	14065
11	38765	49440	48890	10675
12	42747	42747	42747	0
13	32741	17831	32741	14910
14	41530	41070	41070	460
15	40150	44500	44500	4350
16	30730	28094	32074	3980
17	38235	48003	54258	16023
18	42400	24428	37000	17972
19	40270	51610	51610	11340
20	30027	30987	30987	960
Total	778206	801114	825265	**126008**

(*)An example calculation of Opportunity Cost for trial 1;
= Maximum profit – Minimum profit
= 48456 – 39 456 = $ 9000

Figure 5 shows that unit profit model gives better solution than others. 57 times of 100 trials, total profit of UPM model gives the most profitable solution for the Company. Contrary to initial expectations, TPM gives only 17 times best profit than others.

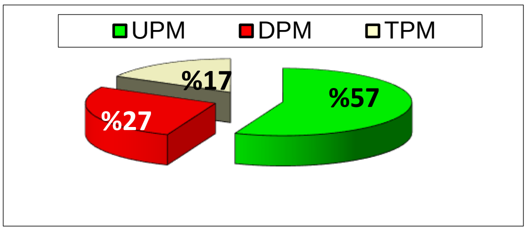

Fig. 5. Frequency of the selected profit models

1. Unit Profit Model: % 57
2. Daily Profit Model: % 27
3. Total Profit Model: % 17

4.2. Benchmark Problem Test Results

In this section, proposed algorithm is tested with well-known scheduling rule WSPT (weighted shortest processing rule due to its superior performance on cost type objective. WSPT rule is modified to be used on maximization problem. This rule sort jobs by increasing p_j / w_j-values.

In this study w_j is defined as unit profit. An easy example and test results are shown in Table 3.

Table 3. Sample test data

	Jobs								
Features	A	B	C	D	E	F	G	H	I
Dm_j	661	348	744	232	660	530	613	612	831
d_j	8	2	5	4	2	4	6	1	1
Pr_j	50	45	12	55	15	20	10	60	5
p_j	210	150	50	250	70	110	46	190	35
p_j/w_j	4,20	3,33	4,17	4,55	4,67	5,50	4,60	3,17	7,00

Depends on WSPT rule, jobs' sequence and total profit value of the sample data set is given in Table 4.

Table 4. Jobs' Sequence depends on WSPT rule

Sequence	Start	Finish	Decision
I	0	29085	0
F	0	58300	1
E	58300	104500	0
G	58300	86498	1
D	86498	144498	0
A	86498	225308	1
C	225308	262508	0
B	225308	277508	0
H	225308	341588	0

Total Profit : 49780 $

The same sample test data is scheduled depends on UPM, DPM and DPM algorithm and results are shown in Table 5 to 7 respectively

Table 5. Jobs' Sequence depends on UPM model

Sequence	Start	Finish	Decision
H	0	116280	0
D	0	58000	1
A	58000	196810	1
B	196810	249010	0
F	196810	255110	0
E	196810	243010	0
C	196810	234010	0
G	196810	225008	0
I	196810	313090	0

Total Profit : 45810 $

Table 6. Jobs' Sequence depends on DPM model

Sequence	Start	Finish	Decision
H	0	116280	0
B	0	52200	1
C	52200	89400	1
A	89400	228210	1
D	228210	286210	0
G	228210	256408	0
E	228210	274410	0
F	228210	286510	0
I	286510	315595	0

Total Profit : 57638 $

Table 7. Jobs' Sequence depends on TPM model

Order	Start	Finish	
D	0	58000	1
F	58000	116300	0
B	58000	110200	0
G	58000	86198	1
C	86198	123398	1
E	123398	169598	0
A	123398	262208	0
H	123398	239678	0
I	123398	152483	0

Total Profit : 27818 $

For this example the highest profit is ***$57638 which is calculated from DPM whereas WSPT rule result is $45810.***

From this point, the proposed agent based model and WSPT rule was simulated on 50 randomly generated test problems. The experimental results showed that the proposed model yielded better results in 40 out of 50 problems. Twenty of the results are presented in the Table 8.

Table 8. Comparison between WSPT rule and proposed algorithm depending on objective function Pr_{max}

TRIALS	WSPT	Proposed Model			Difference btw WSPT and best Algorithm results
		UPM	DPM	DPM	
1	55887	**63255**	50715	50715	7368
2	21501	**35571**	25586	35571	14070
3	28210	**62425**	62425	41980	34215
4	**84658**	69900	58845	58845	-14758
5	51575	**55310**	57890	43790	3735
6	21340	**49585**	33985	49585	28245
7	42797	**51422**	51007	51007	8625
8	28368	39065	37703	**50850**	22482
9	35761	**56901**	56901	56901	21140
10	29150	23910	**34362**	23910	5212
11	**42802**	38522	29002	38522	-4280
12	28415	63720	56480	**65780**	37365
13	39295	**50100**	42791	45260	10805
14	20552	49755	**55227**	50885	34675
15	28795	**49640**	18290	49640	20845
16	**53840**	47324	47324	45209	-6516
17	43485	38265	48495	**48495**	5010
18	28625	**40048**	40048	40048	11423
19	25352	46915	45610	**52500**	27148
20	26083	**38345**	2003	31170	12262
Total					**279071**

As can be seen in the Table 8, the proposed model produces better solution than WSPT rule on average and total opportunity cost was calculated as $279,071 for 20 trial.

4. Conclusions

In the reference model, a profit based scheduling algorithm is prepared and run for a small and non-complex system. The proposed model could maximize the profit of the given orders depending on three profit techniques under the time constraints. MS Excel was selected to execute the model. The experimental studies showed that the UPM model was the most selected technique in the proposed model. Also the proposed model was compared to the WSPT rule due to its superior performance on cost type objective. WSPT rule is modified to be used on maximization problem. Test results show that proposed model outperforms WSPT rule.

For the short execution time, the applicability of the reference model is very high. It is seen that if there is an increase in the number of constraints or number of machines MS Excel will not be an appropriate tool to solve this problem because of the limited number of if-then loops. This study shows that the profit based schedule depending on agent-based algorithm produces effective solutions for companies. Future research may consider studying the problem in the multi-machine environment or extending to the multi-objective optimization.

References

Agnetis, A., Pacciarelli, D., & Pacifici, A. (2007). Multi-agent single machine scheduling. *Annals of Operations Research*, *150*(1), 3-15.

Cheng, S. R. (2014). Scheduling two-agents with a time-dependent deterioration to minimize the minsum earliness measures. Asia-Pacific Journal of Operational Research, 31(05), 1450040.

Cheng, T. E., Ng, C. T., & Yuan, J. J. (2006). Multi-agent scheduling on a single machine to minimize total weighted number of tardy jobs. *Theoretical Computer Science*, *362*(1), 273-281.

Cowling, P. I., Ouelhadj, D., & Petrovic, S. (2004). Dynamic scheduling of steel casting and milling using multi-agents. *Production Planning & Control*, *15*(2), 178-188.

Eren, T. (2009). Minimizing the total weighted completion time on a single machine scheduling with release dates and a learning effect. *Applied Mathematics and Computation*, *208*(2), 355-358.

Hart, E., Ross, P., & Corne, D. (2005). Evolutionary scheduling: A review.*Genetic Programming and Evolvable Machines*, *6*(2), 191-220.

Huang, C. J., & Liao, L. M. (2012). A multi-agent-based negotiation approach for parallel machine scheduling with multi-objectives in an electro-etching process. *International Journal of Production Research*, *50*(20), 5719-5733.

Janiak, A., & Rudek, R. (2008). A new approach to the learning effect: Beyond the learning curve restrictions. *Computers & Operations Research*, *35*(11), 3727-3736.

Ji, M., He, Y., & Cheng, T. E. (2007). Single-machine scheduling with periodic maintenance to minimize makespan. *Computers & operations research*, *34*(6), 1764-1770.

Liao, C. J., & Chen, W. J. (2003). Single-machine scheduling with periodic maintenance and nonresumable jobs. *Computers & Operations Research*,*30*(9), 1335-1347.

Madejski, J. (2007). Survey of the agent-based approach to intelligent manufacturing. *Journal of Achievements in Materials and Manufacturing Engineering*, *21*(1), 67-70.

Meirina, C., Levchuk, G. M., & Pattipati, K. R. (2003, June). A multi-agent decision framework for DDD-III environment. In *2002 International Command and Control Research and Technology Symposium, Monterey, CA*.

Mosheiov, G., & Yovel, U. (2006). Minimizing weighted earliness–tardiness and due-date cost with unit processing-time jobs. *European Journal of Operational Research*, *172*(2), 528-544.

Nong, Q. Q., Cheng, T. C. E., & Ng, C. T. (2011). Two-agent scheduling to minimize the total cost. *European Journal of Operational Research*, *215*(1), 39-44.

Shaw, M. J., & Whinston, A. B. (1983). Distributed planning in cellular flexible manufacturing systems. *Management Information Research Center Technical Report*.

Sousa, P., & Ramos, C. (1999). A distributed architecture and negotiation protocol for scheduling in manufacturing systems. *Computers in industry*,*38*(2), 103-113.

Walker, S. S., Brennan, R. W., & Norrie, D. H. (2005). Holonic job shop scheduling using a multiagent system. *Intelligent Systems, IEEE*, *20*(1), 50-57.

Wooldridge, M., & Jennings, N. R. (1995). Intelligent agents: Theory and practice. *The knowledge engineering review*, *10*(02), 115-152.

Wu, C. C., Wu, W. H., Chen, J. C., Yin, Y., & Wu, W. H. (2013). A study of the single-machine two-agent scheduling problem with release times. *Applied Soft Computing*, *13*(2), 998-1006.

Yin, Y., Wu, W. H., Cheng, S. R., & Wu, C. C. (2012). An investigation on a two-agent single-machine scheduling problem with unequal release dates.*Computers & Operations Research*, *39*(12), 3062-3073.

Yu, X., Zhang, Y., Xu, D., & Yin, Y. (2013). Single machine scheduling problem with two synergetic agents and piece-rate maintenance. *Applied Mathematical Modelling*, *37*(3), 1390-1399.

Zhang, L., Lu, L., & Yuan, J. (2009). Single machine scheduling with release dates and rejection. *European Journal of Operational Research*, *198*(3), 975-978.