Adaptive Dynamic Scheduling in Agent Based Manufacturing Environment: A Budget Approach

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Abstract

The competition environment is characterized by significant market shifting, rapid development and introduction new technologies and global competition with the focus towards customer need. In order to play in such an environment, enterprises need to build reactive and agile manufacturing systems capable of adapting to the variable conditions (internal or external) of the manufacturing systems. Agent based manufacturing systems have demonstrated their ability to be very agile and reactive. The focus of this paper is on the decision-making strategies in order to keep an adequate level of system performance. This paper proposes an innovative decision making strategy for autonomous agents in a cellular manufacturing environment by a budget assigned to each part in order to purchase a manufacturing cell services. The budget manages as a market like approach among agents to coordination the multi agent system.

Keywords: Agile Manufacturing Systems, Multi Agent Systems, Simulation, Fuzzy Logic.

1. Introduction

Today, manufacturing enterprises are in an environment where markets are frequently shifting, new technologies are continuously emerging and competitors are multiplying globally. Manufacturing strategies should therefore shift to support global competitiveness, new product innovation and introduction, and rapid market responsiveness.

According to Shen et al. [1], such manufacturing strategies imply the ability to develop agile manufacturing systems whose base characteristics are: a) distributed organization; b) heterogeneous hardware and software environments; c) programming languages, models, and different computing platforms interoperability; d) open and dynamic hardware and software structures; e) ability to fully co-operate with suppliers, partners, and customers; f) integration of humans with software and hardware; g) agility, i.e. the ability to react to market changes and to adapt to customer needs; f) scalability, i.e. the ability to adapt (expand or shrink) manufacturing system capacity to the market demand and changes; h) fault tolerance, i.e. the ability of a manufacturing system to work in acceptable conditions under failure or degraded working conditions.

Szelke et Al. [2], identifies that in the field of manufacturing, agility and reactivity can be achieved by operating both at system and control level. At the system level, the most common solution is the decomposition of the manufacturing system into smaller units, e.g. manufacturing cells, in order to get simplicity, specialization, scalability, fault tolerance. At the control level, there are two ways to guide the complexity of operation management problems to simplicity, reactivity, scalability and fault tolerance: a) to enhance the reactivity and pro-activity of the scheduling and control systems by sophisticated new control techniques; b) to take advantages from distributed control.

In particular, the scheduling problem in real time is a difficult task in a dynamic environment. In order to operate in such an environment a reactive scheduling or adaptive control needs to be developed.

The adaptive control approach of Flexible Manufacturing Systems (FMS) is based on the control of a set performance measures of the manufacturing system where a decision model analyzes this information and selects an opportune control policy [3]. Thus, there is a different scheduling regime for each period of the manufacturing system. The FMS has to adapt to the changing conditions both external (product mix, volume, manufacturing objectives, etc.) and internal (machine breakdown, delays, etc.).

Many authors have addressed the problem of adaptive scheduling related to FMS with most of the approaches proposed based on heuristics and use dispatching rules. Jeong and Kim [4] have used the simulation to evaluate the manufacturing system performance and select an opportune dispatching rule for the future scheduling period. Several approaches are proposed by learning methods such neural networks, genetic algorithm and knowledge management. Shiue [5], Shiue and Guh [6], Soon and De Souza [7], Wang et Al. [8] have been implemented a learning method based on artificial neural network in order to adopt a scheduling criteria by the past information of the manufacturing system creating a knowledge base. Mesghouni et Al. [9], Rossi and Dini [10], Chryssolouris and Subramaniam [11] proposed a dynamic scheduling approach based on a genetic algorithm. At each event of the manufacturing system (machine breakdown, part arrival, mix change, etc.), it runs a genetic algorithm to select a new scheduling criteria.

Moreover, in manufacturing systems, the Multi Agent Systems (Mass) have demonstrated their ability to build up very agile and reactive systems under several points overview. Sheena et Al. [12] presented a review of Multi Agent applications in intelligent manufacturing systems.

The literature evidences that few publications deal with a very dynamic environment, where the manufacturing systems changing dynamically.
In this paper, an adaptive scheduling approach is proposed capable to operate in a very dynamic environment.
So for this scenario the authors selected decentralized methods performed by MAS.
This method is based on a budget that each part can spend to purchase the service of a resource of the manufacturing system in a Multi Agent System environment. The price computation of the resource is based on the evaluation of the resource and manufacturing system state.
The principal aims of the approach are the following:

- a simple methodology where only one parameter has to be set in order to keep a proper performance level of the manufacturing system;
- the approach can be integrated in a supply chain or extended enterprises because, in fact, the only parameter of information between the shop floor level and the upper management level is the importance of each typology part that is codified in an opportune value of budget assigned to the part.

The principal advantage of the method is the possibility to adapt the scheduling approach to the change of the objective of the production planning activity in an extended enterprise environment by setting the only parameter budget. As a benchmark, the proposed method is compared with an approaches proposed in literature. The comparison has been carried out through a simulation experimental plan. The paper is organized as it follows. Section 2 explains the new proposed method. In section 3, the Budget Fuzzy Engine is described. In section 4 the experimental environment is outlined. Finally, in section 5 results are detailed and conclusions are drawn in section 6.

2. The Budget Approach

The testbed for the proposed negotiation approach will be a production system consisting of a given number of cells. Each cell is able to perform any kind of manufacturing operation so that the resulting manufacturing system is a pure general purpose.
In such a system, the scheduling decisions consist in what manufacturing cell (or resources) the part will perform the next operation, therefore a pure dispatching problem. If decision process is faced in a distributed way, it means that the dispatching problem is solved through a negotiation between autonomous agents representing resources and parts in a real time fashion.
A resource agent is associated to each workstation; it is an intelligent entity whose principle aim is to schedule the resource tasks in order to improve the resource efficiency. Moreover, when a new part arrives to the manufacturing system the corresponding part agent is created; it analyses the part status locating the following activities to be scheduled. Dispatching problems for a given part are faced through a negotiation between part and resource agents based on a Contract Net Protocol [13].
The proposed approach is based on a budget level assigned to each part. The budget is an amount of fictitious money that the part can spend to acquire resources. The financial aspects are not considered because the approach is a shop floor level then no real transfer of money is made. The budget manages as a market like approach among agents to coordination the multi agent system.
The activity UML diagram in figure 1 shows the process. As showed in fig. 1, the activities are the following:

- the first activity is the budget to assign at each part; in this paper to evaluate the approach benchmarked with others approaches, at each part is assigned an infinite budget (all the parts have the same importance). Moreover, a fuzzy tool, called Budget Fuzzy Engine, is proposed to assign the budget level described in the next paragraph.

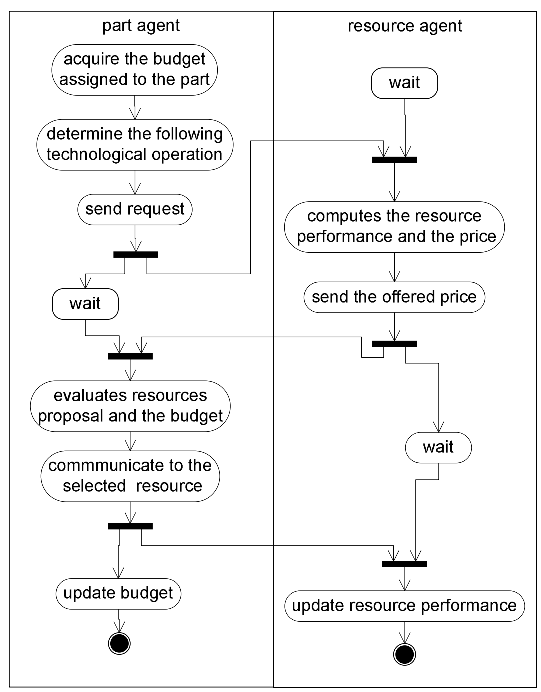

Fig 1. UML activity diagram of the budget approach

- the part agent sends a message to the resources agent about the technological operation requested;
- the resource agent computes the price to submit to the part agent. The price is computed by evaluating the state of the resource. In particular, is computed an internal index (resource characteristics) and external index (it depends by the state of the manufacturing system).

The price is computed by the following expressions.

The first expression computes a performance about the flow time of the parts.

$$StdFlowTime_k(t) = \frac{medwtime}{medwtime + FlowTime_k(t)}$$

(1)

where, *medwtime* is the average service time of the part in the resource. The real service time is obtained by multiplication this value for the efficiency of the resource.

FlowTime$_k$(t) is the expected resource *k-th* throughput time computed by summing up the processing times of the parts waiting in the resource queue plus the residual service time of the part being worked in the machine at the negotiation time *t*.

This index is the measure of workload of the generic manufacturing cell. The index value is one if no parts are in queue and the resource is in idle state; it decreases with the increase of parts in queue.

Then, a Resource Failure Index is computed:

$$RFI_k(t) = 1 - \frac{FT_k(t)}{t} \quad (2)$$

where, is the total time of failure status of the resource until the negotiation time t. The *RFI* in (2) is an index of reliability of the manufacturing cell. The index value is one if no failure happens and decreases with the increase of the failure time.

A Resource Processing Time Index is computed

$$RPTI_k(t) = 1 - eff_k(t) \quad (3)$$

where, $eff_k(t)>0$ is the efficiency of the resource *k* at time *t*. The value of $eff_k(t)$ multiplied to *medwtime* leads to the real working time of the resource.

These indexes are related only to the cell manufacturing. The $RPTI_k(t)$ (3) is the efficiency of the manufacturing cell. In particular, a lower value of $eff_k(t)$ leads to lower time to manufacturing a generic part. Therefore, $RPTI_k(t)$ is the reciprocal of the $eff_k(t)$.

Then, an Internal Resource Index is computed by the following expression as a combination of the two above index:

$$IRI_k(t) = \frac{RPTI_k(t) + RFI_k(t)}{2} \quad (4)$$

and an External Resource Index

$$ERI_k(t) = StdFlowTime_k(t) \quad (5)$$

The *IRI* is the average of the index related to the resource, while the *ERI* is the index related to the manufacturing system status.

The index of the manufacturing cell is the following (Resource Efficiency Index):

$$REI_k(t) = \alpha \cdot ERI_k(t) + (1-\alpha) \cdot IRI_k(t) \quad (6)$$

· It is a weight sum between the internal and external efficiency.

The resource agent computes the price as

$$Price_k(t) = K \cdot REI_k(t) \quad (7)$$

where the constant *K* is the maximum price of the resource.

- the part agent selects the resource with high price, because the high value of the price, involves a high level of performance of the manufacturing cell. If the part doesn't have the sufficient budget to pay the resource, it has to select a resource that requests a price compatible with the budget of the part. If all the resources request a price that the part cannot pay, the part is dispatched to the resource that requests the lowest price and then the worse performances (deadlock avoidance).
- Finally, the part agent and the resource agent update the value of its budget available for the subsequently operation requested.

As the reader can notice, the above procedure is simply an auction based negotiation protocol.

The budget assigned to the parts is the only parameter to set in order to establish a link between the enterprise goals and the shop floor scheduling.

The decision.-maker can describe in linguistic terms the characteristics of each typology part manufactured by the manufacturing system.

Therefore, when the objectives of the enterprise change, the budget allocation is adapted to new requirements. The figure 2 shows the process:

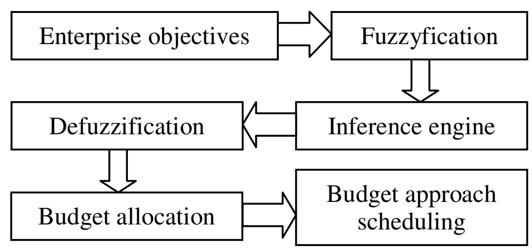

Fig. 2. budget approach integration process

3. Budget allocation

A fuzzy tool, Budget Fuzzy Engine, had been yet proposed by Renna and Padalino [14] to assign the value of budget to each part type. In this research, three input values are proposed. The fuzzy tool can be extended to more inputs that are activated based on enterprise goals.

The figure 3 shows this fuzzy tool as a black box; in particular, the inputs are the following:

- technological operations, is the number of technological operations that the parts have to be submit in the manufacturing system. The increase of the technological operation leads to increase the level of the budget, because the part agent has to purchase more resources to complete the part.
- profit product, is the level of margin that the product can be gain. The increase of the profit leads to increase the level of budget.
- due date, a closer due date leads to increase the budget assigned to the part and it can get the best manufacturing cell.

The only output of the system is the level of budget allocated to the part.

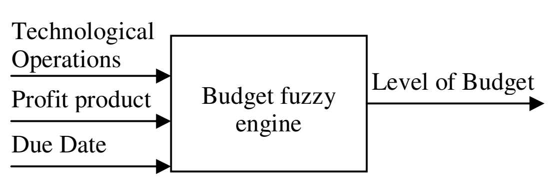

Fig 3. Budget Fuzzy Engine as a Black Box

For each input is defined a fuzzy set; the fuzzy decomposition of a range are reported in figure 4.

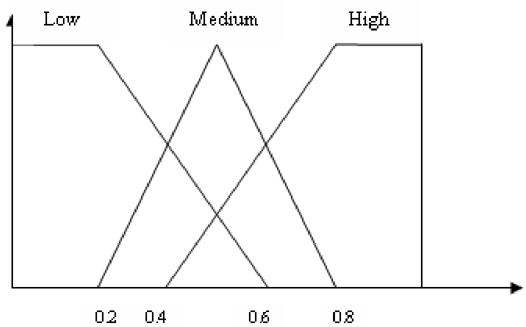

Fig 4. Fuzzy Sets Composition

The decision-maker evaluates the input values as a linguistic term. In this paper, the decision-maker estimates the linguistic terms as reported in table 1.

Table 1: Fuzzy input values

	low	medium	high
Tech. operations	2	3	4
Profit product	1	2	3
Due date	[3-4]	[2-3)	[1.5-2)

Table 1 shows the value of the inputs of the fuzzy systems for the test case, as the reader can notice, the technological operations can assume value 2, 3 and 4. In case of margin of each product is classified in three category of margin, 1 for the low, 2 for the medium and 3 for the high. Table 1. reports the test case, that is a specification of a more general input values table. The number of technological operations or type of product can be hundreds, such as the possible types of profit product. Finally, the due date input is the range of the value to multiplier the technological operation time. The rules inference are the following:

no.	rule		Budget
1	IF Due Date is high	Then	High
2	IF Due Date is Medium	Then	Medium
3	IF Due Date is Low	Then	Low
4	IF Tech. Op. is High	Then	High
5	IF Tech. Op. is Medium	Then	Medium
6	IF Tech. Op. is Low	Then	Low
7	IF Profit Product is High	Then	High
8	IF Profit Product is Medium	Then	Medium
9	IF Profit Product is Low	Then	Low

The budget assigned to the part is obtained by activated above fuzzy rules; among the rules with the same consequent is adopted the rule with higher membership. The rules are arranged by the "maximum" method and the de-fuzzification by the centre gravity approach. The crisp value z leads to assign the budget to the parts by the following expression:

$$Budget = \begin{cases} High & 0.625 \le z\_out \le 1; \\ Medium & 0.325 \le z\_out < 0.625; \\ Low & 0 \le z\_out < 0.325; \end{cases} \quad (8)$$

The proposed approach is face up to efficiency based approaches proposed in Renna et Al. [15], and Amico et Al. [16], these approaches is briefly illustrated in the following paragraphs.

The efficiency based approach (Renna et al. 2001)

Following this approach, the productive function of the resource agent consists in evaluating and providing to the part agent the following three parameters: Expected Part Throughput Time (*ETT*); Resource Failure Index (*RFI*); Resource Processing Time Index (*RPTI*).

The *ETT* is the $FlowTime_k(t)$ explained in the previous paragraph; the RFI is the same of the expression (2); the *RPT* is $eff_k(t)$ multiplied to *medwtime*.

Each parameters is normalized for each *k-th* resource, by the following expression:

$$Normalized\ Index_k(t) = \frac{\max_k index(t) - index_k(t)}{\max_k index(t) - \min_k index(t)} \quad (9)$$

Then, each index is normalized between the maximum and minimum values of the indexes among all the manufacturing cells.

The above indexes are composed by the following expression:

$$\begin{aligned} Eff\ Index &= w \cdot Norm\,EPPT + \\ &+ (1-w) \cdot (Norm\,RFI + Norm\,RPT) \end{aligned} \quad (10)$$

The part agent selects the cell that has the high value of efficiency. The performance of the efficiency-based approach seems to increase when the system becomes more and more dynamic; this, in particular, is more relevant when the manufacturing system size increases.

The fuzzy approach (Amico et Al. 2001)

In the efficiency-based approach the weight of the parameters that compose the index of efficiency of the manufacturing cell are fixed. In this approach proposed in Amico et al. 2001 [16], the weight w (equation 10) is inferred through a proper fuzzy system, whose knowledge base is the statement: "if the cells have a very similar internal rate of efficiency values, then the weight of the external rate index in the index efficiency computation is high". Therefore, the fuzzy system consists of a single rule whose input is the standard deviation of the internal resource index and the output is the weight.

This approach leads to better performances in front of the fixed weight in the efficiency based approach, in particular, in a very dynamic environment.

4. The Experimental Environment

This section describes how a simulation test-bed, model, and case study have been developed into the Arena® simulation environment in order to test the effects of the presented approach. Arena® – based on the known SIMAN simulation language - is well suited for modeling shop floors of production systems in which each entity (part) follows a manufacturing route through production resources (servers, material handling systems, buffers, and so forth) [17],

The objective is to evidence the difference of the proposed approach compared to the approaches proposed in [15] and [16], therefore the simulations have been conducted by an infinity level of budget to obtain a typology parts that have the same importance.

The test-bed, which has been implemented, models four general-purpose cell able to perform each manufacturing operations requested by the four different parts. It has been assumed parts arrive into the system with three different exponentially distributed inter arrival times as reported in table 2 in order to investigate different degree of congestion.

Table 2: Exponential inter-arrival time (*IAT*)

	Scenario 1	Scenario 2	Scenario 3
IAT	Expo (13)	Expo(16)	Expo(19)

The mix part and the number of visit to the manufacturing cell of the four different topologies are reported in table 3.

Table 3: Mix parts

	Part 1	Part 2	Part 3
Number of visit	2	3	4
Mix	30 %	40 %	30 %

The mean manufacturing time is 31 (*medwtime*), but for each manufacturing cells the effective manufacturing time is obtained like a product of the efficiency of the cell (reported in table n.4) and the mean manufacturing time.

In order to test the proposed approach in a real dynamic environment a production stage is considered; in each production stage, the characteristics of the manufacturing cell are modified. The efficiency is reported in table 4 while the mean time between failures in table 5.

Table 4: Manufacturing cells efficiency

	Cell 1	Cell 2	Cell 3	Cell 4
Stage 1	0.30	0.60	0.20	0.31
Stage 2	0.36	0.66	0.44	0.39
Stage 3	0.42	0.72	0.68	0.50
Stage 4	0.48	0.80	0.82	0.60
Stage 5	0.54	0.88	0.90	0.75

Table 5: Manufacturing cells mean time between failures

	Cell 1	Cell 2	Cell 3	Cell 4
Stage 1	12.00	8.00	10.10	9.00
Stage 2	10.60	6.40	8.40	8.50
Stage 3	9.30	5.12	6.10	7.40
Stage 4	7.70	4.10	4.90	6.30
Stage 5	6.30	3.27	3.40	5.20

The time to repair is computed by exponential distribution with parameter $1{,}5 \cdot medwtime$.

The length of each stage is relation to the average process time of the parts. The stage length *sl* has been obtained by the following expression: $sl = k \cdot medwtime$, where *k* is a stage length factor as reported in table n. 6.

The stages showed in table n.6 mean that the manufacturing systems is more dynamic from case one to case 4, otherwise in case 5 the manufacturing systems is static from the point of view of the cell manufacturing characteristics. In the case 5 (fixed) the parameters of the stage are the same of the stage 3.

Table 6: Stage length factor *k*

Case 1	20
Case 2	10
Case 3	5
Case 4	2.5
Case 5	Fixed

Therefore a 15 experiment classes are developed as reported in table n. 7.

Table 7: Experiment classes

	k	***IAT***		***k***	***IAT***
1	20	19	**6**	20	16
2	10	19	**7**	10	16
3	5	19	**8**	5	16
4	2.5	19	**9**	2.5	16
5	**Fixed**	**19**	10	**Fixed**	**16**

	k	***IAT***
11	20	13
12	10	13
13	5	13
14	2.5	13
15	**fixed**	**13**

5. Simulation results

Results have been compared in terms of throughput time (average flowtime), throughput, Work in Process (WIP), the number of parts in delay (% delay parts) and the total time of delay. For each experiment class a number of replication able to assure a 5% confidence interval and 95% of confidence level for each performance measure has been conducted. Table 8 and 9 report the results between budget and efficiency based approach, budget and fuzzy approach.

The efficiency based and fuzzy approaches proposed in Renna 2001[15], and Amico 2003[16] are extended in this paper to the performances of delay in order to compare the proposed approach on these performances too.

From the analysis of the results reported in table 8 and 9, the following observation can be made:

- The budget approach leads to better performance both in confront to efficiency and fuzzy approaches. That is due to the different approach to compute the index of the manufacturing cell. In particular, in the budget approach the performance index computed leads to a better selection among the cells.
- The performance of the budget approach is better when the congestion of the manufacturing systems is high. This complies with the above considerations about the selection of the manufacturing cells. When the congestion is high, the selection of the cell is more important to distribute the workload among the cells.
- The performance of the proposed approach is better when the environment is more dynamic.
- The main performance that the budget approach is able to improve is the total time of delay of the parts with a reduction about the 25% (table n.9).

Table 8: Budget - Efficiency results

	Wip	**throughput**	**Average flowtime**	**% delay parts**	**Total delay time**
1	-43.70	1.63	-43.41	-53.33	-72.88
2	-43.04	1.09	-42.96	-62.27	-79.73
3	-42.85	0.72	-42.69	-69.39	-84.40
4	-41.06	0.61	-40.91	-70.68	-83.61
5	-61.71	13.82	-60.70	-30.74	-70.18
6	-58.78	4.98	-58.60	-48.11	-76.46
7	-62.71	4.62	-62.38	-57.23	-84.54
8	-62.21	3.96	-61.99	-62.10	-86.13
9	-57.24	2.95	-57.25	-61.36	-83.03
10	-30.79	15.37	-31.26	-2.52	-25.80
11	-42.60	13.05	-42.27	-6.57	-43.32
12	-42.90	12.62	-43.29	-7.51	-45.24
13	-36.42	9.37	-38.25	-7.20	-40.93
14	-28.99	6.12	-31.65	-6.15	-34.70
15	-13.62	13.13	-19.98	-0.38	-11.67
average	-44.57	6.94	-45.17	-36.37	-61.51

Table 9: Budget - Fuzzy results

	Wip	**throughput**	**Average flowtime**	**% delay parts**	**Total delay time**
1	-6.91	0	-7.1	-10.81	-12.79
2	-6.34	0.15	-6.44	-10.57	-11.85
3	-8.31	-0.05	-8.26	-16.34	-20.01
4	-9.59	0.14	-9.67	-21.05	-26.05
5	-1.07	-0.07	-1.79	-3.47	-2.16
6	-10.05	0.17	-10.44	-13.3	-18.16
7	-15.23	0.2	-15.13	-19.34	-32.84
8	-19.52	0.42	-19.36	-25.75	-43.81
9	-25.85	0.69	**-25.65**	**-33.54**	**-53.52**
10	-0.75	0.08	-6.71	-1.19	-7.94
11	-24.19	4.59	-26.49	-4.29	-29.56
12	-29.38	8.24	-31.13	-5.26	-33.11
13	-30.64	8.72	-33.17	-5.7	-35.37
14	-28.76	8.29	-31.57	-5.9	-33.37
15	-0.61	0.26	-13.68	-0.57	-14.83
average	-14.48	2.12	-16.44	-11.81	**-25.02**

The simulations are conducted by an infinite budget assigned to each part, in order to match up to other approaches. Further simulation is conducted in order the test the fuzzy tool to allocate the budget to the parts and verify the selectivity among the typology parts. Therefore, three typology parts have been hypothesized and the level of the budget is showed in table 10.

Table 10: Budget of the parts

High	100
Medium	20
Low	10

The price of each cell manufacturing is computed as:

$$P_k(t) = [100 \cdot REI(t)_k]^+ \qquad (11)$$

The factor 100 is the maximum value of the budget that can de assigned to the part.

The table n. 11 shows the results. As the reader can notice, the parts those have the high importance obtaining a better performance in terms of flow time and delay parts.

The performance of the parts with medium and low importance gets worse performances. The fuzzy engine enables to assign a budget to each part correlating to the importance of the part. The fuzzy engine can be adapt to the change of the importance of the parts in real time and this leads to a selective and adaptable system to perform the scheduling decision in manufacturing systems. Therefore, the fuzzy engine leads to a selective approach; the performance of the medium and low parts is very low because an opportune setting of the fuzzy tool is necessary to obtain an acceptable performance for the medium and low parts.

Table 11: Budget fuzzy allocation results

	Infinity budget	**fuzzy budget**	**% difference**
flowtime HIGH	164.26	80.28	-51.12 %
flowtime MEDIUM	127.47	4149	3154.88 %
flowtime LOW	86.964	3756	4219.03 %
% delay part 1	7.71 %	2.4 %	-68.8 %
% delay part 2	6.56 %	16 %	144 %
% delay part 3	2.78 %	19.5 %	601 %

6. Discussions and Conclusion

This paper proposes an innovative scheduling approach about a flexible manufacturing system in a dynamic environment. An approach based on internal and external index of efficiency of the cell manufacturing systems has been proposed. Moreover, it is considered a budget to assign at each part that arrives to the manufacturing systems and it can use to acquire the service of the manufacturing cells. In this research phase, first, it is assumed that the budget is equal and infinity for each part, then fuzzy tool is developed to assign an opportune value of budget to each typology of part. The proposed approach is compared with two approaches: efficiency and fuzzy reported in literature. Then, Multi Agent Architecture has been developed to test the proposed approach by Arena package. The simulation results show that the proposed approach leads to better performance. The proposed approach is more suitable for the manufacturing systems where the dynamic environment regards the manufacturing systems and the typology of the parts to be manufactured. The budget to assign at each part allows obtaining a scheduling approach able to select the parts that have been the better performance. The approach has a high level of versatility and it able to operate in extended manufacturing environments keeping a high level of performance.

Future development concerns a proper sensitive analysis has been conducted to define the value of budget assigned to each typology part. Moreover, artificial intelligence approaches can be developed to learning the opportune level of budget to assign.

Finally, the development of a distributed production planning in an extended enterprise environment in order to test how the proposed approach can be integrated in this environment and the advantages in a more complex system.

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