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Journal:	*International Journal of Production Research*
Manuscript ID:	TPRS-2010-IJPR-0169.R1
Manuscript Type:	Original Manuscript
Date Submitted by the Author:	05-Jul-2010
Complete List of Authors:	Renna, Paolo; Università degli studi della Basilicata, DIFA
Keywords:	MANUFACTURING SYSTEMS, PREVENTIVE MAINTENANCE, MULTI-AGENT SYSTEMS, DISCRETE EVENT SIMULATION
Keywords (user):	

Influence of maintenance policies on multi-stage manufacturing systems in dynamic conditions

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Abstract

Manufacturing systems are subject to a degradation process and if no actions are taken, the degradation leads to machine failures. Machine failures decrease the performance of the manufacturing system with loss of profits. The research concerns the evaluation of the manufacturing system performance in dynamic conditions when different maintenance policies are implemented in a multi-machines manufacturing systems controlled by Multi Agent Architecture. There are two extreme conditions of maintenance policy: no preventive maintenance, the actions are taken on failure state; on the other hand an intensive preventive maintenance can eliminate unforeseen failure, but with high costs. A dynamic policy maintenance is proposed to reduce the number of maintenance operations of the preventive policy. A discrete simulation environment has been developed in order to investigate the performance measures and the indexes of maintenance policies costs. The simulations have been conducted for several levels of fluctuation of mix, products' demand and working time uncertain. The simulation results show that the proposed approach leads to better performance for the manufacturing system and the number of maintenance operations (cost index of the maintenance policy), except in case of mean time between failure characterized by very low standard deviation.

keywords: manufacturing systems performance, preventive maintenance, multi agent system, discrete event simulation

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Abstract

Manufacturing systems are subject to a degradation process that leads to machine failures if no actions are taken. Machine failures decrease the performance of the manufacturing system with loss of profits. The research proposed concerns the evaluation of the manufacturing system performance in dynamic conditions when different maintenance policies are implemented in a multi-machines manufacturing system controlled by Multi Agent Architecture. There are two extreme maintenance policies that can be applied: no preventive maintenance, the actions are taken on failure state; on the other hand an intensive preventive maintenance can eliminate unforeseen failures, but with high costs. Dynamic policy maintenance is proposed to reduce the number of maintenance operations of the preventive policy. A discrete simulation environment has been developed in order to investigate the performance measures and the indexes of maintenance policies costs. The simulations have been conducted for several levels of fluctuation of mix, products' demand and working time uncertain. The simulation results show that the proposed approach leads to better performance for the manufacturing system and reduces the number of maintenance operations (cost index of the maintenance policy), except in case of mean time between failure characterized by very low standard deviation.

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1. Introduction

In realistic situations, the equipment of the manufacturing systems may not available because of periodical repair, preventive maintenance, or unforeseen breakdowns. Nowadays market conditions are characterized by continuous new products introduction, unforeseen demand fluctuation, reduction of life cycle of the products and margin profit. For the above reasons the maintenance policy needs to be integrated with the scheduling in order to react to the rapidly changes of the market and improve the manufacturing system performance. Two extreme maintenance policies can be considered: no preventive maintenance, therefore the actions are taken on failure state; on the other hand an intensive preventive maintenance can eliminate unforeseen failures, but with high costs. Therefore, a proper maintenance policy in a manufacturing system is necessary for it to improve performance and to reduce production costs.

In literature, the following definitions were provided for the above extreme policies:

- *periodic preventive maintenance policy (PM)*; a unit is preventively maintained at fixed time intervals kT ($k=1,2...$) independent of the failure history of the unit, and repaired at intervening failures where T is a constant.

- *failure limit policy*; maintenance is performed only when the failure rate or other reliability indices of a unit reach a predetermined level and intervening failures are corrected by repairs: corrective maintenance (CM) (Wang, 2002).

In this paper, it has been investigated the impact of the preventive maintenance on manufacturing system performance, then a proper maintenance policy based on manufacturing system status has been proposed. The maintenance policy is related to production scheduling in order to obtain a balance trade-off between the maintenance and scheduling requirements. In this research, the dynamic actions of maintenance and scheduling are supported by the use of multi agent architecture. The performance measures are evaluated in several environmental conditions: from static to very dynamic.

The paper is organized as follows. A literature review of maintenance policies based on manufacturing system status and related to scheduling is discussed in section 2. The manufacturing system context is presented in section 3. The Multi Agent Architecture proposed to support the scheduling and maintenance policy actions is presented in section 4. The simulation environment used to test the proposed approach is described in section 5. In section 6 the simulation results is discussed, while in section 7 the conclusions and future development is discussed.

2. Literature review

The survey paper (Wang, 2002) summarized, classified and compared various existing maintenance policies for both single-unit and multi-unit systems.

Several studies have been done to evaluate the maintenance policies in a single machine or two parallel machines context. Iravani and Duenyas (2002) considered a make-to-stock production/inventory system consisting of a single deteriorating machine which produces a single item. They formulated the integrated decisions of maintenance and production using a Markov Decision Process.

Dellagi et al. (2007) described a new preventive maintenance approach for manufacturing systems under environment constraints. The manufacturing system under consideration consists of a single machine that produces a single product in a Just-in-Time context.

Xu et al. (2008) investigated two parallel machines scheduling problem with almost periodic maintenance activities in order to minimize the makespan. They proposed a polynomial time approximation algorithm to solve the problem. They showed that it is unlikely to find a polynomial approximation algorithm that has lower worst-case bound than 2.

Jin et al. (2009) addressed production scheduling and PM planning for a single machine. The purpose of the scheduling problem is to choose an optimal sequence for the jobs as well as an optimal preventive maintenance planning which minimise the total weighted expected completion time of the jobs. Genetic algorithm is used to search for the optimal flexible-interval preventive maintenance planning and job scheduling.

Mosheiov and Sarig (2009) studied a single machine scheduling problem. The objective function is minimum total weighted completion time. The problem is proved to be *NP-hard*, and an introduction of a pseudo-polynomial dynamic programming algorithm indicates that it is *NP-hard* in the ordinary sense. They also presented an efficient heuristic, which is shown numerically to perform well.

The above approaches have been developed for a simple manufacturing system consisting of a single machine of two parallel machines. Another area of research concerns the performance analysis of multiple-machines manufacturing systems.

Gupta et al. (2001) presented some state-dependent preventive maintenance policies that are consistent with the realities of production environment. They also developed polling models based analysis that could be used to obtain system performance metrics when such policies are implemented. The numerical test was conducted by M/G/1 queues.

Savsar (2005) discussed a procedure that combines simulation and analytical models to analyze the effects of corrective, preventive, and opportunistic maintenance policies on the performance of Flexible Manufacturing Systems (FMS). The FMS performance is measured by its operational availability index, which is determined using the production output rate of the FMS under a variety of time between failure distributions and different operational conditions. The effects of various maintenance policies on FMS performance are simulated and the results are compared to determine the best policy for a given system. The number of machines is limited, the approach proposed is difficult to adapt at different manufacturing systems and only the productivity performance is considered.

Guo et al. (2007) proposed an experimental model to evaluate the effect of corrective and preventive maintenance schemes on scheduling performance in the presence of machine failure where the scheduling objective is to minimize schedule duration. Further, they showed that parameter values can be chosen for which preventive maintenance does better than corrective maintenance.

Yang et al. (2008) propose a new method for scheduling of maintenance operations in a manufacturing system using the continuous assessment and prediction of the level of performance degradation of manufacturing equipment. A genetic algorithm based optimization procedure is used to search for the most cost-effective maintenance schedule, considering both production gains and maintenance expenses. This approach does not include the information concerning the external conditions as the demand fluctuations and product mix changes. Moreover, the approach does not react rapidly to changes of the manufacturing system, in fact the genetic algorithm have to be run every time the conditions change.

Lee and Wu (2008) investigated a multi-machine scheduling problem in which job processing times are increasing functions of their starting times and machines are not always available. The objective is to minimize the makespan. The problem was resolved by the developed of several heuristics.

Levrat et al. (2008) proposed a novel approach for integrating maintenance into production planning. The approach uses the 'odds algorithm' and is based upon the theory of optimal stopping. The objective is to select, among all the production stoppages already planned, those which will be optimal to develop maintenance tasks preserving the expected product conditions.

Naderi et al. (2009) investigated job shop scheduling with sequence-dependent setup times and preventive maintenance policies in order to minimize makespan. Four metaheuristics based on simulated annealing and genetic algorithms as well as adaptations of two metaheuristics in the literature are employed to solve the problem. The performances of the proposed algorithms are evaluated by comparing their solutions through two benchmarks based on Taillard's instances.

Lu and Sy (2009) presented a fuzzy logic approach for decision-making of maintenance. Some linguistic variables and rules-of-thumb are used to form the fuzzy logic models, based on the domain experts' experiences in production line and maintenance department. The historical production data are used to train and tune the fuzzy models.

Caputo and Salini (2009) proposed some approximate queueing models to assess the impact of preventive maintenance interval on Work In Process (WIP). It is shown that WIP value is strongly influenced by the preventive maintenance interval and that maintenance intervals corresponding to a minimum maintenance cost or minimum WIP can be quite different. This kind of analysis can help in making more informed decisions involving WIP and cost trade-offs.

In recent years, some studies concern the cost and manufacturing performance analysis of maintenance policies.

Gharbi and Kenné (2005) discussed the production and preventive maintenance control problem for a multiple-machine manufacturing system. The objective of such a problem is to find the production and preventive maintenance rates for the machines so as to minimize the total cost of inventory/backlog, repair and preventive maintenance. The simulation experiments allow to determine an approximation of the optimal control policies and values of input factors.

Kenne and Nkeungoue (2008) proposed numerical methods for solving optimal control problem in order to minimize a discounted overall cost consisting of maintenance cost, inventory holding and backlog cost.

Safei et al. (2010) proposed a multi-objective integer programming approach to investigate the impact of the use-based preventive maintenance policy on the performance of the cellular manufacturing system. The objective is to minimise the machine cost, inter- and intra-cell material handling and maintenance costs. The proposed model was solved by an interactive fuzzy programming; the approach proposed was a centralized approach.

The analysis of a dynamic job shop problem is discussed in few papers in literature.

Vinod and Sridharan (2006) consider dynamic job shops with sequence-dependent setup times, and a discrete event simulation model of the job shop scheduling was developed. Two types of scheduling rules (ordinary and setup-oriented rules) are applied in simulation model. Their experimental results demonstrate that the setup-oriented rules outperform the ordinary rules. Zhou et al. (2006) propose an immune algorithm to investigate dynamic job shop problem.

As far as we reviewed, there is much less literature on integrating job shops scheduling with preventive maintenance. In particular, from the discussion of the literature the following issues can be drawn:

- most of the papers proposed mathematical approaches; these approaches can be used practically with reduced number of machines, because the problem of scheduling and maintenance is an *NP-hard* problem;
- some papers proposed the queue network approach to analyze the performance of the manufacturing systems and evaluate the maintenance policies.
- few papers proposed methodologies derived by artificial intelligence as genetic algorithm and fuzzy logic to select the best maintenance policies.

In summary, the studies concern few performance measures and the dynamicity degree of the external conditions of the manufacturing system was not investigated (demand and mix changes).

The originality of the research developed in this paper can be summarized as follows:

- a multi agent architecture is developed to support the scheduling and maintenance activities in job shop manufacturing systems with several machines.
- a dynamic maintenance policy is proposed in this paper in order to improve the performance of the manufacturing system.
- a discrete event simulation environment is developed to evaluate a wide range of performance measures (throughput, throughput time, work in process, tardiness and machines utilizations) for several degree of dynamicity of the market conditions (demand fluctuations and product mix changes).

3. Problem statement

The manufacturing system consists of a given number of cells; each cell is able to perform a particular set of manufacturing operations. Moreover, each manufacturing cell consists of a given number of machines. In such a system, the parts visit the manufacturing cells according to their routing; the scheduling decision consists in what machine, within the manufacturing cell, the part will perform the next operation.

The assumptions of the job-shop scheduling problem researched in this paper are the following:

- Each typology part has been given processing order, processing time and due date.
- Orders for production of different parts arrive randomly.
- Operations cannot be preempted.
- Each machine can process only one task at once.
- The queues are managed by the First In First Out policy in order to investigate only the proposed strategy.
- Each machine can breakdown randomly.

In this research, the material handling time is included in the machining time, and the handling resources are always available.

3.1 Parameters

The parameters considered can be classified in two categories: external and internal parameters. The external parameters concern the market conditions; in particular, it has been considered the workload of the manufacturing system, the degree level of demand fluctuation (from static to very dynamic) and mix product changes (from static to very dynamic changes). In this research, the internal parameters regard the maintenance parameters. In case of PM policy, the parameters are time between Periodic repair actions (*Tp*) which is related to machine maintenance requirements and it is a fixed value. The Mean Time To Repair (*MTTRp*) is the time to maintenance the machine; the actions in preventive maintenance are known because no failures are happened. Then, the *MTTRp* is the minimum possible and it is considered fixed in case of preventive maintenance operations.

In case of CM policy the parameters are the Mean Time Between Failure (*MTBFc*) which is related to machine reliability with mean μF_c and standard deviation $stdvF_c$ (it is assumed a normal distribution).

The preventive maintenance allows to improve the life of the components, therefore the *MTBFp>MTBFc*, then a parameter *d* is used to define the ratio:

$$d = \frac{\mu Fc}{\mu Fp} \in [0,1] \qquad (1)$$

The Mean Time To Repair (*MTTRc*) is not known at priori because the generic machine is in failure state. Therefore, the *MTTRc* is major of the *MTTRp* considering two factors, as reported in expression 2:

$$MTTRc = MTTRp \cdot K \cdot M \qquad (2)$$

$$K = MAX\left[\frac{time\ from\ last\ failure}{Tp}, 1\right] \qquad (3)$$

$$M = UNIFORM\left[1, \max value\right] \qquad (4)$$

The expression (3) means that the time of a maintenance action is greater when the time from the last maintenance action increases considering *Tp* as base value.

The expression (4) means that the time of the maintenance actions are not known at priori when the machine is in failure state; therefore the increment does not follow a particular distribution. It is assumed a uniform distribution between one and *maxvalue* for this incremental parameter.

The value of *Tp* is evaluated considering the probability to avoid a failure event during the time between two subsequent maintenance actions. If $Tp = \mu Fp$, the probability that the machines will be in failure status is the 50%; Table 1 reports the probability of failure state reducing the value of *Tp* (in simulation environment section the *Tp* is defined).

[INSERT TABLE 1 ABOUT HERE]

3.2 Dynamic policy

The maintenance policy proposed in this paper (DM) concerns the possibility to determine a dynamic time between two interruptions of the machine working state. In order to evaluate if the interruption can be activated, it has been evaluated the state of the manufacturing system:

- ◊ state of the manufacturing cell; the main index evaluated is the total number of parts in queue, the work in process of the manufacturing cell that specifies the congestion level.
- ◊ state of the manufacturing system; the indexes evaluated can be the following: the work in process, throughput time and the tardiness performance.

The above indexes can be combined in a single function that evaluates the state of the manufacturing system. In this paper, it has been considered the state of the manufacturing cell, and in particular the number of parts in queue of the generic machine.

The maintenance strategy performed by the generic machine is the following:

IF Time from the last operation is >= Tp AND NQi=0 THEN performs maintenance operation (5)

The expression (5) allows to apply the PM policy if the resource is in idle state, otherwise the maintenance operation is postponed and it can occur a failure of the machine. NQ_i is the number of parts in queue of the generic machine *i*.

The strategy proposed is between the two opposite strategies of PM and CM. Then, the *MTBF* and *MTTR* are evaluated by the following index:

$$DMf = \frac{Nopf}{Noptot} \quad (6)$$

where, *Nopf* is the number of maintenance operations in failure state of the machine and *Noptot* is the total number of maintenance operations. *DMf* assumes values between 0 and 1; if the value is 0 the DM policy is the same of the PM, if the value is one the DM policy is the same of the CM. This index evaluates the position of DM between the extremes PM and CM policies.

The value of *MTBFd* of the DM policy, is computed by the following expression:

$$MTBFd = MTBFc \cdot (1 + d \cdot (1 - DMf)) \quad (7)$$

The expression (7) defines a linear dependence between PM and CM policies; If *DMf=0* then *MTBFd=MTBFp*, if the *DMf=1* then *MTBFd=MTBFc*.

The MTTRd of the DM policy is computed considering the state of the machine when the maintenance operation is performed. If the generic machine is idle (PM condition) the MTTR is the same of PM policy, otherwise, the machine is in failure state and the MTTR is the same of CM policy (see expression 8).

$$MTTRd = MTTRc \cdot (1 + d \cdot (1 - DMf)) \quad (8)$$

4. Multi Agent Architecture

The Multi Agent Architecture consists of three types of agent: a Manufacturing Cell Agent (MCA) is associated to each manufacturing cell; it manages the cell in order to perform the operation requested by the part agent and the scheduling of the maintenance actions. A Machine Agent (MA) 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 according to the manufacturing cell objectives. Moreover, when a new part enters the system the corresponding Part Agent (PA) is created; it analyzes the part status locating the following activities to be scheduled and performs the strategy to assign the part to the workstation.

The actions performed by the agents for the scheduling problem are the following: (see figure 1):

- part agent analyzes the part status and it locates the next technological operation required by the part process plan;
- it sends a message to the MCA informing them that a part requests to perform a manufacturing operation and the typology of the operation required; afterwards, it remains waiting for the MCA agents' answer;
- MCA verifies if it can perform the technological operation required by the PA; in affirmative case the MCA sends a request to the MAs of the manufacturing cell, otherwise the MCA goes in wait state for another request.
- MA evaluates the workstation status at the negotiation time *t* and it provides the workload of the machine. The work load is computed as the sum of the working time needed by the parts in queue;
- MCA receives such evaluations from all the resources, it assigns the part to the MA that provides the minimum value of workload .
- finally, the MCA communicates the assignment to the MA and PA.

[INSERT FIGURE 1 ABOUT HERE]

Figure 2 shows the interaction between Manufacturing Cell Agent and Machine Agent for the maintenance control policy.

The actions performed are the following:

- at the initial state the MCA selects the maintenance policy and the MA monitors the machine's status.
- the MCA, in case of PM policy, schedules the next interruption for the maintenance operation. In case of DM policy, the MCA evaluates the next interruption of PM policy and if the queue of the machine is empty, decides to perform the maintenance operations. In case of CM policy, the MCA waits for the signal by the MA that the machine is in failure state.

- after the maintenance operation, the MCA updates the information on the manufacturing cell.

[INSERT FIGURE 2 ABOUT HERE]

As the reader can notice, the above procedures define the environmental relations of the autonomous agents involved in the work, but makes no assumption towards the agents' decision-making mechanisms. This means that the above protocols can be adapted to different objectives and decision mechanisms of the autonomous cell and job agents.

5. Simulation environment

The objective of the simulation experiments is to measure the performance of the maintenance policies CM, PM and the proposed dynamic policy DM in a very dynamic environment.

The author selected the Arena® discrete event simulation platform by Rockwell Software Inc. it was used to develop the simulation model of the presented approaches.

Discrete event simulation – in many commercial tools and simulation packages, nowadays the simulation model is automatically created from high level modelling languages and notations – allows to validate and optimize dynamic and discrete systems such as production systems, but also workflows such as negotiation mechanisms. These models facilitate evaluating different coordination scenarios and maximizing their potential output and benefits. Arena® – based on the known SIMAN simulation language - is well suited for modelling 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), (Law and Kelton, 2000).

The manufacturing system consists of three manufacturing cells, each cell consists of two workstations that are able to perform the same technological operations. The manufacturing system is called to manufacture a set of two different parts (they differs for the working time required "*workload*"). Each part needs several disjointed visits to the manufacturing cells; the number of visits for each part is reported in table 2, where, also the production mix is provided.

[INSERT TABLE 2 ABOUT HERE]

In particular, the parts with low workload are characterized by a working time of 10 unit times in each manufacturing cell, while the high workload is 20 unit times for each manufacturing cell. The working time is the same in each manufacturing cell in order to evaluate only the maintenance policies. The due date is obtained by the following expression:

$$due\,date = (\sum_{i=1}^{3} workingtime_i) \bullet duedate_{index} \quad (9)$$

The due date is obtained by the technological working time multiplied with an index; this index is fixed to 3 in this paper.

Parts enter the system following an exponential arrival stream whose inter-arrival times are reported in table 3. The simulations are performed for three congestion levels of the manufacturing system (low, medium and high).

[INSERT TABLE 3 ABOUT HERE]

In order to emulate a dynamic environment the manufacturing characteristics (demand fluctuation and mix changes) changing during the production run consisting of several alternating stages; each stage is characterized by a length that defines the stability of the environment in which operates the manufacturing system. Moreover, the uncertain of the working time is introduced.
Table 4 reports the data of demand and mix fluctuations for the three alternating stages considered.

[INSERT TABLE 4 ABOUT HERE]

The inter-arrival exponential parameter changes between 15 and 10, while mix parts changes over the three consecutive stages. Table 5 reports the data related to failures of the manufacturing resources.

[INSERT TABLE 5 ABOUT HERE]

It has been considered that the *MTBFp* has the same standard deviation of the normal distribution *MTBFc* ($stdvF_c$). The parameter *maxvalue* (see expression 4) is fixed to 1.2; this means that the mean time to repair for the corrective policy has an uncertain of 20% (in corrective policy the actions to perform are not known at priori).
The simulations have been conducted for six levels of dynamicity (see table 6), from static (1) to very dynamic (6), the simulations are conducted for a 30240 total unit times. The row "*Alternating stages*" reports how many times the stages are alternated during the length of the simulation.

[INSERT TABLE 6 ABOUT HERE]

Table 7 reports the five different environmental conditions in which the manufacturing system is tested.

[INSERT TABLE 7 ABOUT HERE]

Moreover, the working time uncertain has been considered as a deviation from the working time of the parts ($working\ time_u$). This uncertain can be caused by unforeseen events that affect the manufacturing operation (tool change, part load time, etc.). The working time uncertain follows a uniform distribution as showed in expression 10.

$$working\ time_u = working\ time \cdot UNIFORM[a,b] \qquad (10)$$

The working time uncertain is considered at two levels 20 % (in expression 10, a=0.9 and b=1.1) and 40 % (in expression 10, a=0.8 and b=1.2) for the case four in table 7. The experimental case five with all fluctuations is simulated with the level of 20% for the working time uncertain.

Therefore, it has been conducted 32 experimental classes. Five cases (table 6) for four cases of table 7, because the case 4 is tested for two level of uncertain.

6. Simulation results

For each experiment class, a number of replications able to assure a 5% confidence interval and 95% of confidence level for each performance measure have been conducted.
The performance measures investigated are the following:

- average throughput time of the parts; it is the average time that the two typology parts spend in the manufacturing system (*throughput av*).
- throughput of the manufacturing system (*throughput*);
- Work In Process (*WIP*);
- average tardiness of the parts; it is the average time of delay of the parts respect the due date (*tardiness av*).
- average number of maintenance operations; it is an index of the costs of maintenance related to the calls of the maintenance team (*Maintenan op av*). Each call is characterized by a fixed cost.
- average time of maintenance operations (*Maint time av*); it is an index of maintenance costs, but in this case, it is the variable cost related to the time of operation of the maintenance team.
- percentage of maintenance operations in failure state of the machines (*Failure av*); it is an index of the number of intervention in failures state of the machine that can affect the quality of the parts.
- average of the single maintenance operation (time to repair). it is obtained by the ratio between the average time of the maintenance operations and the number of maintenance operations (*Av TTR*).

The simulation results reported are the percentage difference compared to the PM policy.
Figure 3 reports the simulation results over the three levels of congestion of the manufacturing system for the CM maintenance policy and in static environmental conditions. The CM policy leads to reduce the number of maintenance operations on the manufacturing system, and therefore the costs related to this maintenance activity. All the other performance measures are worst compared to the PM policy, in particular the average tardiness of the parts is the performance that is drastically reduced. Moreover, the benefits of the PM policy are more important when the congestion of manufacturing system is low (inter-arrival 15).

[INSERT FIGURE 3 ABOUT HERE]

Figure 4 reports the simulations results over the three levels of congestion of the manufacturing system for the DM maintenance policy and in static environmental conditions. In this case, the proposed approach leads to better performance measures for the manufacturing system. The main benefit regards the average tardiness of the parts. When the congestion level is high (inter-arrival 9) the benefits of DM are very low. Moreover, the DM policy leads to increase the number of maintenance operations in failure state of the machines, but this number is always under the 10% of the total maintenance operations, therefore a limited number.

[INSERT FIGURE 4 ABOUT HERE]

Table 8 reports the simulations results introducing the dynamic condition one at time. The values reported are the average percentage difference compared to the PM policy over all the stage lenghts considered (see table 6). The worst performance are highlighted in the table. From the anaysis of the table the following issues can be drawn:

- the mix changes is the environmental element that leads to worst performance for the CM policy, with the excpetion of the average tardiness of the parts that is more influenced by the working time uncertain.
- in case of DM policy, the high level of working time uncertain and the mix changes leads to worst performance.
- the throughput is the performance with less influence by the environmental conditions.

[INSERT TABLE 8 ABOUT HERE]

Figures 5 and 6 report the trend of the performance measures over the stage lenght for the CM and DM policy when all the enviropmental conditions change when the stage lenght varying (see table 6).

[INSERT FIGURE 5 ABOUT HERE]

In particular, the performance of the CM policy are very stable, except for the average tardiness of the parts. The tardiness is very high when the environment conditions are stable (stage lenght 10080), it decreases when the the conditions are more dynamic.

[INSERT FIGURE 6 ABOUT HERE]

The DM policy leads to significantly benefit for the tardiness performance in case of stable (stage lenght 10080) or more dynamic (stage lenght 630). The other performance measures have low fluctuation over the stage lenghts.

Table 9 reports the simulation results when all the environmental conditions changes for different values of the *stdvFc* (standard deviation of the mean time to failure). The values are the percentage difference compared to the PM policy and the average over the stage lengths.

[INSERT TABLE 9 ABOUT HERE]

The simulation results show that the performance are the same for low and medium standard deviation; when the standard deviation is high the CM policy has a modest improvement of the performance, while the benefits of the DM are significantly reduced.

7. Conclusions

The research deals with the performance investigation of different maintenance policies in dynamic conditions. The effects considered are the mix, inter-arrival and working time changes under a scheduling approach base on Multi Agent System architecture. In this research, three maintenance policies are investigated: preventive, corrective and a dynamic policy proposed in this paper.

The simulation results show that the mix changes and working time uncertain have significant effect on the performance of the manufacturing system, in particular these changes lead to obtain major benefits when the preventive maintenance policy is used. Moreover, the proposed approach shows significantly improvements in terms of tardiness performance and maintenance operations without increase the average time of the maintenance operations. The tardiness is a performance of the manufacturing system, while the number of the manufacturing operations and average time of its are the indexes of the costs of the maintenance policy. Therefore, the proposed approach improves a particular performance measures (the other performance measures have low difference with preventive maintenance) with a reduction of the maintenance costs. The investigation on the dynamicity of the manufacturing system shows the robustness of the proposed approach. Finally, the effect of the standard deviation of Mean Time to Failure is investigated; the results show that the proposed approach reduced drastically the benefits when the standard deviation is very low. In this case, the preventive policy is the better strategy.

Further research paths concern the effect on the parts of the maintenance operations when the resources are in failure state. To be more precisely, if the failure of the machine can cause the waste product or the re-working of the part. This aspect can be connected to the real costs of the maintenance policy, in order to investigate the best policy not only in term of costs of the policy, but also with the effects on the parts. Moreover, the implementation of the proposed approach in a real case study allows to evaluate the real benefits.

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List of Tables

Tp	Probability to failures state
μ_c-$stdvF_c$	15.86553%
μ_c-$2*stdvF_c$	2.27501%
μ_c-$3*stdvF_c$	0.13499%
μ_c-$4*stdvF_c$	0.00317

Table 1.Tp values

	Part 1	Part 2
Mix	50%	50%
Number of visits	3	3
workload	Low (30 unit times)	High (60 unit times)

Table 2. Mix part

	low	medium	High
Inter-arrival	9	10	15

Table 3. Inter-arrival stream

	Stage i	Stage i+1	Stage i+2
Inter-arrival time	15	10	-
Mix Part 1	50%	80%	20%
Mix Part 2	50%	20%	80%

Table 4.demand changes over the stages

MTTRp	45
μFc	450
stdvFc	67.5
μFp	510
Tp	μFp **-2 sigma=450**
M	1.2

Table 5.Failures' data

	1	2	3	4	5	6
	Static	10080	5040	2520	1260	630
Alternating stages	**1**	3	6	12	24	48

Table 6.Stage length

1	2	3	4	5
No changes	Mix fluctuations	Inter-arrival fluctuations	Working time uncertain	All fluctuations and working time uncertain

Table 7.Experimental cases

	CM	DC	CM	DM	CM	DM	CM	DM
	MIX		Inter-arrival		Working time 20%		Working time 40%	
Throughputav	**25.39**	-2.02	20.54	-2.99	20.98	-2.41	21.41	**-1.7**
Throughput	-0.50	-0.71	-0.03	0	-0.21	0.06	-0.05	-0.08
WIP	**25.75**	**-1.66**	20.62	-3.02	20.74	-2.41	17.37	**-1.74**
Tardinessav	87.92	-1.41	88.45	-10.73	**133.92**	-18.70	**125.73**	**5.78**
Mainten op av	**-10.44**	-5.86	-12.20	-4.69	-11.75	-4.10	-11.79	**0.31**
Maint time av	**18.18**	-0.90	15.81	-3.89	16.48	-0.74	16.42	**-0.51**
Failuresav	100	**7.01**	100	5.48	100	5.95	100	**7.05**
Av TTR	31.96	**5.28**	31.91	3.60	31.98	3.56	31.98	**4.53**

Table 8.Simulation results - dynamic conditions

	CM	DC	CM	DM	CM	DM
	stdvFc=33.75		stdvFc=67.5		stdvFc=135	
Throughputav	17.35	-2.61	17.75	-2.44	16.21	-1.34
Throughput	-0.13	0.06	0.06	0.13	-0.25	-0.13
WIP	17.43	-2.55	18.00	-2.37	16.31	-1.38
Tardinessav	58.50	-7.85	59.34	-7.55	53.42	-4.48
Mainten op av	-11.76	-5.02	-11.47	-4.67	-4.73	-3.71
Maint time av	16.45	-1.20	16.83	-0.56	14.48	2.74
Failuresav	100	3.79	100	4.78	100	8.67
Av TTR	31.96	4.03	31.97	4.31	31.98	5.56

Table 9.Simulation results - stdvFc changes

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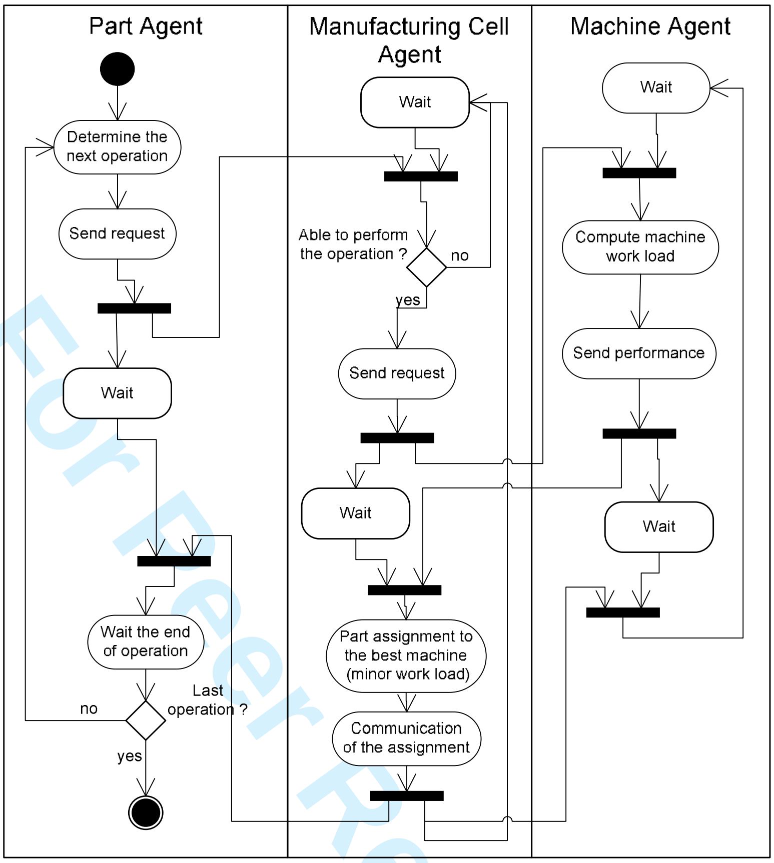

Figure 1. Multi Agent activity diagram interaction - scheduling

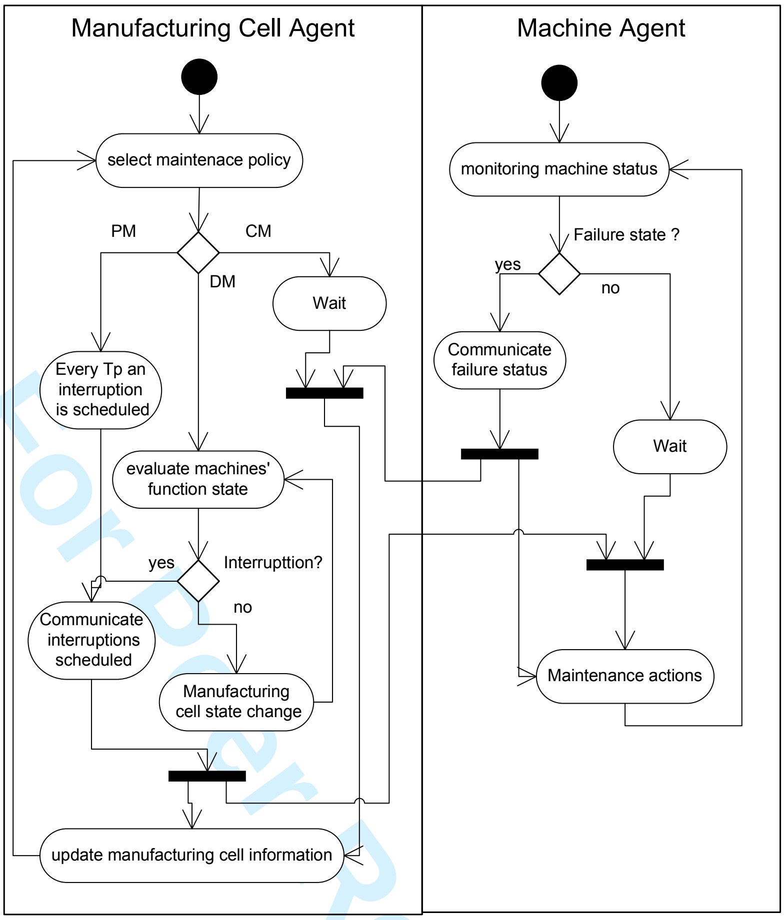

Figure 2. Multi Agent activity diagram interaction - maintenance policies

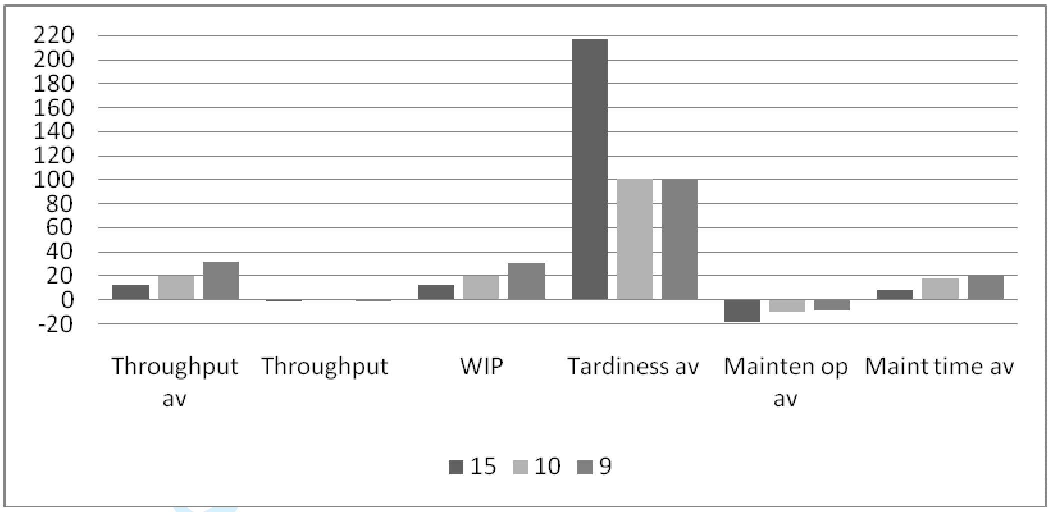

Figure 3. Simulation results CM policy - static

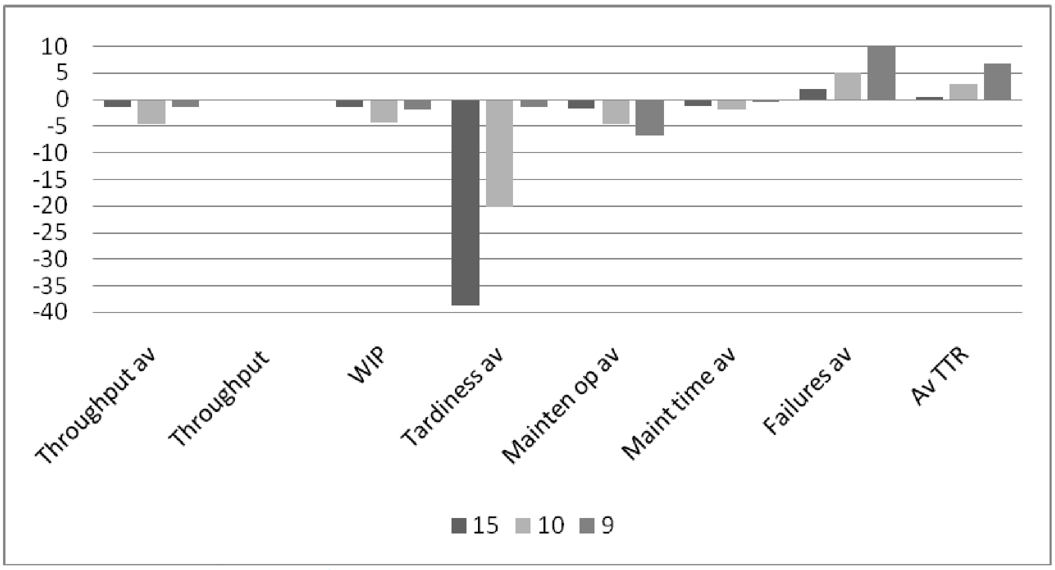

Figure 4. Simulation results DM policy - static

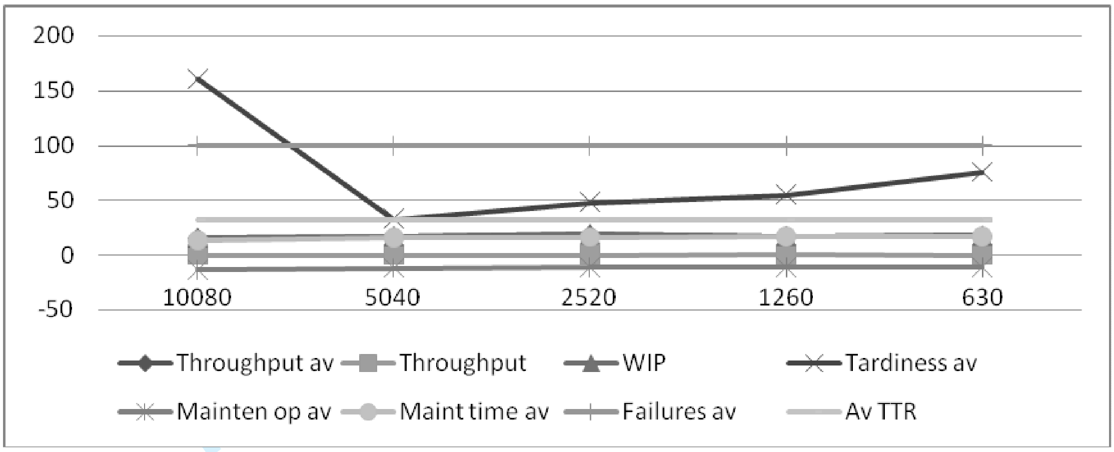

Figure 5. Simulation results CM policy over the stage lenght

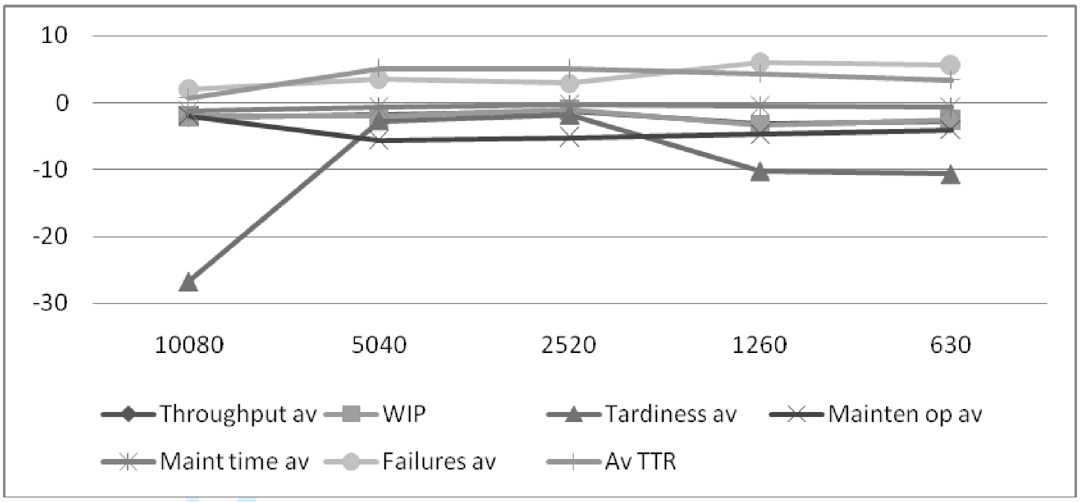

Figure 6. Simulation results DM policy over the stage lenght