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Abstract. Scheduling problem in manufacturing companies with high rework rates remains an actual complex research source. This paper presents a method combining a predictive schedule to a proactive decision making based on smart lots. Each batch embed an algorithm allowing it to predict its quality on the next workstation. As soon as a lot determines that its process is too hazardous a collaborative re-scheduling decision, using analytic hierarchical process, is initiated with its peer. A simulation model, inspired from a lacquering robot case study is described. Then, the results of different scenarios are presented and discussed.

Keywords: proactive decision making, AHP, quality prediction, smart lots

1 INTRODUCTION

Scheduling problems are some of the most important activities in manufacturing control management. Since 1960, many exact and heuristic approaches were proposed in the literature to achieve the best outcome like maximum profit or lowest cost ([1],[2]). The classical technics, which allow to determine a global optimized schedule, are not very useful in case of disturbances like for example when companies suffer from high reworks rate. This can be explained by the fact that, as soon as a rework appears, the schedule becomes unsuitable and cannot be used anymore because these centralized/predictive solutions are not agile enough. That's why the decision could become distributed to let the system adapt itself to the situation. However, such systems are suffering from myopia. According to these facts, the elaboration of hybrid monitoring system, based on holonic architecture [3], becomes full of interest by conjugating predictive, for global optimization and reactive based on distributed solution, to answer to disturbances. The aim of this paper is to propose hybrid manufacturing system combining global optimized schedule to proactive distributed decision based on AHP process.

The document is organized as follow: next section presents the context. Third section explains the proposal which combines centralized scheduling with non-quality prediction and real-time distributed decision making. Section four presents the industrial application (Acta-mobilier case study), the simulation model developed, the hypothesis and simplification performed and the obtained results. Finally, last section draws some conclusions and outlooks.

2 RELATED WORK

As said before, hybrid architecture is a good mean to adapt production flows to disturbances. Indeed, many companies have really heavy non-quality rates which create flow disturbances and make global centralized schedules obsolete. One way to solve this problem is to improve products quality. An optimal parameters setup to limit the non-quality via a neural network that informs the co-worker of the best way to setup the workstation has been proposed [4]. This model depends of a bench of intern and extern factors: the actual setup of the workstation, the production range of the next product to be processed, and environmental factor as air humidity or temperature. But it is still insufficient as soon as the companies are working at the technological restrictions. Another solution, which could be combined to the preceding one, is to try to predict the non-quality. [4] proposed a model based on neural network able to predict the risk of non-quality for a particular product at a particular time. With the combination of these two proposed solutions, the co-worker is informed of the non-quality risk rate and of an alternative setup which will reduce it. Plus, the hybrid architecture based on smart products combining a global schedule made without taking into account the reworks problem and local schedules that are made for every work-centers following their own optimizations and recalculate themselves on the need, that was proposed [3] could encapsulate this combination. So here, our objective is to propose to embed each product with an instance of the quality prediction neural network model. We assume that an optimized schedule has already been provided to the workstation. But knowing that variant extern factors like the atmospheric pressure or the air humidity could extremely impact the quality of the process, the choice to let the products decide if the schedule should be altered or not was taken. The products in the queue of the workstation must normally be processed following the optimal global schedule. But to prevent non-quality, the risk prediction process could permit to dynamically perform, directly by the products, a local re-scheduling under certain conditions to determine.

3 PROPOSAL

3.1 HYBRID CONTROL SYSTEM USING QUALITY PREDICTION

We can consider that products are always proceeded in undividable batches (in extremal case, batches may be constituted by one unique product). [3] proposed to elaborate hybrid manufacturing system combining, smart products based, distributed system to centralized optimization. To do so, our proposal, here, is to embed the batches (minimal product agents) with their own instance of the neural network quality prediction model, trigger it before the setting up of a batch on the workstation. If the risk is weak (under a certain threshold) then the batches are processed following the forecast global schedule Figure 1.

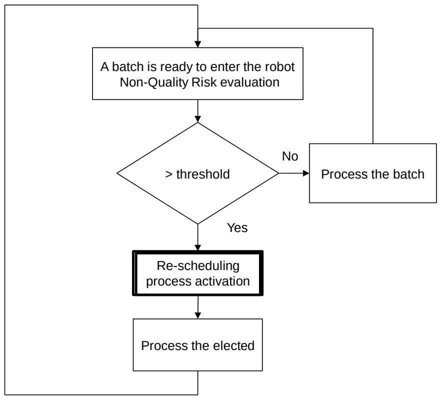

Figure 1: Risk of non-quality detected

Else, if the neural network determines that the risk is over the threshold, for the next batch to produce, then the system enters in a collective decision making with the other batches present in the queue of the workstation (Figure 2). The goal of this negotiation is to determine which batch present in the queue must be the next one to be processed. The decision should be taken regarding different criteria like for example: the risk of non-quality, the due-date of the products, the balance between the different product family flows, the setup time implied by the batch change and the system nervousness (the number of schedule alterations created by swapping batches).

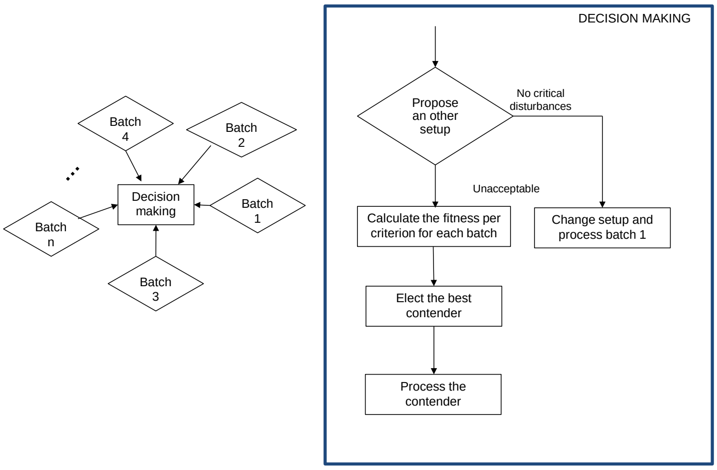

Figure 2: Re-scheduling process

Following these criteria, the batches will decide together which one will be the next to be processed. The first possibility is given by the neural network [4]. It proposes an alternative setup to reduce the non-quality risk, but this change could imply, in return, a longer processing time which could lead the other batches to be in overdue. The second option is to switch the first batch with another one from the queue

which fit better regarding the whole criteria. The following paragraph explains the chosen algorithm for the selection.

3.2 COLLABORATIVE DECISIONS BASED ON SMART LOTS

Numerous techniques of collective decision have been implemented in multi-agent systems. Some of them are inspired by the social behaviors like consensus [5] and majority voting [6], some mimic biology like swarm robotic [7],especially ant [8] or bee [9] colonies. Others are taken from the domain of game theory [10]Here, the use of Analytic Hierarchy Process (AHP), introduced by [11] was chosen. AHP is particularly well appropriate to deal with complex decision making and allows decision makers to prioritize. The principle is to convert complex decisions to pairwise comparisons, in order to make a synthesis of the results. AHP permits to take into account both subjective and objective aspects of a decision. Plus, AHP uses also an incorporated technique to check the consistency of the evaluation.

So AHP is one of the most used means in decision making, especially then there are uncountable variables. This method is already used in scheduling problems, for instance [12] coupled an AHP to a genetic algorithm to solve production-distribution problem, [13] combined AHP to data envelopment analysis in computer simulations to find optimum alternatives with multiple quantitative and qualitive variants. [14] proposed an application of AHP and ANP (Analytic Network Process) to prioritize, schedule and optimize power unit price allocations.

Our implementation of the AHP is inspired from [15]. Each batch is compared to the others, criterion by criterion, to elaborate some comparisons matrices. It is composed by ones on the diagonal and where values are between 1/3 and 3. $A_{i,j}$ express the valorization of batch i to batch j regarding the criterion A. Each matrix respects the properties:

- $A_{j,i} = 1/ A_{i,j}$
- $A_{i,j} > 0$

After that, normalized vectors are made using the columns of each matrix. Then the vectors are summed with weight factors and the highest value gives the chosen batch. The global functioning of the method is represented on Figure 3. "c" represents the loop value allowing to explore each of the m criteria, "K" is a nxn matrix which allows to save the $A_{i,j}$ described before. "E" is a nxm matrix which represents the sum of the values for the batch i regarding the criterion c. The function "Compare" calculates the valorization of batch i compare to batch j regarding the criterion c. The function "Normalize(K)" is just used to normalize the columns of the matrix K. The algorithm returns the number of the batch with the highest value.

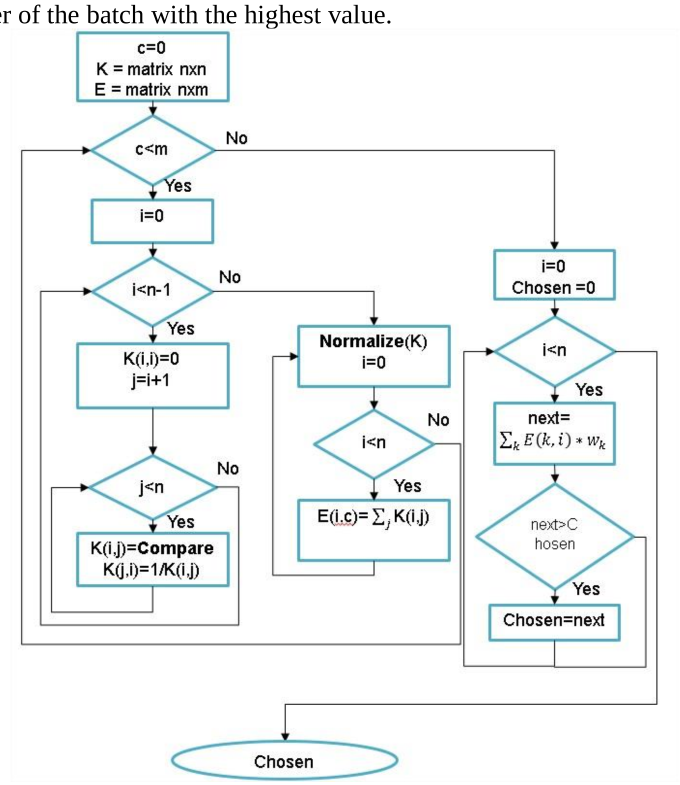

Figure 3: Functioning diagram of the AHP protocol

4 CASE STUDY

4.1 INDUSTRIAL CONTEXT

Our proposal studies the specific case of the lacquering robot of Acta-mobilier. This robot must feed two distinct product flows the brilliant and the mat products (which correspond to two products families) having different customer workstations but should arrive at the same time in the shipment workstation (Figure 4).

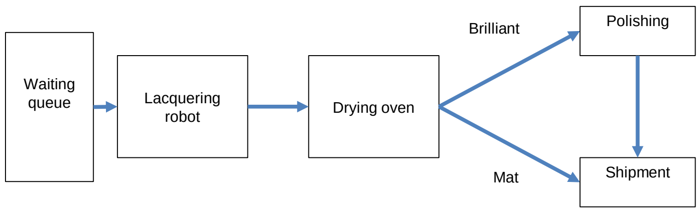

Figure 4: Acta-Mobilier robot workflow

Acta-mobilier suffers from a high rework rate upper than 30% due to the high-quality level required by the customers. To reduce the rework rate, one of the solution is to work on the quality problems. It is actually very hard to improve the processes or the materials due to technological limitations. Another option is to predict the risk of non-quality regarding all the factors that impact on the quality. In a workstation, like this robot, where the quantity of products to process together must be important to be profitable (at least 2.5 m²) to prevent rework is a crucial concern. If a quality default would appear, it would impact the whole batch of products. And the problem lies in the fact that defaults can only be detected after the drying time which takes 7 hours minimum. Some defaults need only a simple adjustment, but others need a complete re-lacquering implying one more time 7 hours of process. Moreover, the sensitivity of the lacquering process regarding the quality defaults depends on several factors. Some of them, like the air humidity and pressure, are unmanageable. The neural network described in [4] was made to analyze all the factors, predict the probability of default appearance and propose a different setup of the robot which will lower the risk. The next section describes the simulation model, developed to be as near as possible of the real case.

4.2 SIMULATION MODEL

A simulation model written in Python has been made. In this model, the number of batches able to discuss has been limited to the 5 firsts. So here, n (the number of batches used in the previous section) is set to 5. To do so, the model has been made with 5 parallel entering queues with a capacity of one, numbered from i1 to i5. These five queues represent the five batches, able to discuss in case of non-quality risk detection as presented in preceding section. The batches arrived on the queues according to the optimized forecasted schedule. In normal functioning the queue i5 is the one selected to be proceed by the machine. Figure 5 illustrated this scenario, the batches B1 to B5 are sorted according to the global schedule and without non-quality detection B1 is the first batch to be processed. Each time a batch enters the machine the others are moving to the next queue. Then according to the product information, the robot realizes the corresponding program (the needed time to realize the operation is proportional to the surface to work) and the batch leaves the machine with a remaining time reduced by seven to represent the time it should stay in the drying oven. At the output, a random is launched to determine if the batch has a default. In such a case, it returns in the input queue to be re-proceed. Otherwise, it exits the machine and add itself to one of the two possible customer queues (brilliant or mat). Before entering the robot, the batch in i5 will launch the computation of its embedded neural network to determine the non-quality risk percentage. If the risk is upper than the threshold described in section 3, set up to 25% in this case, the AHP based procedure is called. Then the computation described in the previous section is launched to determine which batch seems to be the best one to go next, according to the algorithm presented in section 3. Figure 6 shows the scenario where B1's neural network has evaluated a too heavy risk of potential non-quality, so the five batches entered in discussion and as a result B3 was chosen to be the next to be processed. The variants of the model are the following:

- Inherent to the production range:
  - Area is the total surface of the products composing the batch expressed in m²
  - Program is the number of the program the machine should use to realize its operation on the batch
  - Due date is the remaining time in hour before the delivery of the batch
  - Number of pass is used to count how many times a batch is done and maybe re-done on the machine
- Inherent to the criteria:
  Each of the five criteria is weighted by a factor going from 0 to 1
- Inherent to the workstation:
  - The 4 programs with their own duration time expressed in hour per m²
  - The two possible setup times expressed in hour:
    - The first one is used until the current product has the same finishing as the previous (brilliant/brilliant or mat/mat)
    - The second is for a finishing change
- The defect happening represents the appearance of a defect after the process

A summary of all these variants is presented inTable 1.

Next section explains the chosen conditions of simulation, and the obtained results are discussed.

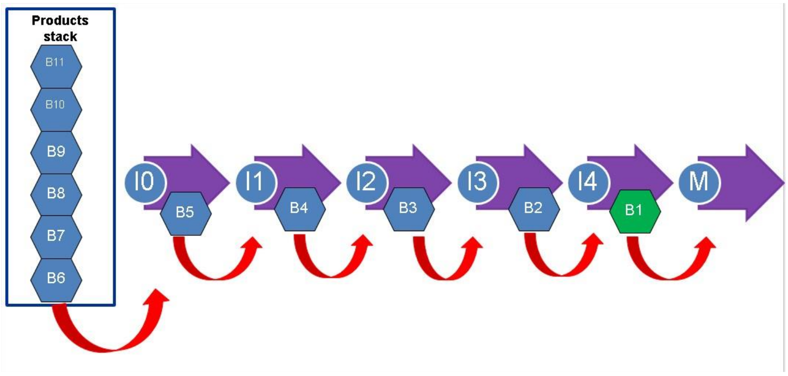

Figure 5: Normal function

Products		
Area	Float	[2,5;40]
Program	Integer	1: 1 brilliant side 2: 2 brilliant sides 3: 1 mat side 4: 2 mat sides
Due date	Integer	[0;50]
Number of pass	Integer	[1,10]
Criteria		
Weight	Float	[0,1] => set to 1 for the first experiments
Machine		
Program1	h/m²	0.28
Program2		0.04
Program3		0.03
Program4		0.02
Setup without finishing changes	h	0.03
Setup with finishing changes	h	0.05
Model		
Defect happening	Float	[0;100]

Table 1: List of variants

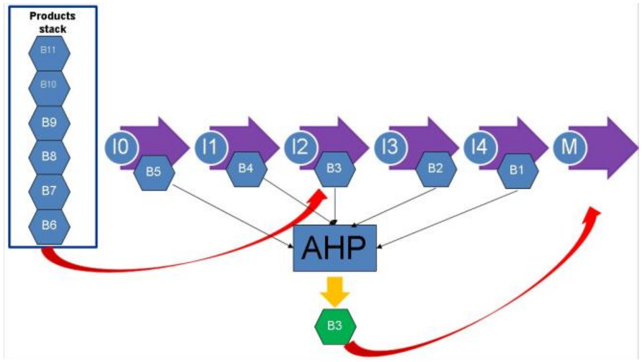

Figure 6: In case of non-quality risk detection

4.3 EXPERIMENTATION PROTOCOL

To validate the proposed method, simulations in several distinct conditions with and without the use of the AHP dynamic decision were made. For each case, a set of ten simulations have been made. The means and the standard deviations for each case is presented. To take conclusions about the benefits of the AHP method, a global cost function, express in euro, described as the weighted sum of the three following sub-function also express in euro is compared:

- The lateness represents the number of overdue hours multiplied by a penalty cost. It is an approximate way to express the cost of the lateness, which is really complex to represent, because a product in overdue implies a heavy impact on the company brand-building with a customer confidence loss and in some cases complementary truck departure.
- The rework cost which is the cost implied by the fact of re-doing the product on the robot taken directly from the real cost of the company.
- The workforce cost is calculated by multiplying the cost in man-day of two operators (minimal number of person needed to pilot the robot) by the makespan.

The subject of this paper is to evaluate the benefits in the use of the AHP method with quality prediction function compared to the classical schedule optimization taken alone. That’s why, for these simulations an equal weight was set for all the preceding criteria in the evaluation of the global cost.

The following paragraphs summarize the different cases, the reason to test them and the obtained results.

- The first case studied is an actual example taken from the production of the robot in Acta-mobilier when even the schedule optimization isn’t made. The production of a team (8 hours of work) was used

Real case	Lateness		Rework		Workforce cost		global cost	
	mean	std	mean	std	mean	std	mean	std
FIFO	1541.0	1510.2	9718.8	6563.1	107.1	23.5	11366.9	7884.5
AHP	91.4	193.1	3884.4	3245.1	80.8	9.2	4056.5	3310.6

Table 2: Real case

This table highlights that even regarding each cost separately the AHP algorithm gives a better solution on a non-optimized dataset. The rework cost is 61% lower than the FIFO for a global reduction of 64 %.

Equal distribution	Lateness		Rework		Workforce cost		global cost	
	mean	std	mean	std	mean	std	mean	std
FIFO	2935.4	2427.5	13494.0	7713.3	118.8	25.6	16548.2	10003.4
AHP	385.7	441.5	3666.0	2238.1	81.5	8.5	4133.1	2464.3

Table 3: Equal distribution

- Then a simulation with an optimized schedule having an equal balance of the flow loads to determine the benefit of the proposal placed in the optimal possible case.

With a dataset already scheduled in order to balance the two-customer workstation loads and representing a production where all the batches have the same surface, the AHP still offers an improvement of 73% regarding the rework for a global enhancement of 75%.

The different extreme cases are treated to evaluate if the solution remains effective faced to a situation where one of the criteria is not enabled:

- The two extrema of the load distribution (only brilliant products and only mat products) which also impacts on the minimization of the setup time

Only brilliant	Lateness		Rework		Workforce cost		global cost	
	mean	std	mean	std	mean	std	mean	std
FIFO	2501.3	2560.2	11544.0	6955.2	115.7	24.5	14160.9	9468.1
AHP	60.0	140.7	2964.0	1594.3	78.1	8.8	3102.1	1674.1
Only mat	Lateness		Rework		Workforce cost		global cost	
	mean	std	mean	std	mean	std	mean	std
FIFO	1677.5	2482.0	12394.0	8303.2	102.5	18.5	14173.9	10727.0
AHP	101.3	176.0	4680.0	2651.5	73.2	6.6	4854.5	2682.3

Table 4: Extrema load distribution

Faced to a situation where the criterion of load balancing is unenabled, the AHP still gives an average cost 72% lower than the FIFO.

- All the products having the same due date

Same due date	Lateness		Rework		Workforce cost		global cost	
	mean	std	mean	std	mean	std	mean	std
FIFO	68.1	215.4	5959.2	4857.2	84.9	9.8	6112.2	4892.2
AHP	0.0	0.0	4929.6	4026.5	84.9	9.8	5014.5	4033.3

Table 5: Same due date

As soon as all the products have the same due date with an optimised schedule the benefits brought by the AHP are almost exclusively on the rework cost and a bit on the lateness. This time the improvement is at 18%.

- The non-use of the neural network to know if the AHP is efficient even without the predictive aspect.

No risk of non-quality	Lateness		Rework		Workforce cost		global cost	
	mean	std	Mean	std	mean	std	mean	std
FIFO	57.3	181.2	5545.8	5101.9	86.4	13.4	5689.5	5252.9
AHP	284.6	381.5	3775.2	1281.2	82.0	7.9	4141.7	1454.0

Table 6: Without using risk of non-quality

Faced to a simulation where the criterion risk of non-quality isn't taken into account the AHP is 5 times worse than FIFO regarding the lateness cost but prevent 32% of rework and this way offers an enhancement of 28% for the global cost.

5 CONCLUSIONS AND OUTLOOKS

In this work, hybrid manufacturing control which combined a centralized global optimisation with a proactive distributed decision making based on AHP method in case of a heavy risk of non-quality prediction, is proposed. It inscribed itself well in the global project of the hybrid architecture, introduced in [7].
Even the simulation results show interesting improvement of different KPIs, there are still many issues and complemental scenarios to explore: runs on longer simulation based on actual data form the company to evaluate the behaviour of the shop floor on a longer period. Take into account the expert knowledge to estimate more precisely the weight of the different criteria and adjust them dynamically. In addition to the costs,

the profiles of the brilliant and the mat loads should be analysed. Togo further, complements should be provided to the model to make it even more realistic. For instance, the consumption speed of the two customer queues should be added in the model. The fact that others workstations also feed them and that different kind of reworks with different process times may happen (from simple correction to total reproduction) should also be taken into account. The following steps are to implement this proposal on a testing machine in our laboratory and after validation incorporate it in the company.

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