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Distributed Fuzzy Decision Making for Production Scheduling

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Abstract

In production systems, input materials (educts) pass through multiple sequential stages until they become a product. The production stages consist of different machines with various dynamic characteristics. The coupling of those machines is a non-linear distributed system. With a distributed control system based on a multi-agent approach, the production system can achieve (almost) maximum output, where lot size and lot sequence are the most important control variables. In most production processes high throughput and low stock are conflicting goals. In order to compare and compensate between these multiple goals, a fuzzy decision making approach is employed here that decides about the material flow and machine states, based on variables like working load or order queue length.

1 Introduction

The topology of production systems is built according to the sequential character of material processing. Materials are transformed or assembled with other materials through several stages until they become a product. Production stages build a chain to transform raw material sequentially to a finished product.

Each production stage has its own (time) characterics. Some production processes are more time consuming than others. To compensate for that there may be one or more machines at one stage in parallel, each machine performing the same operation. The more time-consuming a single production step is, the more machines will be arranged in parallel. If the capacity of the production system needs to be enhanced, new machines will be installed additionally, parallel to the existing machines in each stage. So we get a heterogeneous mixture of machines at every stage.

In this paper we examine a real world tire production system, with two stages. A special characteristic of this system is the very long reconfiguration time at the second stage. The task is to minimize the setup cycles at this second stage. State of the art at this plant is a semi-manual scheduling system. We

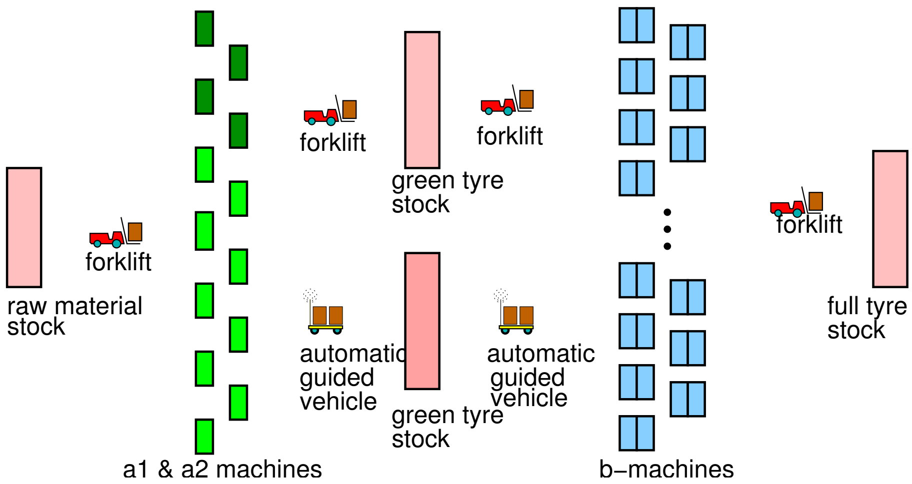

Figure 1: Machines in both stages are arranged in parallel. Material flows from left to right. At the beginning, in the middle and at the end there are stocks for material in different process states. Transportation is done either by forklifts or by automatic guided vehicles.

developed a hierarchical rule-based multi agent system to manage the scheduling automatically. We compare two variants of our system: a crisp rule based single feature system, and a fuzzy rule based multi feature system.

2 Tire Production

We investigate a real world tire production system, as shown at figure 1. The tire production takes two steps to transform raw material into tires. The first production step is done at the first machine stage, the so-called A stage. At the A stage there are 13 machines of two kinds, 4 fast (a1) and 9 slow (a2) machines. The second stage (B stage) involves 53 machines each having two production slots. These 53 machines with two slots are considered as 106 separate machines, the B machines. All machines at each stage are arranged in parallel.

At the beginning of the production process, the raw material is stored in a raw material stock. There are 128 different kinds of tires. The types of tires differ only in shape, i.e. diameter or width. So all types need the same raw materials. The raw materials are transported by forklifts from the stock to the first production stage. At the first stage the material is worked up to so–called green tires. After this step the green tires are delivered either by forklifts or by an automatic guided vehicle system to one of two intermediate stocks between both stages. One stock is charged by the forklifts, the other one exclusively by the automatic guided vehicles. Green tires have a durability of four days, after this time the tires cannot be processed any more and they are separated

machine type	machines [number]	cycle time [min]	setup time [min]	break down rate [percent]
a1	4	8	22	7%
a2	9	15	25	5%
b	106	55	480	3%

Table 1: characteristics of a1, a2 and b machines. A machines are located at the first stage, B machines at the second stage

out. Green tires reach the second stage also by forklifts and automatic guided vehicles. At this last production step full tires are produced by the B machines. After the second stage, forklifts do all the transportation to the product stock.

The machines at both stages have different characteristics, see table 1. One production cycle on an A1 machine takes 8 minutes, on an A2 machine 15 minutes. The processing time at the second stage is significantly longer; one production cycle takes 55 minutes there. Machines may break down with a certain probability at each production step. A1 machines have a break down rate of 7%, A2 machines of 5%. Machines at the second stage break down for 3% of all produced tires. In the case of a break down the production is stopped and the machine has to be set up again before continuing production.

Prior to operation, machines have to be set up for a particular product. After the setup a machine is able to continuously produce instances of this particular product without further setup. Setup times at the first stage are relatively short. The A machines take nearly the same time, A1 machines 22 minutes, and A2 machines take 25 minutes. However,the machines at the second stage take a very long time to set up. Every setup cycle takes about 8 hours. Hence, the main task of scheduling in this scenario is to minimize the setup cycles at the second stage.

Currently, the tire production process considered here is controlled in a semi–manual way that is known to produce sub–optimal results. In order to determine an appropriate architecture for the automation of this process the following problem features were taken into consideration: The topology of the production network is quite complex; the process has multiple tasks and constraints; the solution has to be flexible, because the plant topology is changed frequently; and the solution has to be transferrable to other (similar) production processes. A good choice for a process like this seems to be a decentralized approach, where individual production functionalities (such as orders or machines) are represented by decision making entities (agents) representing the corresponding tasks and constraints. In the next section we will present an architecture for such a distributed approach.

3 Distributed Scheduling

The main goal of scheduling is to minimize the number of machine reconfigurations. This is done by maximizing lot sizes. Unfortunately, high lot sizes cause orders to wait for a long time before being processed. Therefore the simulation is based on a model which is focused on order scheduling. Transportation and stocking details, e.g. stock capacities, are not considered, because these capacities are sufficient at the real tire production. So the raw material stock is considered as infinite material source and the product stock has an unlimited capacity. Each single order has one material as its counterpart. By processing orders the material flow is effected immediately.

Machines at each production stage are assigned to groups. Each group stands for one tire type. Initially all machines are assigned to a special group for 'not initialised' or 'defect' machines. Reassigning machines to other machine groups means reconfiguring them for producing another type of product. For this reconfiguration, each machine needs its machine type specific setup time. So, at each time instant there are as many machine groups as there are types of products (plus one special group).

The basic principle of the decomposition of the scheduling task is the frequency of the occurance of decisions. Usually decisions which occur more often have a shorter duration. In this way the scheduling task is partitioned into three sub tasks that are performed at different frequencies. First, each order is assigned to a group of orders by 'order agents'(Figure 2). At this level we have a high frequency of decisions. The temporal scope of each decision is the processing time of materials. Second, the processing of the grouped orders is managed by the machine group agents, which have a lower frequency of decision. Finally the setup agents have to decide about the reassignments. The effect of these decisions has a duration of setup time plus processing time of the resulting lot size.

Order agent The order agent receives orders from the stock at the beginning of the manufacturing line. The orders are grouped by order type and sent to the appropriate machine group (figure 3).

Group agent Each machine group is controlled by its group agent. A group agent has an order queue fed by the order agent of its stage. Group agents distribute orders to the machines assigned to its group. The working load of every machine is balanced with respect to their individual capacitiy.

Setup agent The most sophisticated element in this approach is the setup agent, see figure 5. This agent decides about reassigning machines to other machine groups. So the agent has to decide which machine will be reconfigured and which machine group will benefit from the setup.

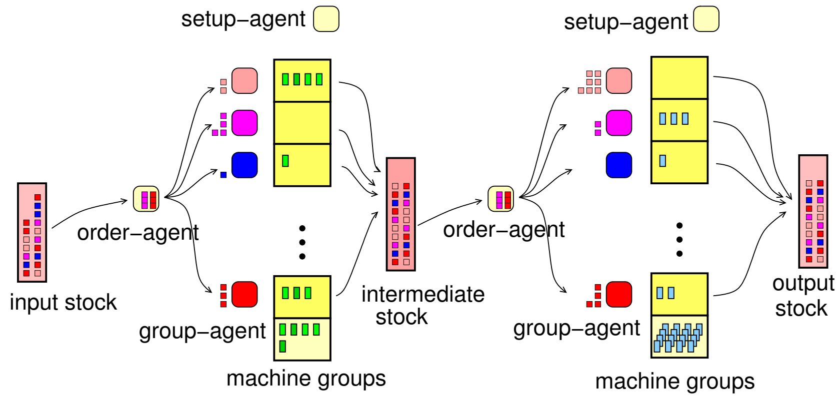

Figure 2: The scheduling task is partitioned. The order agent manages individual orders, the group agent combines orders to groups. The setup-agent reassigns machines to machine groups.

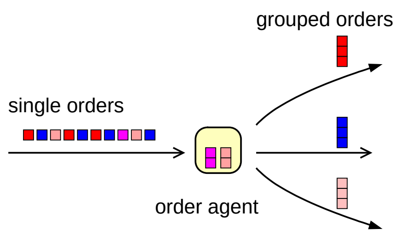

Figure 3: The order agent takes each single order and builds groups of orders.

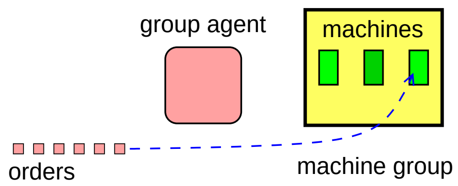

Figure 4: Each machine group has one group agent which manages the machines of this machine group. A group represents a pool of machines capable of producing the same kind of material.

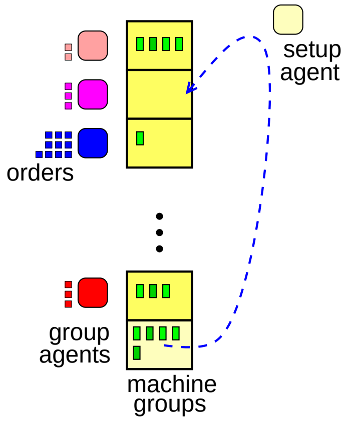

Figure 5: The setup agent reassigns machines from one to another machine group.

4 Scheduling decision methods

The main criteria for a good scheduling of this kind of production processes are

A1: low number of machine setups,

A2: high productivity,

B1: high yield rate, and

B2: low stock level.

Notice that A1 and A2 are highly correlated with each other, as well as B1 and B2. Moreover, the pair A1/A2 is somewhat contradictory to B1/B2. For example, zero stock level (B2 is optimal) implies a low productivity (A2 is bad). Taking into account the multi–criterial character of these tasks, we developed and compared two scheduling algorithms: single feature crisp decision and multi feature fuzzy decision.

Single feature crisp decision The single feature crisp decision method considers the order queue lengths of all machine group agents of one stage. A re-assignment is done if its advantage is greater than its disadvantage. To determine the benefit of a re-assignment, the setup agents first calculate the estimated order queue processing time:

$$estimated\, processing\, time = \frac{orders\ in\ queue\ *\ order\ processing\ time}{number\ of\ machines\ in\ machine\ group}$$

For machine groups with no assigned machines the number of machines is set to 0.1. This avoids a division by zero and leads to a high priority of unassigned machine groups. Each setup agent compares the estimated processing times with and without an additional machine in each group. If the reduction in processing time caused by the reassignment is greater than the time overhead resulting from setup time, the setup process is started.

In case of reassignment, the reassigned machine is taken from the group with the least loss of estimated processing time. This machine is reassigned to the group with the largest profit from the setup.

```
   G = numberOfMachinegroups
   foreach MachineGroup g do
      lessmch_g = estimatedQueueProcessingTime(g, -1)
      moremch_g = estimatedQueueProcessingTime(g, +1)
      equalmch_g = estimatedQueueProcessingTime(g, 0)
   end

   advantage = max_{g=1..G}(equalmch_g - moremch_g)
   disadvantage = min_{g=1..G}(lessmch_g - equalmch_g) + setuptime

   if (disadvantage < advantage) do
      mchToSetup = takeMchFrom(groupOf(disadvantage))
      setup(mchToSetup, groupOf(advantage))
   end
end
```

Multi feature fuzzy decision The multi feature fuzzy decision method takes two features into consideraton. First the age of all queued orders of all machine group agents at one stage. Second the estimated order queue processing time of all machine group agents at one stage. Since these two criteria are difficult to compare explicitly, we use a fuzzy approach, where we can simply compare the memberships of criticality. For the two membership functions μ_A (figure 6 left) and μ_L (figure 6 right) we use the s-function defined as:

$$s(x,a,b) = \begin{cases} 0 & \text{for } x < a \\ \frac{(x-a)^2}{((b-a)^2/2} & \text{for } a < x \leq \frac{b+a}{2} \\ 1 - \frac{(b-x)^2}{(b-a)^2/2} & \text{for } \frac{b+a}{2} < x < b \\ 1 & \text{for } x \geq b \end{cases}$$

For our simulations we examined about ten different sets of parameters (a, b) that all yielded very similar results. The best results were obtained with the parameter values given in Figure 6. In the final implementation, however, these parameters will be readjusted by the plant experts.

If one of the characteristic values is above a threshold μ_{th} then a reassignment will be made. The machine to be reassigned is taken from the machine group

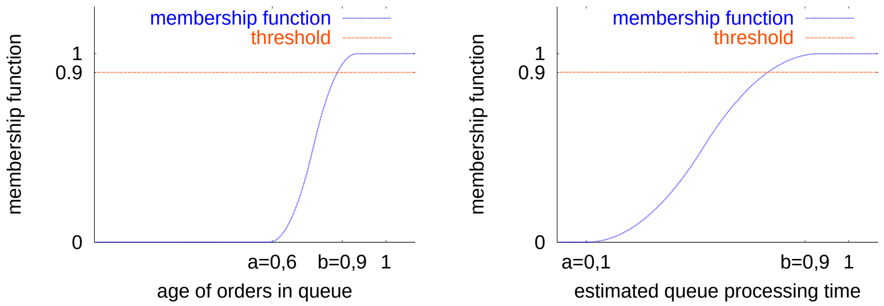

Figure 6: Membership functions for multi feature fuzzy decision (MFFD). Left: relative age of orders in queue. Right: relative queue length

with the lowest estimated queue processing time. For the assignment of the machine to a new group, both criteria are considered: the age of the queued orders or the order queue length. We consider the most critical of these criteria, i.e. the one that yields the highest membership. The machine is then assigned to the most critical (highest membership) group.

`procedure decideAboutSetup_mffd()`
   `foreach MchGroup g do`
      $\mu_{A,g}$ `=s(max`$_{o=1..\#ordersInQueueOf(g)}$`(waitingTime`$_o$`), A`$_a$`, B`$_a$`)`
      $\mu_{L,g}$ `=s(estimatedQueueProcessingTime(`g`) / maxTime , A`$_l$`, B`$_l$`)`
   `end`

   G `= numberOfMchGroups`
   $maxi$ `= max`$_{g=1..G}$`(`$\mu_{A,g}$ `;`$\mu_{L,g}$ `)`
   `if (`$maxi$ `<` μ_{th} `) then do`
      `return`
   `end`
   $mini$ `= min`$_{g=1..G}$`(` $\mu_{L,g}$ `)`

   `mchToSetup = takeMchFrom(groupOf(`$mini$`))`
   `setup(mchToSetup, groupOf(`$maxi$`))`
`end`

Notice that this approach uses the five parameters $A_a, B_a, A_l, B_l, \mu_{th}$, where only two parameters would be sufficient, if the thresholds were defined directly for the input domains. Due to the complexity of this distributed approach, however, we prefer the five parameter approach, because it has a better interpretability for the plant experts.

All these procedures are called once per second in a quasi–parallel agent environment. One could construct cases, where these approaches lead to oscillations between two or more almnost equivalent solutions. Instabilities like these, how-

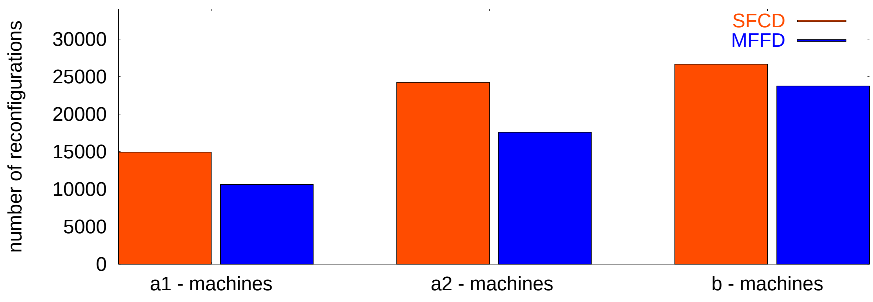

Figure 7: The number of reassignments is reduced by about 27% at the A stage and by 11% at the b stage when applying the MFFD instead of the SFCD control algorithm

ever, could not be observed during our tests. To make effects like these even more unlikely, hysteresis might be added to the decisions, i.e. security gaps could be added to the thresholds.

5 Simulation results

The distributed scheduling methods and a simulation of the tire production process have been implemented in our proprietary simulation tool 'SiProSim'. The java based tool uses a multi agent system, where the agents represent simulation entities such as machines and controllers. The agents are implemented in a flexible, easy configurable way. The characteristics of entities are defined by a set of parameters, stored in separate files. So the tool is flexible enough to simulate a broad range of typical production and supply chain scenarios. The simulations are time discrete.

The simulated duration of production time is 10 million seconds, i.e. about 115 days, which consumed about half an hour of real time to simulate. Initially all machines had been assigned to the 'unassigned' group, so that they had to be setup before production. All stocks had been empty at the beginning. Order types were generated randomly using a uniform distribution among all 128 types of tires, which is the worst case scenario.

Figure 7 shows number of reassignments needed with the single feature crisp decision (SFCD) and the multi feature fuzzy decision (MFFD). MFFD leads to a significant reduction of the number of reassignments for all three machine types.

Reducing the number of setups means that the machines have more time for their actual production tasks. Figure 8 shows the increase of productivity of about 20%.

The average lot size is defined as the number of produced materials divided by the number of reconfigurations. The average lot sizes for both methods are

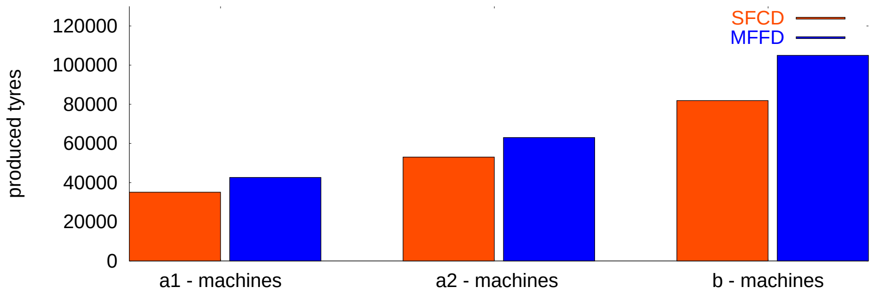

Figure 8: Increased productivity due to decreased number of reassignments. Machines at A stage produced 21% (a1) resp. 19% (a2) and machines at B stage produced 28% more tires using MFFD instead of SFCD.

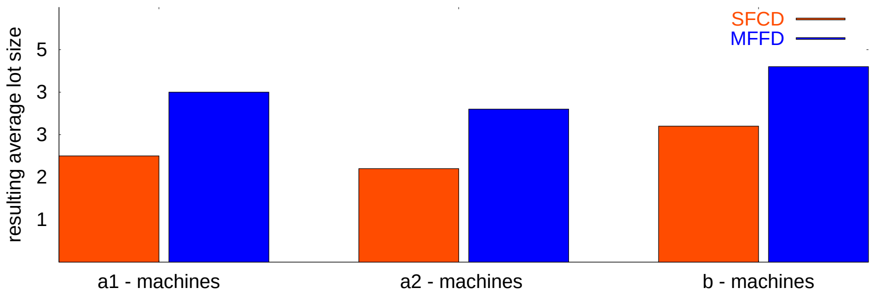

Figure 9: The average lot size is the number of produced materials divided by the number of reconfigurations.
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shown in figure 9. MFFD leads to an increase of 60% at the A stage and 44% at the B stage compared to SFCD.

The relative increase of the average lot size at the A machines is larger than the increase of the average lot size at the B machines. But the relative increase of the produced materials at the B machines is larger than the relative increase of the produced materials at the A machines. Due to the ratio of cycle time to setup time, B machines benefit more than A machines from the reduction of setups.

Figure 10 shows the content of the intermediate stock over time. Growing stock content means that B machines produce slower than A machines and vice versa. SFCD leads to higher fluctuations than MFFD. MFFD has a 20% lower average stock size than MFFD. The maximum stock size is even 54% lower.

Figure 11 shows the same plot as figure 10, but only for the first three days. At the very beginning (about the first 8 hours) of the simulated production the content of the intermediate stock is rapidly increasing for both methods.

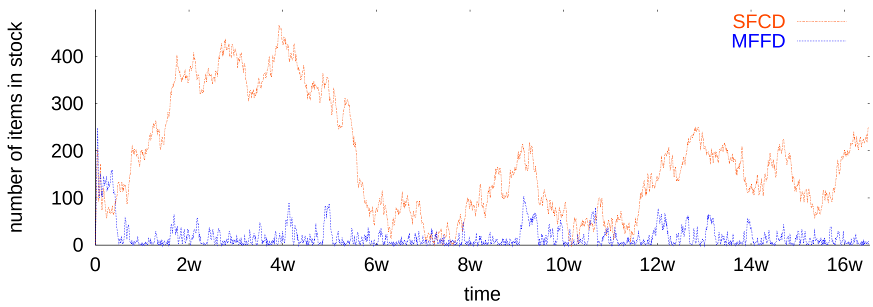

Figure 10: Number of tires in the intermediate stock over time. The simulation covers about 16 weeks of production.

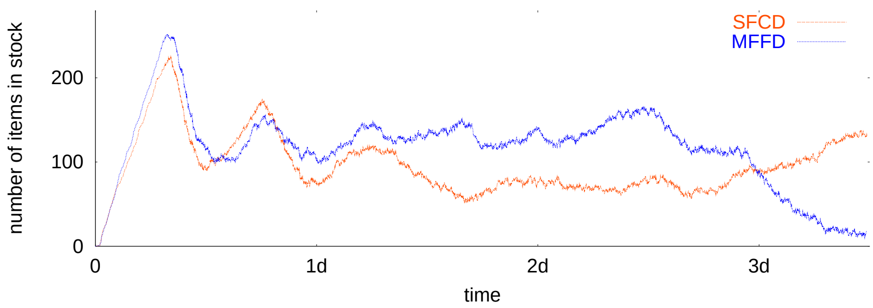

Figure 11: Number of tires in intermediate stock over time (First 3 days only).

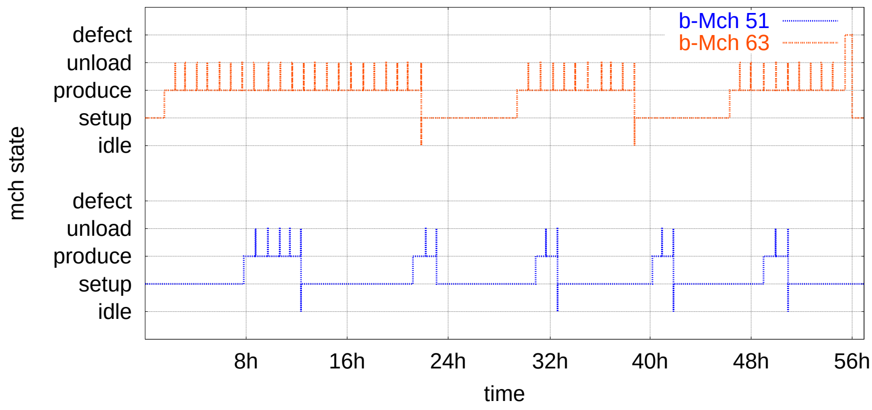

Figure 12: States of two B machines: machine 51 is reassigned six times, machine 63 only four times. Due to the high setup time, machine 51 produces only 13 tires, compared with 41 tires of machine 63.

Initially the A machines and the B machines are setup nearly at the same time. Due to the shorter setup time of the A machines they start to produce before the B machines do. After about 8 hours, which is the setup time of machines at the B stage, the B machines start to produce. Because there are 106 B machines in parallel, compared to only 13 A machines, the inventory at intermediate stock shrinks fast; this is the first 'wave'. All machines have been setup at nearly the same time, synchronously. After producing some products, some of the machines have to be set up again to produce other product types. This leads to the second wave, which is less pronounced than the first one. After about three of these waves the production system is in an almost steady state.

Figure 12 shows the machine states of two B machines over time for about 56 hours. The top diagram shows a machine that produces 41 tires with 4 reassignments, the bottom diagram shows a machine with 6 reassignments that produces only 13 tires. This shows how the number of reassignments can strongly affect the productivity of B machines.

Figure 13 shows a histogram of storage times at the intermediate stock for both methods. Less inventory level leads to smaller storage times. So storage time with MFFD is significantly lower than with SFCD.

The output rate of the whole production system is effected too. The standard devation of the output rate is about 30% less with MFFD compared to SFCD. This results from a more continuous production, that is less often interrupted by setups.

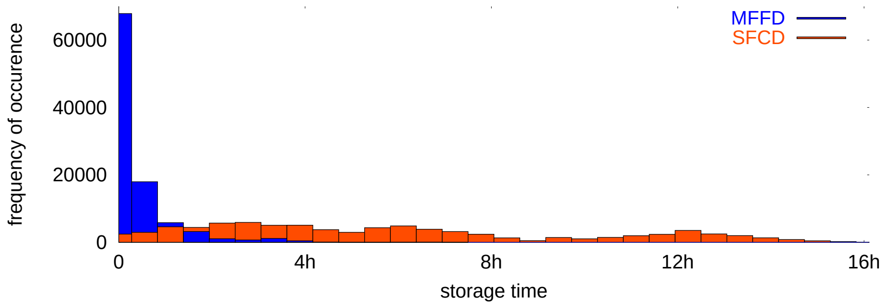

Figure 13: Histogram of storage times at the intermediate stock. The MFFD method leads to a significantly shorter storage time than the SFFD method.

6 Conclusions

In this paper we examined a two stage tire production system that is currently scheduled in a semi manual way. We introduced and examined two control algorithms: single feature crisp decision (SFCD) and multi feature fuzzy decision (MFFD). Both algorithms are a first approach to fully automated scheduling.

The MFFD method leads to a significantly better system behavior than the SFCD method. The number of reassignments is reduced, which leads to a much smoother output rate. Also the inventory level is reduced and the storage time is decreased while productivity is increased.

Nevertheless, here are some starting points for further improvement of MFFD. For example the maximum durability of green tires could be used to sort orders at the B stage in a better way. Another aspect is an exchange of information between both stages, a coupling agent. This agent could adjust production at both stages. These aspects will be discussed in a forthcoming report.

Acknowledgments

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