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Fuzzy decision-making method for product holons encountered emergency breakdown in product-driven system: an industrial case

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Abstract. In this paper a fuzzy decision-making method is proposed to make local decisions in case of breakdown occuring in a context of product-driven systems. To cope with breakdown uncertainty, three parameters, α, β and γ are created to evaluate the impact of it. Further, a fuzzy rule based on a membership function is designed to decide between centralized and distributed decisions concerning the re-arranging of the remaining parts. Simulation results show that appropriate decisions could be made by the proposed fuzzy decision-making method with certain suitable parameters. This method was applied on an existing industrial case; it can be easily extended to make decision for breakdown events in other contexts.

Keywords: fuzzy decision-making method, product-driven system, breakdown, holonic manufacturing systems

1 Introduction

To cope with the increasing global market competition, various intelligent approaches have been suggested to improve flexibility, reconfiguration and scalability of manufacturing systems. Among them, product driven systems (PDS) based on intelligent products, change the vision from passive to active products (Morel et al. 2007). Especially, PDS significantly improve visibility, robustness and adaptation of local decisions on the shop-floors thanks to Auto-ID technologies. The concept of PDS was firstly proposed by McFarlane in 2003 (McFarlane et al. 2003), after that, it brought attention of several research teams. Among the recent works, Herrera proposed a generic framework for PDS (Herrera, C., et al. 2012). This proposition is an extension of their previous studies. Here, we mainly focus on how the active product can make proper local decisions in case of unforeseen events as breakdowns occurring on the shop-floor.

PDS concept sets that the product could be active and/or could take decisions. That leads to two main ways for decision making system structures: hierarchical and/or

heterarchical structures. In hierarchical structure, each level is in charge to plan or schedule the production plans and to report the implementation results to the higher level. This centralized decisions structure is usually qualified to lead to poor agility and robustness. Conversely in PDS, each active product has high ability to make local decision through cooperation and interaction with other active products in heterarchical structures. Facing with unforeseen events occurring on the shop floor, the active products try to solve the problems through cooperation with other products. However, if the products are not able to solve the problem by any autonomic approaches, they will ask to switch in a centralized situation. Obviously, switching in centralized situation would lead to cost and time increases.

In the PDS, the active product can obtain the accurate breakdown starting time thanks to communication with other active products, but the ending time is not precisely known. In addition and resulting from the scheduling process, each product belongs to one lot. For this reason, when a breakdown occurs on a work center transforming a product, this product has to decide what to do concerning itself and the other remaining products belonging to its lot. Consequently and due to the breakdown duration uncertainty, it is difficult for active product to make, as quickly as possible, proper decisions by traditional approaches. As far as we know, few researches have tackled this problem. That is why we propose in this paper a fuzzy decision-making method to address the breakdown duration uncertainty and the way to re-schedule the remaining parts to manufacture.

In the next section, a brief overview of PDS is done. Section 3 describes an industrial PDS case which is used as research subjects. A fuzzy decision-making method useful to face with the emergency of breakdown is introduced in detail in section 4. In the last section, simulation is used to analyze and compare the effectiveness of the proposed fuzzy decision-making method.

2 A brief review of PDS

Historically, ‘centralized’ approaches have been implemented thanks to MRP2 and ERP systems, with tools and methods mainly based on operational research concerning production activity control. In centralized approaches, decisions are hierarchically broadcasted from the higher decisional levels down to the operational units. These approaches are mainly used to provide long term optimization of production planning given a relatively stable industrial context. Facing the eighties’ market challenges, various decision-making strategies have emerged. To improve reactivity and flexibility of manufacturing systems, several distributed approaches such as anthropocentric and visual management methods are proposed and used in practice. Unfortunately, these ways can only control inputs and outputs from “black boxes” and highlight the need for more and more real-time closed-loop information systems. In the 90’s, manufacturing systems have changed from the traditional mass production to the mass customization to cope with the increasing global market competition. High competition between enterprises and market volatility led enterprises to be more agile. In order to improve the agility of systems, various intelligent manufacturing systems (IMS) with

heterarchical structures are proposed in the past two decades. The common denominator for all these systems is to bring intelligence and autonomy as near as possible to (or even in) the physical system. Among them, holonic manufacturing system (Van Brussel et al., 1998) and agent-based manufacturing system (Shen, W. and Norrie, D. H., 1999) are most attractive ones and become the typical tools to establish other intelligent systems. Borangiu proposed an implementation framework for holonic manufacturing control system for agile job shop with networked intelligent robots (Borangiu T. *et al.*, 2009). And then, Borangiu suggested a solution for changes occurring in resource status and production orders by global product scheduling at aggregate batch horizon (Borangiu T., 2009). Some modified architectures of holonic manufacturing systems were suggested to solve industrial cases (Cossentino M. *et al*. 2007; Valckenaers P. 2005). A software platform was built for holonic manufacturing systems by agent technology (Cossentino M. *et al*. 2007). An agent-based control system was suggested to solve industrial cases by using RFID technology in real-time programmable logic controller based manufacturing systems (Vrba P. 2008).

Most recently, as a novel IMS, product driven systems based on intelligent products attract more researches' attention. The main difference between PDS and other IMSs is that a product can be an active actor throughout its lifecycle thanks to Auto-ID technologies. The notion of product intelligence was introduced in 2002 when several of the authors presented an alternate vision for the way in which supply chains might work (Wong et al., 2002; McFarlane et al., 2003). Further, various intelligent products have been used in manufacturing systems to improve flexibility and robustness (Sallez et al., 2009; Shi et al., 2011; Meyer et al., 2011; Meyer and Wortmann, 2010). Especially, Thomas and his research team in CRAN have been paying their attention on PDS and made many achievements. Pannequin et al. (2009) defined a benchmarking protocol and proposed a component-based generic architecture to support a benchmarking protocol for PDS. With simulation, they found that PDS can perform as good as traditional centralized control, and that its robustness depends mainly of the local decision-making processes. Further, Pannequin and Thomas (2012) proposed a product driven system architecture based on a particular interpretation of the concept of stigmergy, where cooperation between production actors is achieved thanks to attributes attached to products. El Haouzi et al. (2009) proposed a methodological approach to design a PDS and validate its feasibility and efficiency using a real industrial case. The approach is based on the six sigma method and discrete event simulation. Herrera et al. (2012) proposed a generic PDS framework for dealing with production planning and control. The framework is based on viable system model (VSM), which allows modeling and considering autonomy, self-organization and adaptability for the systems.

3 Problem description

As an extended study, the case used in this paper has the same model and parameters as in Pannequin and Thomas (2009, 2012). The case concerns a production cell of

an automotive-industry subcontractor. For simplicity, we don't present the case in detail and the detailed statement of the case can be found in Pannequin's papers published in 2009 and 2012. The production process is divided into two stages. The first line (called SF) manufactures semi-finished products, which are further assembled on three independent assembly lines (called FA, FB and FC). The production module includes four lines and an inventory of semi-finished products. Here, four finished products have been launched in 18 lots and the semi-finished products are handled in SF. In the further step, the lots are scheduled on the three assembly lines thanks to a centralized optimization approaches (in this paper, each *item* represents a specific product and will be divided into a series of sub-groups by certain optimization approaches and each sub-group is called *lot)*. Because the main aim of this paper is to discuss the decision mechanism useful to tackle the problem of an unforeseen breakdown, the detailed scheduling process of production schedule of each line will be ignored and the Gantt chart of the predictive schedule is only showed in Figure 1. The lots concerning the same items are presented with the same color in the Gantt chart. Note that because the color of the lots is randomly created by the computer, each figure may have different colors for the same item, but this phenomenon doesn't affect description of the production plans.

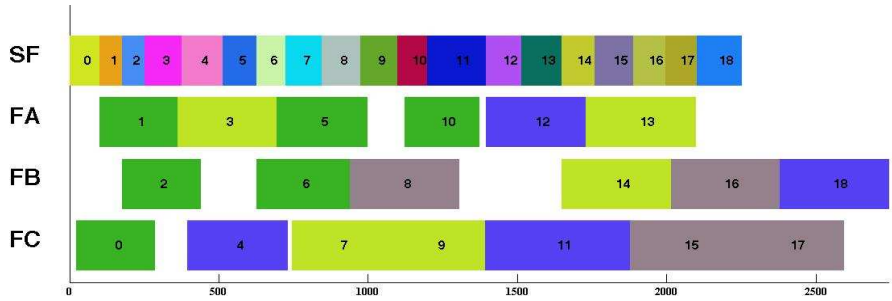


Figure 1. Gantt chart of production plans in all lines

As previously described in hierarchical systems, it is common that each level generates production schedules which will be disaggregate to the following level. In addition, if an emergency occurs in the heterarchical structure, each active product can make certain local decisions by cooperation and interaction with other products. According to the interpretation provided by Pannequin and Thomas, a product-driven system is usually composed by two structures simultaneously, hierarchical and heterarchical, and then, each product is an active product and has autonomic decision ability but can also ask the hierarchical part of the system to help it to find a re-scheduling solution. Moreover, as stated before, each active product belongs to a lot according to optimization objectives. Consequently, when a product encounters an emergency, it must make a certain decision for itself and all the following products belonging to the same lot. In our case, each product has two choices to deal with the sudden breakdown: switching in a centralized situation and ask to the higher level for rescheduling

the plan, or making a local decision by certain automatic approaches (distributed situation). It is obvious that the former choice is the most slowly and costly way.

It is also admitted here that the active product can obtain the precise breakdown starting time but must estimate the predicted breakdown ending time through interacting with active resources. According to the uncertainty of ending time, it is difficult to determine exactly how many products need to be dealt with. On the other hand, according to the dynamic characteristics of the system, each active product continuously has to perceive the manufacturing environment and make autonomic decisions. For these reasons we suggest that only the remaining parts of the lot which encounters the breakdown needs to be dealt with. Moreover, it is the first product of this lot which has to determine to keep staying in distributed situation or not to solve the problem.

4 Fuzzy decision-making method

As mentioned before, to cope with a breakdown, the product firstly needs to determine whether to switch in centralized situation or not. It is noteworthy that it is easy to make such a decision according to the quantity of lots concerned by the breakdown if we know the accurate breakdown starting and ending times. However and as previously stated, if the starting time can be obtained precisely, the ending time is usually inaccurate in practice. As the result, the decision should be built with a predicted breakdown ending time. Although there are several research issues about product driven systems, as far as we know, no research provided any decision approach with respect to breakdown event in detail. In fact, there are many factors influencing the decision process, among them and for a reactive manufacturing system, the time to decide what to do to face the unforeseen event is very important: the decision must be determined as quickly as possible. With consideration of uncertainty and rapidity, a parameter is created to evaluate the breakdown duration criticality as follows.

$$\alpha = \frac{L}{RC_T} \qquad (1)$$

Where L represents the duration of the breakdown, which is a predicted value provided by the resource concerned with the breakdown. RC_T represents the remaining capacity of all remaining work centers of the product routing. The remaining capacity is the sum of all idle times existing into the predictive product schedule, and the remaining capacity must be calculated according to the forecasted breakdown ending time.

Obviously, when the value of parameter α is less than one, it implies that the system has enough time to solve the situation, so a deterministic decision should be implemented to stay in current distributed situation and then deal with the emergency through certain automatic approaches. On the contrary, we can't assert that there is no enough time to cope with the breakdown when the value is more than one. For example, when the value of L is slightly larger than RC_T, a decision of switching in centralized situation could be implemented. However, if the breakdown is finished before the

forecasted ending time, it is possible to deduce a α value less than one. It means that an extra cost and time should be pay for an inappropriate decision. For this reason, it is rather risky to directly determine if we have to switch in centralized situation or not according to the value of parameter α. Here and using a fuzzy logic, a membership function with respect of α is generated to provide the basis for decision as follows.

$$mf(\alpha)=\begin{cases}0 & \alpha<1\\ \dfrac{\alpha-1}{t-1} & 1\le\alpha<t\\ 1 & \alpha\ge t\end{cases} \qquad (2)$$

Where t is an available parameter decided by the user. Through changing the value of t, different function values can be obtained for the same variable α on the interval $(1,t)$.

Then, the decision will be made under the following rule based on the function values.

· *if the function value mf(α) is more than p_α, then switching in centralized situation, otherwise, staying in current distributed situation.*

Here, p_α is a value of the threshold determined at interval (0,1) to cope with the uncertainty of the breakdown event. For the same values α and t, larger value of p_α means centralized situation may be selected with smaller probability and vice versa. Combining with parameter t, it is easy to change the switching threshold between two situations. For example, if p_α and t are set to 0.3 and 2 respectively, when the value of α is 1.5, the decision of switching in centralized situation will be implemented according to the function value (0.5) computed if the above formula is more than p_α (0.3). However, when the value of t increases to 3, a contrary decision will be adopted according to the fact that the new function value (0.25) is less than p_α (0.3). It is obvious that when the value of α is more than one, the decision of switching in centralized situation will be adopted with lower probability, while the value p_α or t increase.

Once the active product has determined to stay in current distributed situation, it has two ways to deal with the breakdown. The first one is to keep waiting until the breakdown is eliminated, and the other way is to re-arrange the remaining products of the lot by certain autonomic approaches. For simplicity, the former decision is denoted as DC_1 and the latter is denoted as DC_2. Obviously, DC_1 is the simplest method to deal with the breakdown. Without changing the production order, the remaining lots will be suggested to have the same delay, which is equal to the breakdown length. Due to the fact that the due date remains the same, such decision will not affect the scheduled production plan. Contrarily, DC_2 usually needs to change the scheduled plan by interacting among the active products to cope with the breakdown. As stated before, according to the uncertainty and dynamic characteristics and among the remaining scheduled lots, only the first lot needs to be dealt with. Note that one basic premise of waiting decision is that there is enough idle time (slack) to absorb the breakdown. The other key factor is the quantity of remaining parts of the first lot. In order to evaluate these two factors, two parameters are defined as follows.

$$\beta = \frac{L}{RC_B} \text{ and } \gamma = \frac{RL_B}{RC_B} \quad (3)$$

Where the variable RC_B represents the remaining capacity of the line taking into account of the breakdown, the value of RC_B is equal to the total idle time remaining after the predicted ending time taking into account of the breakdown (slack time). RL_B represents the production time of the remaining parts of the first lot that needs to be dealt with. Note that although RL_B can be also used to evaluate the quantity when it is divided by the unit production time. With consideration of breakdown uncertainty, the values of β and γ are divided into two classes, *small* and *larger*, and then two membership functions are created for each parameter as follows. It implies that β can be regarded as a *small* with the probability of $\mu_{S\beta}(\beta)$ and a *larger* with the probability of $\mu_{L\beta}(\beta)$. It is the same case for γ.

$$\mu_{S\beta}(\beta) = \begin{cases} 1-\beta & 0 \le \beta < 1 \\ 0 & otherwise \end{cases} \quad \text{and} \quad \mu_{L\beta}(\beta) = \begin{cases} \beta & 0 \le \beta < 1 \\ 1 & \beta \ge 1 \\ 0 & otherwise \end{cases} \quad (4)$$

$$\mu_{S\gamma}(\gamma) = \begin{cases} 1-\gamma & 0 \le \gamma < 1 \\ 0 & otherwise \end{cases} \text{ and } \mu_{L\gamma}(\gamma) = \begin{cases} \gamma & 0 \le \gamma \le 1 \\ 0 & otherwise \end{cases} \quad (5)$$

Then, two rules are generated to make decision between DC_1 and DC_2 for each parameter. Traditional fuzzy techniques induce discrete outputs, so there are no fuzzy classification and defuzzification steps for the outputs here. For this reason, the rules are described as follows.

- *if β is small, then DC_1 is selected with the probability $\mu_{S\beta}(\beta)$*
- *if β is large, then DC_2 is selected with the probability $\mu_{L\beta}(\beta)$*
- *if γ is small, then DC_1 is selected with the probability $\mu_{S\gamma}(\gamma)$*
- *if γ is large, then DC_2 is selected with the probability $\mu_{L\gamma}(\gamma)$*

Without any defuzzification process, selection between two decisions can be simply implemented by comparing the probability values obtained. At first, *min* or *max* operator is used to evaluate the final selection probability of each decision. For example, to a deterministic β and γ, two selection probabilities of DC_1, $\mu_{S\beta}(\beta)$ and $\mu_{S\gamma}(\gamma)$ are obtained by the first and third rules, and we assume that $\mu_{S\beta}(\beta)$ is greater than $\mu_{S\gamma}(\gamma)$. If a *min* operator is adopted, the final selection probability of DC_1 is $\mu_{S\gamma}(\gamma)$. Conversely, DC_1 has a final selection probability of $\mu_{S\beta}(\beta)$. Then, the decision with higher selection probability is finally adopted to deal with the breakdown. For example, if β and γ are 0.2 and 0.7 respectively, then we can get the values of probabilities: $\mu_{S\beta}(\beta)$=0.8, $\mu_{L\beta}(\beta)$=0.2, $\mu_{S\gamma}(\gamma)$=0.3 and $\mu_{L\gamma}(\gamma)$=0.7. With *min* operator for DC_1 and *max* operator for DC_2, we can conclude that the final selection probabilities of DC_1 and DC_2 are 0.3 and 0.7 respectively. Consequently, the final decision is DC_2 for its higher selection probability.

According to the above analysis, three decisions could be selected to deal with the breakdown: switching in centralized situation (denoted as DC_3 for convenience), waiting for repairing (DC_1) and make local decisions to arrange the remaining parts of the

first lot (DC_2). A fuzzy decision-making method based on three parameters (α, β and γ) is provided to solve this problem. As mentioned before, when DC_3 is adopted, the re-schedule decision will be done by the higher level. The solution of scheduling problems in this higher level is not the research focus in this paper, so how to deal with the breakdown in DC_3 will not be discussed in detail. In DC_1 case, the lots needn't to do anything but the new production starting time will be found according to the breakdown duration. Consequently, we focus our researches on the way to solve the DC_2 case.

As stated before, only the remaining parts of the first lot need to be dealt with when DC_2 is adopted. The basic principle of solution in DC_2 is to save the setup cost and reduce its impact on other scheduled lots. The concerned active product firstly looks for the longest idle time in the schedules of all lines. If the idle time is long enough to arrange all the remaining parts of the first lot, obviously an acceptable solution is to manufacture this remaining parts during this idle time; otherwise, enlarger the longest idle time through advancing or delaying the production of relative lots would be another way. And then, the remaining products ought to be put together with the lots of similar products as much as possible. Without enough idle time, the remaining products should be divided into sub-lots and distributed in several idle intervals. The flow graph of the fuzzy decision-making process and the decision procedure of DC_2 are shown in Figure 2 and 3. Notations in the figures are listed as follows.

RC_T: total remaining capacity of all lines
RC_B: remaining capacity of the line with breakdown
RL_B: quantity of the first lot after the predicted breakdown ending time
DC_1: waiting for repairing
DC_2: make local decisions to arrange the remaining parts of the first lot
DC_3: switching in centralized situation
RL: the first lot after the starting time of the breakdown
C_1: there are lots belonged to the same item of RL among all the remaining lots
C_2: there is an enough idle interval more than the production time of RL
D&D: divide and distribute RL according to the length of idle intervals
Max (*x*)*: maximize the idle time of x through advancing or retarding the lots*

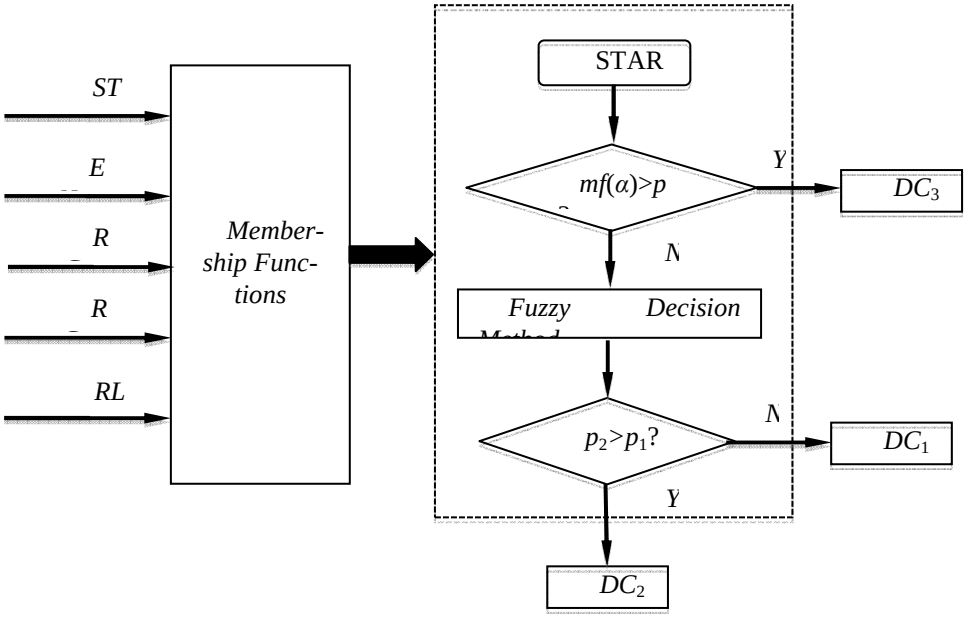


Figure 2. The flow graph of fuzzy decision-making pro-

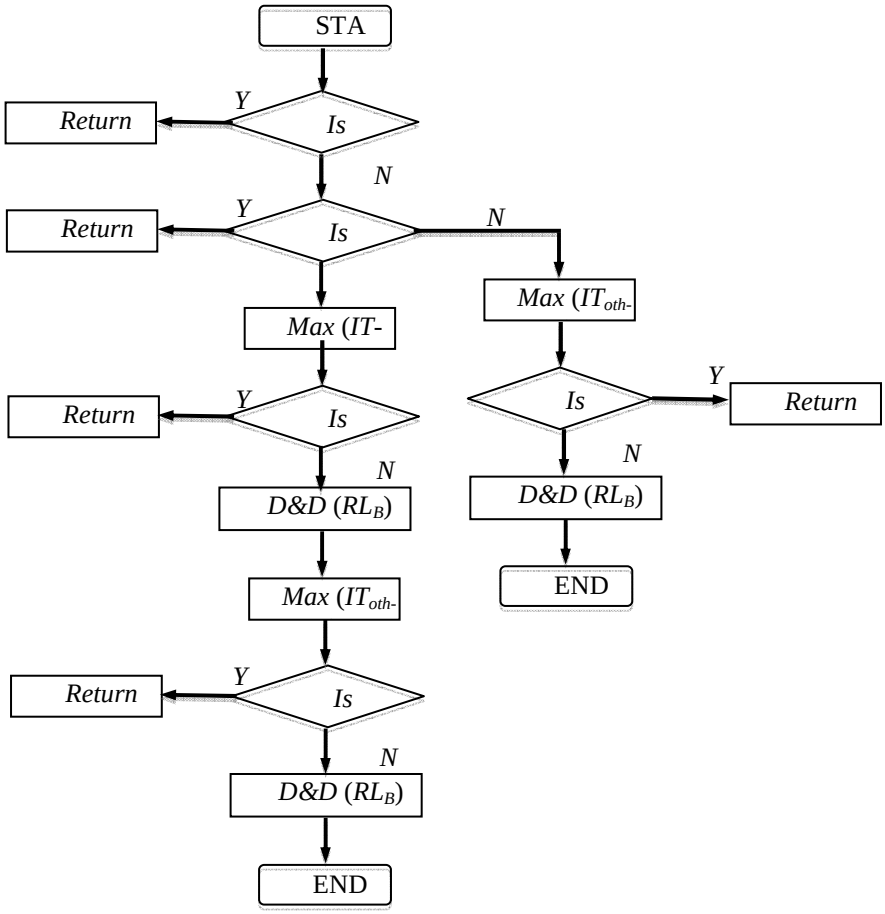


Figure 3. The flow graph of decision procedure in DC_2

5 Simulation

In order to verify the effectiveness of proposed fuzzy decision-making method, 8 typical breakdowns are generated in different lines and the final decisions are made with four combinations of *min* and *max* operators. The production limitation of all three lines is set to 2800. The final decisions of each case are summarized in the following Table 1. Case 4 to 6 are used to analyze the influence of parameters p_α and t, the values of (p_α, t) are (0.2, 1.5), (0.3, 1.5) and (0.2, 2.0) for case 4 to 6, respectively. In other cases, the values of p_α and t are not considered because the value of α is always less than one. If the decision of DC_3 is abandoned, four different combinations of two operators are used to make final decision: (*min*(DC_1), *max*(DC_2)), (*max*(DC_1),

min(DC_2)), (*max*(DC_1), *max*(DC_2)) and (*min*(DC_1), *min*(DC_2)), and the results are successively recorded in the last column in Table 1. Following we use the case 1 to explain the decision process. In case 1, the breakdown occurs in assembly line FB with the starting time of 1400 and the predicted ending time of 1550. Because the function value of *mf*(α) is less than one, DC_3 is firstly abandoned. According to the membership functions and decision rules of parameters β and γ, for parameter β, DC_1 is selected with the probability of 0.037 and DC_2 with the probability of 0.963. Similarly, the two probabilities are 1 and 0 respectively for parameter γ. Then, four different methods are used to make final decision. Firstly, (*min*(DC_1), *max*(DC_2)) is used to evaluate the selection probability of DC_1 and DC_2. As the result, the selection probability of DC_1 is 0.037 for *min* operator and that of DC_2 is 0.963 for *max* operator. Because DC_2 has higher selection probability, the final decision is DC_2. Similarly, (*max*(DC_1), *min*(DC_2)) operators can obtain the selection probability of 1 and 0 for DC_1 and DC_2, which leads to the final decision of DC_1. The results of two selection probabilities in (*max*(DC_1), *max*(DC_2)) and (*min*(DC_1), *min*(DC_2)) are (1, 0.963) and (0.037, 0), respectively. Consequently, the final decision is DC_1 in these two methods. The Gantt charts of solution are drawn in the figures in Appendix when DC_2 is implemented.

Table 1. Final decision with different combination of operators

Case	***Breakdown***	***mf* (α)**	***Decision* (β)**	***Decision* (γ)**	***Final Decision***
1	1400~1550 (FB)	0	0.963/DC_2 0.037/DC_1	0/ DC_2 1/ DC_1	**DC_2** DC_1 DC_1 DC_1
2	450~600 (FB)	0	0.350/ DC_2 0.650/ DC_1	0/ DC_2 1/ DC_1	DC_1 DC_1 DC_1 DC_1
3	200~2200 (FC)	0.266	-	-	DC_3
4	200~2200 (FC)	0.266	1/ DC_2 0/ DC_1	0.042/ DC_2 0.957/ DC_1	**DC_2** DC_1 **DC_2** **DC_2**
5	200~2200 (FC)	0.133	1/ DC_2 0/ DC_1	0.042/ DC_2 0.957/ DC_1	**DC_2** DC_1 **DC_2** **DC_2**
6	950~1100 (FA)	0	0.199/ DC_2 0.801/ DC_1	0.312/ DC_2 0.688/ DC_1	DC_1 DC_1 DC_1 DC_1

7	0~100 (FB)	0	0.15/ DC_2 0.85/ DC_1	0/ DC_2 1/ DC_1	DC_1 DC_1 DC_1 DC_1
8	1850~2700 (FA)	0	1/ DC_2 0/ DC_1	0.288/ DC_2 0.711/ DC_1	**DC_2** DC_1 **DC_2** **DC_2**

In case 1, although there is no lot during the breakdown interval, the first lot (lot 14) after the breakdown starting time is still re-arranged behind the lot 13 when ($min(DC_1)$, $max(DC_2)$) is implemented (*see* Figure 4). Obviously, if the breakdown finishes at predicted ending time, it is not a proper strategy to select DC_2 for an extra change cost. However, when the length of the breakdown becomes very large, it is a good way to make effective decision in advance. We can conclude that ($min(DC_1)$, $max(DC_2)$) is the most positive strategy. In all cases, ($max(DC_1)$, $min(DC_2)$) is the most conservative strategy because it always trends to make decision only between DC_1 and DC_3, waiting or switching in centralized situation. Except in case 1, the other two strategies have the same decisions as which with ($min(DC_1)$, $max(DC_2)$). Comparing case 3, 4 and 5, facing to the same breakdown, different decisions of switching between centralized and distributed situations are determined through changing the parameters of membership function of α. Such comparison illustrates that the selection probability of DC_3 can flexibly controlled by the parameters p_α and t. The remaining part of the first lot are divided into two parts (*see* Figure 7) and arranged in two idle intervals in the last case because there is no enough idle time to arrange the whole remaining part.

6 Conclusion

Using an industrial case, a fuzzy decision-making method is proposed to deal with unforeseen breakdowns. At first, to cope with breakdown uncertainty, a parameter α and its membership function are used to decide to switch in centralized situation or not. Especially, the selection probability of two different situations can be adjusted easily by reset the parameters p_α and t in membership function. This idea can increase flexibility and adaptability of local autonomic decision-making process. Once the decision is to stay in current distributed situation, two parameters β and γ are used to evaluate the impact of the breakdown. And then, four membership functions, four fuzzy rules and two operators, are designed to choose between two decisions, waiting for repairing and re-arranging the remaining parts. At last, a local re-arranging approach of the remaining parts is proposed and described in detail. Simulation results show that proper decisions could be obtained by proposed fuzzy decision-making method with correct selection of operators. Although the fuzzy decision-making method is proposed for a specified case, it can be easily extended to deal with break-

down events in other manufacturing systems. In our future work, we will consider some other factors such as due date and changing cost in fuzzy decision-making method.

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Appendix

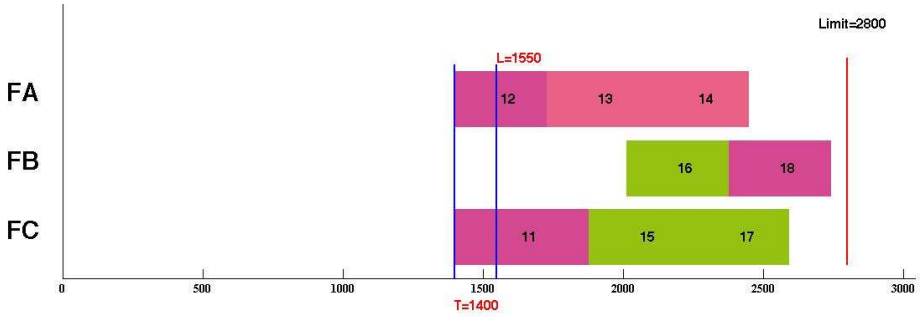


Figure 4. Re-scheduled plan of remaining lots in case 1

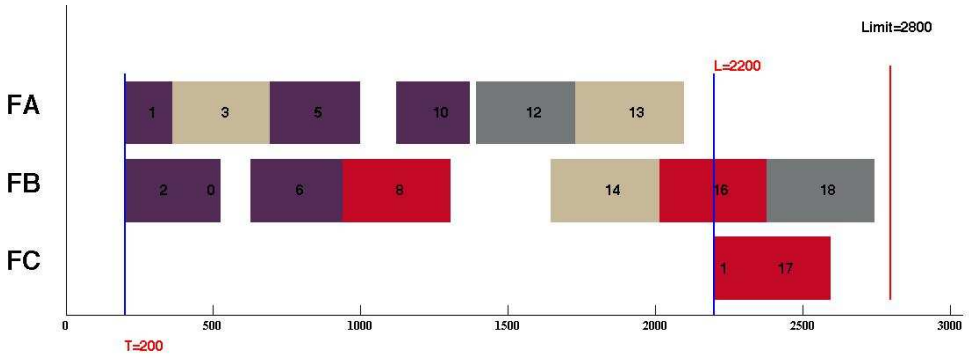


Figure 5. Re-scheduled plan of remaining lots in case 4

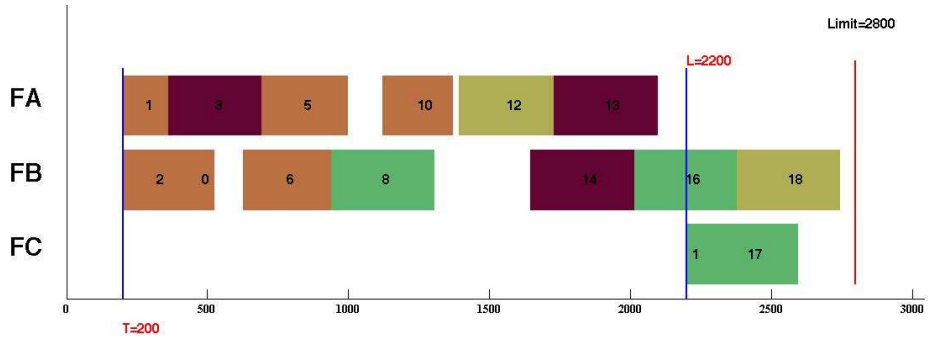


Figure 6. Re-scheduled plan of remaining lots in case 5

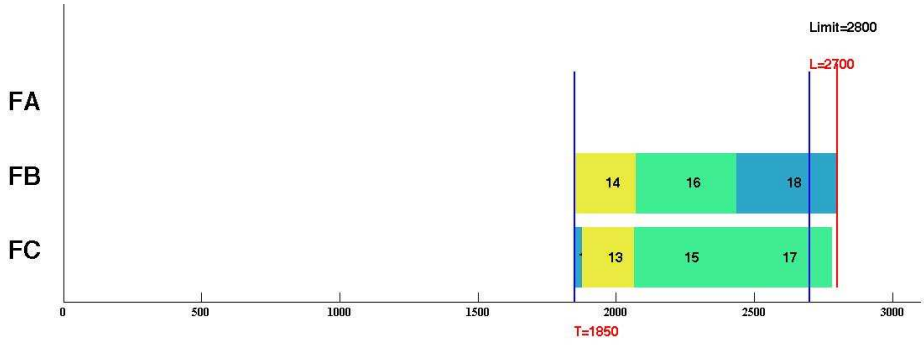


Figure 7. Re-scheduled plan of remaining lots in case 8