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Digital Twin Based Flexible Manufacturing System Modelling with Fuzzy Approach

Safiye Turgay[1,a,*], Ömer Bilgin[2,b], Necip Akar[1,c]

[1]*Sakarya University, Dept. of Ind.Eng, Sakarya, Turkey*
[2]*Datacore Bilgi Sistemleri, Esentepe Mah. Milangaz Cad. No:75 Monument, D: Kat 6, Kartal, İstanbul, 34870, Turkey*
[a]*safiyeturgay2000@yahoo.com*, [a]*sencer@sakarya.edu.tr*, [b]*omer.bilgin.9@ogr.sakarya.edu.tr*, [c]*necip.akarrr@gmail.com*
[*]*Corresponding author*

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Abstract: The digital twin-based fuzzy decision mechanism provides great opportunities for the realization of the optimization process, especially in the flexible production environment, with big data and new business modes beyond expectations. Developing technology has brought with it the increasing amount of data and the development of big data analysis techniques. We can give Internet of Things (IoT), 5G, digital twin and cloud computing technologies as examples. Digital twin covers the process of monitoring and directing the production processes in the virtual environment in line with the increasing amount of data and the ability to respond quickly and accurately to customer services. The digital twin provides the internal and external changes in the production environment allow instant analysis of data. In this approach, it is aimed to optimize the production process, reduce costs and increase operational efficiency. It provides continuous learning in the production system environment and self-optimization of the system. It includes a digital twin-based integrated smart production model and the evaluation of the fuzzy approach in decision-making in a flexible production environment

1. Introduction

Customer behaviours and demands, collecting and analyzing all parameter values in the production process brought the concept of big data along, and thanks to digital twin, instant changes in data are analyzed and production is directed in line with customer demands. In the proposed smart production process, data comes instantly through sensors, and fuzzy numbers are used in the process of monitoring and evaluating the data. With this approach, at the same time, production can be intervened instantaneously in case of any hitches, malfunctions and stops that may occur in production. For this purpose, a decision support system (DSS) has been developed for port flexibility that advances simulation optimization used in the flexible and efficient forecasting processes of KDS with its digital matching capabilities.

Some of the researchers have drawn attention to the digital twin and its applications. As an example of these; Li et al. focused to the digitization of physical resources and increasing production efficiency with a collaborative structure [1]. Jens et al. analyzed the digital twin and block chain architecture together and made a performance analysis [2]. Zhou et al. examined the flexible structure of decision support systems in digital twin systems [3]. According to Vikkalonga et al. drew attention to the digital twin structure in the decision-making process [4]. Flora et al. gets the importance of the digital twin structure in their production systems [5]. They especially emphasized the importance of increasing the quality of production. The system model structure is examined in detail and the operational constraints and the variables that make up the system are defined and the effective parameters are revealed with the digital twin [6-8]. Thanks to this modelling structure, interactive parameters and flexible parameters are also defined. A new approach is proposed here to solve task allocation in a flexible production system (FMS) environment by using fuzzy decision mechanism in digital twin approach that enables optimal decisions in a dynamic system structure [9-13]. This work could further encourage the development of digital twin-enabled decision support in other traditional industries [14-18].

The remainder of the article is organized as follows: Section 2 reviews the big data analytics framework for flexible manufacturing systems. Section 3 explains the fuzzy approach for suggested system. Section 4 presents the decision support system for digital twin focused on flexible manufacturing system, Section 5 covers the case study and the results of numerical experiments, section 6 provides final explanations.

2. Big Data Analytics Framework for Flexible Manufacturing Systems

Costs can be reduced by testing new design or production options in production in a virtual environment and testing possible situations that may be encountered. Thanks to the digital twin, any changes that can be made in the virtual production environment, product design or manufacturing strategy can be tested. This concept also encompasses the change that takes place in the structure of the physical environment and the stochastic environment. With this structure, the production planning and productions situation monitoring process can be followed instantly. With this structure, operational uncertainty situations that may occur later in the system can also be analyzed [19].

The simulation model is quite difficult to create complex mathematical models and define the experimental environment and simulation parameters, data analysis is easier in a data-based process environment with digital twin. Thanks to big data analysis, more effective results are obtained by defining the relationship between the data in the decision-making situation. The data is collected and the preliminary analysis process is carried out along with digital twin [20].

Production data is obtained in a healthy way through sensors

Correlation analysis of parameters affecting production performance is made, possible changes in the system are determined

Determining the system performance factors and using them in the rule structure used in the decision-making process is provided by statistical and machine learning methods of processes such as estimation, error detection and classification.

According to the determined target parameters, decision making methods are applied to improve the system performance.

By examining the product design, the variables that make up the product, the production process structure and all kinds of process steps in the system, both the new product design and the planning and scheduling activities in the production process can be designed efficiently [21]. Correlation+estimate+correction approaches are also used in this process structure.

(1) The relationship between the variables is evaluated using correlation analysis.

(2) In the estimation process, internal and external factor parameters are analyzed using machine

learning techniques, and parameters such as product production time and product sales amount are analyzed.

(3) Existing parameters and threshold values are rearranged to improve system performance and optimize control variables.

3. Fuzzy Approach for Suggested System

The system relies on the acceptance of inputs perceiving information from the external environment or functions. The main components of the knowledge structure are [Definition, Trait, and relations between traits]. General rule sets are created using the previous knowledge structure. It retrieves and learns information from the system's knowledge base and sets a set of rules from that information. The more knowledge of the system is equipped with, the richer the rule base.

The Task Base has an important role in the coordination of the system. It involves solving the received task, problem solving, and updating activities by comparing the defined task with the relevant rule base. The broker is capable of efficiently obtaining the relevant database and functions to be performed. In the realization of the task, a review of the infrastructure is also made.

Various function alternatives are examined under different criteria and the obtained values are evaluated in the final decision process. When an input is received by the system, the evaluation process begins in the fuzzy-multiple evaluation criteria matrix. The decision module is connected to the user interface and the decision module evaluates the data and information received from the user as well as the performance of the system in the user interface (in Fig.1).

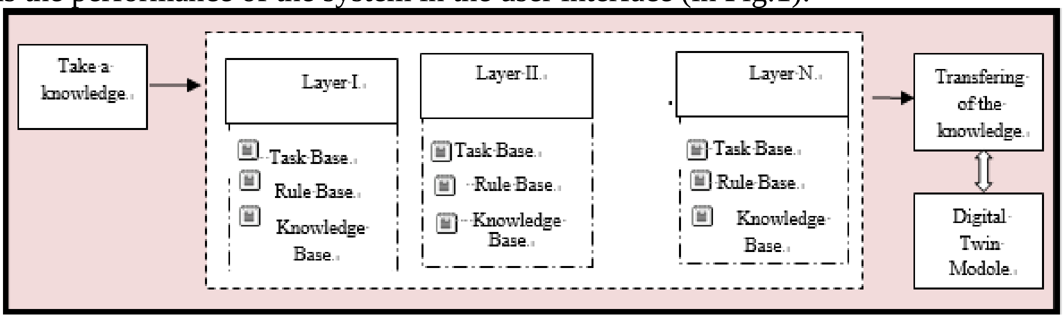


Figure 1: Digital Twin Layer’s Processing Style

In the process of modeling the digital twin structure in the fuzzy decision model, variables, constraints and layers were modeled as a triple { $\tilde{X}$, L, C}. The variables $\tilde{X}$ and fuzzy structures $\tilde{X} = (\tilde{X}_1, \tilde{X}_2, ..., \tilde{X}_n)$ in each layer were expressed. Each layer Li $\in$ $L = \{L_1, L_2, ..., L_r\}$; and the parameters in these layers and the rule structures of the layers are expressed. In this notation format, X represents the variables, L represents the layers of the digital twin, and C represents the constraints $C = \{C_1, C_2, ..., C_m\}$ of the variables and event states. In this section, each parameter is symbolized by the cartesian product in relation to each other. A constraint Ci is a k-ary relation on $\tilde{X}_i = (\tilde{X}_{i1}, \tilde{X}_{i2}, ..., \tilde{X}_{ik}) \subseteq \tilde{X}$, i.e. $C_i(\tilde{X}_{i1}, \tilde{X}_{i2}, ..., \tilde{X}_{ik})$ and is a subset of the cartesian product $L_1 x L_2 x ... x L_{ik}$, where each $L_{ij} \in D$. Membership function values $\mu_{C_i} \in [0,1]$ that each parameter or variable can take take values between 0 and 1 and are expressed with previously determined linguistic values. In order for system variables to be expressed in the rule structure, they must take a value equal to or greater than the specified μ_{C_i} threshold value. The value we have determined is 0.5. The model can be used as a network where the constraints Ci are nodes interconnected by shared variables, $\tilde{X}_{ij}$.

In the fuzzy decision-making process, the comparison process is made by taking into account the criteria values and targets. When the relationship between existing values and goals is established, the rule emerges and the decision mechanism starts to work. The task distribution and objectives of each layer are defined in the decision-making structure. Values, criteria and targets work depending on the threshold value and the decision is made as a result.

4. Decision support system for Digital Twin Focused Flexible Manufacturing System

A “Digital Twin” is a dynamic, virtual digital representation of an asset or physical object, a product, a process, a service, or a system. It digitally models and displays the state, properties, condition and attributes of the real-world counterpart in context. Using data from multiple sources, a "Digital Twin" constantly learns and updates itself to represent the current state or operating conditions of the asset or object, product, process, service or system. End users and decision makers gain a deep understanding that they apply to improve their knowledge and awareness or optimize the performance of the modelled entity and the larger systems it interacts with.

Digital twins act as a bridge and link between the physical world and the information world and can provide more real-time, efficient and intelligent services. Digital twin is also an advanced application powered by the Internet of Things. It consists of 5 layers with the traceability and dynamism feature of the digital twin model with mathematical representation

Digital Twin =f{PL(Physical Layer), WML(Virtual Model Layer), Ss(PL services for WT), DL(WT DT data), CN (Connection)}

During the digital twin modelling, five dimensions are taken into account; these are the physical components that make up the system, FL, the virtual components, that is, the behavioural model obtained from the geometric or physical model that makes up the physical component. This model generates the behaviour pattern of the system by obtaining the necessary data from the sensors. These behavioural patterns also form our rule base.

(1) Physical layer (PL): In the physical layer, there are sensors, detection devices and data protocols where production activities are monitored. The physical layer contains data sources such as work pieces, equipment, tools, measuring instruments and operators, which may contain static and dynamic information. It covers all elements of the system.

(2) Virtual Model Layer (VML): It refers to the virtual layer that reflects the traceability and dynamic structure of the system. It is the process of modelling the realistic, dynamic structure of the physical state and process with multi-time scales. It includes a virtual modelled geometry model, a physics model, a behaviour model, and a rule model. Components and behaviour patterns in the three-dimensional structure are examined.

(3) Communication layer (CL): It is the layer where data is transmitted and separated, together with wired and wireless networks.

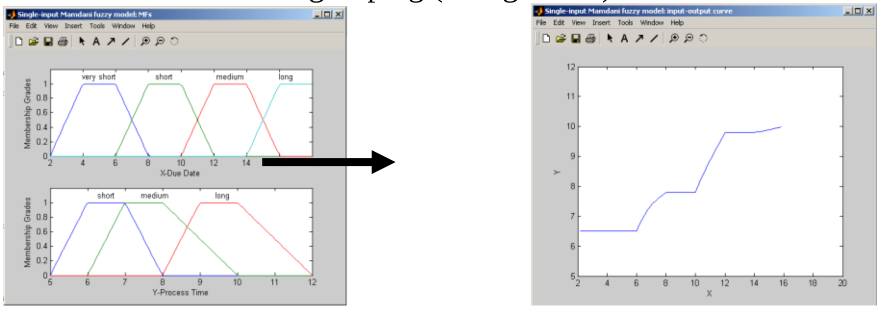
(4) Data layer (DL): It is the area where data is stored and used to create information and rules. Definition of the database system used by the components that make up the virtual level, types of parts, types of machines used in production, and definition of the relationship between them

(5) Service layer (SL): It covers data pre-processing, using the production method, supporting the process quality, monitoring and analyzing the collected data and issuing the production rules. In this section, there is the structure where the connection between the physical level and the virtual level is provided. Service system, technical characteristics of the machine running during production, power usage status, determination of power components that will be required at virtual level (time, cost, reliability), in-process, empty and broken alternative states definition

5. Case Study

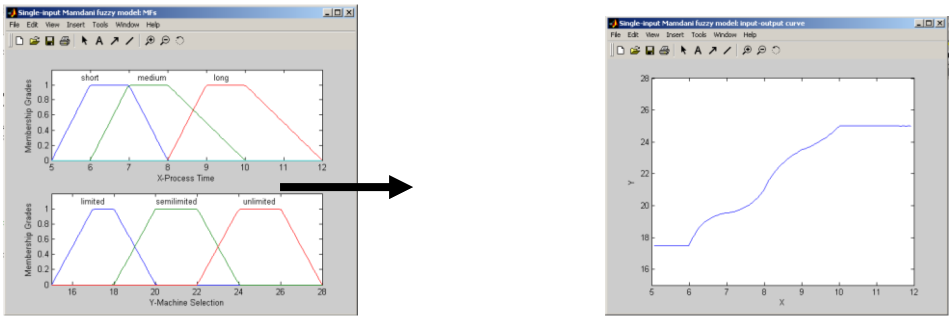
Based on the proposed structure flexible manufacturing system, it was aimed to determine the appropriate assignments by examining the part-machine-tool relations. In particular, it was aimed to perform the assignment process in the digital twin environment, based on the fuzzy relationship between the system components and the relationship between them. Considering the data obtained, uncertain and incomplete situations and current situations were evaluated and the system decision structure was revealed.

The components affecting the decision mechanism, the assumed knowledge status among each other and their relation is given below. This study presents the possible operational activities to occur within the system and the related rules without details. The system try to find the answers to the questions stated in the table above with the fuzzy logic. The criteria to be taken into consideration during the decision making process are given below in details on the basis of the system. Fuzzy calculation will be applied hierarchically. In the application process, the system decision mechanism will be formed taking into consideration the Machine→ Process, Process → PartA and Part C→ Duedate relation respectively. Aligning and grouping the incoming orders listed. The amount should also be indicated in grouping (in Figure2-4).



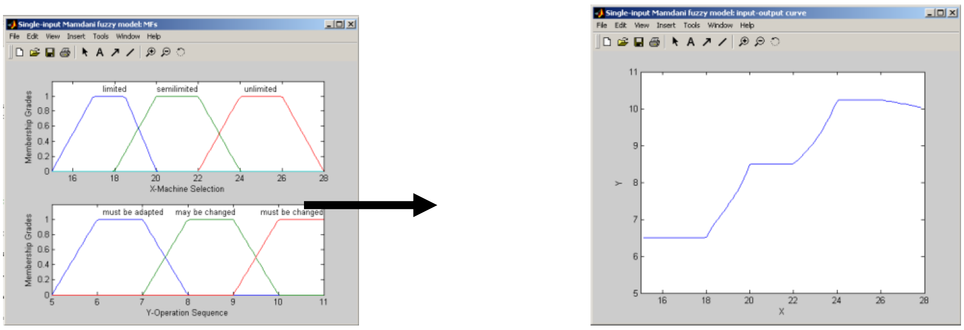
a. Membership grades for Part b. Mamdani single input output curve for Part

Figure 2: Constructing the rule structure of the Part Selection Process



a. Membership grades for Operation b. Mamdani single input output curve for Operation

Figure 3: Constituting the rule structure of the Operation Process



a. Membership grades for Machine b. Mamdani single input output curve for Machine

Figure 4: Constructing the rule structure of the Machine Process

Under this system structure, the way the system works is supported by some rules and data in the task base and knowledge base. It will be necessary to use this data, perform certain master tasks and process steps within the master decision making architecture. Here, the system will automatically and intelligently ensure that the system adapts quickly to the decision mechanism, taking into account the changing operating rules. Here, it is essential to address issues such as the clear definition of operational steps and the appropriate evaluation of possible situational alternatives by the system. The decision mechanism is going to operate considering the following situations in evaluating the Part selection's rules. PA_X refers to the system input value interval; PA_Y determines the system output value interval and P characterizes the probability values of the cases faced within the system [21] .

PA_X ={Very Short, Short, Medium, Long} → Due Date

PA_Y ={Short, Medium, Long} → Process Time

P ={b1, b2, b3, b4} → [0,1]

$$\underset{\sim}{PA\_Y_1}=\left\{\frac{0.5}{S}+\frac{0.4}{M}+\frac{1}{L}\right\},\quad \underset{\sim}{PA\_Y_2}=\left\{\frac{0.7}{S}+\frac{0.8}{M}+\frac{0.4}{L}\right\},\quad \underset{\sim}{PA\_Y_3}=\left\{\frac{0.2}{S}+\frac{0.6}{M}+\frac{1}{L}\right\},\quad \underset{\sim}{PA\_Y_4}=\left\{\frac{1}{S}+\frac{0.4}{M}+\frac{0.5}{L}\right\}$$

b1 =0.7 b2=0.6 b3=0.9 b4=0.4

D(a1)=D(S)= $(\bar{b}1 \cup P1\_Y_1) \cap (\bar{b}2 \cup P1\_Y_2) \cap (\bar{b}3 \cup PA\_Y_3) \cap (\bar{b}4 \cup P1\_Y_4)$

= $(0.3\vee0.5) \cap (0.4\vee0.7) \cap (0.1\vee0.2) \cap (0.6\vee1)$

= $0.5\wedge 0.7 \wedge 0.2 \wedge 1 =0.2$

D(a2)=D(M)= $(0.3\vee 0.4) \cap (0.4\vee 0.8) \cap (0.1\vee 0.6) \cap (0.6\vee 0.4)$

= $0.4 \wedge 0.8 \wedge 0.6 \wedge 0.6 =0.4$

D(a3)=D(L) = $(0.3\vee 1) \cap (0.4\vee0.4) \cap (0.1\vee 1) \cap (0.6\vee 0.5)$

= $1 \wedge 0.4 \wedge 1 \wedge 0.5 =0.4$

The probability of Part Selection to apply the rule 1 will be 0.2. It will be 0.4 for rule 2 and 0.4 for rule 3.

The decision mechanism is going to operate considering the following situations in evaluating the Operation Selection's rules.

OA_X ={Very Short, Short, Medium, Long} → Process Time

OA_Y ={Short, Medium, Long} → Machine Selection

P ={b1, b2, b3, b4} → [0,1]

$$\underset{\sim}{OA\_Y_1}=\left\{\frac{0.6}{L}+\frac{0.4}{SL}+\frac{1}{UL}\right\},\quad \underset{\sim}{OA\_Y_2}=\left\{\frac{0.8}{L}+\frac{0.2}{SL}+\frac{0.4}{UL}\right\},\quad \underset{\sim}{OA\_Y_3}=\left\{\frac{0.7}{L}+\frac{0.6}{SL}+\frac{0.4}{UL}\right\},$$

b1 =0.2 b2=0.8 b3=0.4

$\bar{b}1$ =0.8 $\bar{b}2$ =0.2 $\bar{b}3$ =0.6

D(a1)=D(L)= $(0.8\vee0.6) \cap (0.2\vee0.8) \cap (0.6\vee0.7)$

= $0.8\wedge 0.8 \wedge 0.7 =0.7$

D(a2)=D(SL)= $(0.8\vee 0.4) \cap (0.2\vee 0.2) \cap (0.6\vee 0.6)$

= $0.8 \wedge 0.2 \wedge 0.6 =0.2$

D(a3)=D(UL) = $(0.8\vee 1) \cap (0.2\vee0.4) \cap (0.6\vee 0.4)$

= $1 \wedge 0.4 \wedge 0.6 =0.4$

The probability of Operation Selection to apply the rule 1 will be 0.7. It will be 0.2 for rule 2 and 0.4 for rule 3.

The decision mechanism is going to operate considering the following situations in evaluating the Machine Selection's rules.

MA_X ={Very Short, Short, Medium, Long} → Machine Selection

MA_Y ={Must be Adapted, May be Changed, Must be Changed} → Operation Sequence

P =\{b1, b2, b3, b4\} → [0,1]

$\underset{\sim}{MA\_Y_1} = \left\{ \frac{0.6}{MA} + \frac{0.7}{C} + \frac{0.3}{MC} \right\}$, $\underset{\sim}{MA\_Y_2} = \left\{ \frac{0.8}{MA} + \frac{0.4}{C} + \frac{0.6}{MC} \right\}$, $\underset{\sim}{MA\_Y_3} = \left\{ \frac{0.7}{MA} + \frac{0.2}{C} + \frac{0.8}{MC} \right\}$,

b1 =0.4 b2=0.7 b3=0.8

$D(a1)=D(MA)= (0.6 \vee 0.6) \cap (0.3 \vee 0.8) \cap (0.2 \vee 0.7)$

$= 0.6 \wedge 0.8 \wedge 0.7 = 0.6$

$D(a2)=D(C)= (0.6 \vee 0.7) \cap (0.3 \vee 0.4) \cap (0.2 \vee 0.2)$

$= 0.7 \wedge 0.4 \wedge 0.2 = 0.2$

$D(a3)=D(MC) = (0.6 \vee 0.3) \cap (0.3 \vee 0.6) \cap (0.2 \vee 0.8)$

$= 0.6 \wedge 0.6 \wedge 0.8 = 0.6$

The probability of Machine Selection to apply the rule 1 will be 0.6. It will be 0.2 for rule 2 and 0.6 for rule 3. Table 1 shows the relations of part, machine, operations and tools.

Table 1: Fuzzy rule based part-operation-machine-tool matrice

				M1							
				M1					M2		
				M1		M2			M3		
				m1	m2	m5	m4	m3	m6	m7	m8
				t1	t2	t6	t4	t3	t2	t5	t1
Part	PA	P1	p1	1	1	0.5	0.6	0.7	0.3	0.2	0
			p3	1	0.8	0.5	0.8	0.6	0.1	0.2	0.1
		P2	p2	0.8	0.7	0.6	0.7	0.5	0	0.2	0.3
			p6	0.8	0.6	0.5	0.2	0.3	0.2	0.1	0.2
	PC	P4	p5	0	0.4	0.1	0.2	0.4	0.7	0.6	0.8
			p4	0.3	0	0.1	0	0.3	0.8	0.7	0.8
		P3	p8	0.2	0	0.2	0.3	0.2	0.3	0.9	0.9
			p7	0.1	0.2	0.1	0	0.1	0.4	0.9	0.9

The proposed method is an example of an instant, dynamic system model with versatile and multi-source resource sharing. Receiving, storing, classifying data provides a heterogeneous application opportunity in the IoT environment. With this structure, it provides the integration of the physical environment and the computer environment.

6. Conclusion

The system will be possible to adapt to changing production conditions at a lower cost and develop more effective manufacturing strategies, together with a more efficient and flexible decision-making structure in the flexible manufacturing system. It will be possible to better understand and model the dynamic structure with this structure. The right decisions can be made for short-term periods under changing conditions. With the proposed decision support system, a decision support model that determines the most appropriate strategies can be developed by considering different objective functions and the behaviour model of the system. Adaptive parameter control and process optimization are performed with the proposed system.

The processes in the system concisely include the following activities:

- Realization of the perception activity
- Perception by the digital twin and then conversion of the knowledge to rules.
- Questioning and decision-making

The performing the task activities; starting the task, following the task and completing the task process are summarized in the system. In conclusion, such a modelling ensures constructing a decision-making process by making a complex structure easily understood. When the architectural structure is activated, the system can become more useful, understandable and rapid and be efficiently arranged. This modelling structure provides the adaptation in every system situation without difficulty.

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