Simulation of an Affordance-Based Human-Machine Cooperative Control Model Using an Agent-Based Simulation Approach

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Abstract. An automated system relies mostly on a robot, rather than a human operator. In the automated system considered in this paper, a human operator mainly verifies the product quality, where the performance of the human is affected by his or her characteristics. To present this kind of system, an ABM is better than DES to simulate the role of the human operator. This is because the human characteristics are dynamic and are affected significantly by time and environment. This paper presents a DES-ABM model which simulates the performance of a human operator in a human-machine cooperative environment. It may enable this model to be utilized for further development in controller toward the supervisory control.

Keywords: Human and robot collaboration · Affordance theory · Agent-based simulation

1 Introduction

As a manufacturing environment gets complicated, the adaptive process control in manufacturing systems focuses on improving both the manufacturing flexibility and efficiency. Automation is regarded as the driving force in strengthening productivity and efficiency [1]. However, it is almost impossible to operate a fully automated factory without human operators, not only due to economic reasons, but also due to technical shortcomings [2, 3]. In manufacturing systems, there exist tasks which should be done, or would be more efficient when done, by a human operator [4]. The optimal task allocation between human and machine is necessary to manage the combined systems effectively with dynamic human and machine interactions. Specifically, modeling and control of a human-involved semi-automated manufacturing system is a major issue in the automotive industry, because human operators play a key role for complex options and tasks in the manufacturing processes [5–7].

In human-involved manufacturing systems, a human can act as one of the most flexible system resources by performing a large variety of physical tasks ranging from material handling to complex tasks like inspections and assembly [8]. Thus, integrating humans into manufacturing systems has been considered a critical aspect in human-involved manufacturing systems modeling and control. A few modeling methods for this heterogonous system are suggested to represent interactions among the

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manufacturing resources [9, 10]. In this research, we specifically focus on an FSA (Finite State Automata) based approach classifying a human operator as a system component that can execute tasks without any physical constraints through logical process [11, 12].

A formal modeling of human-involved manufacturing system is presented [9]. The formal model used in this paper is specifically based on affordance-based Message-based Part State Graph (MPSG) which is a formal modeling methodology for control of discrete manufacturing systems [10]. The presented model incorporates a supervisory control scheme to fit into more flexible and efficient manufacturing. The implementation of the proposed manufacturing system integrates an affordance-based MPSG control model into an agent-based simulation of human and machine behaviors. The simulation result is used to make a manufacturing processes plan and control the human-machine cooperative manufacturing systems under dynamic situations.

In order to verify the affordance-based modeling and control scheme, simulation results of an existing auto-part manufacturing case with human-robot collaboration is investigated. The simulation model is planned to be implemented with hybrid modeling of DES and ABM. This is because the human characteristics are dynamic and are affected significantly by factors like time, environmental factors and operator's level of expertise. Therefore, the combined simulation model of DES and ABM is expected to mimic the human-robot collaborative manufacturing system. The productivity of the system is compared to validate the feasibility and applicability of the affordance-based modeling of human-machine cooperative systems.

The rest of this paper is organized as follows. The MABA-MABA and supervisory control are introduced in Sect. 2. The proposed implementation model of affordance based MPSG is described in Sect. 3. Section 4 illustrates the application of the implemented formal model using a simulation of the manufacturing and inspection process for plastic injection manufacturing line of automobile door, and provides an analysis of the simulation result in terms of productivity and efficiency. Section 5 presents the conclusion and scope for future works.

2 Related Work

2.1 MABA-MABA and Supervisory Control

Men Are Better At, Machines Are Better At (MABA-MABA) is provided by Fitts [13]. To design the effectiveness automated system, task allocation to human operator or automated machine is based on behavior' strength. Figure 1 shows an example of classification standard of each task.

Sheridan [3] applied the MABA-MABA theory to a task allocation of human-involved automated system. He suggested a role of human operator in automated system to improve the system flexibility, and a role of an automated machine to reduce mechanical failure by operator. The study of MABA-MABA not only classifies a task allocation of human-machine, but also provides the guideline of a system operation design [4]. The supervisory control means that a human is not only taking his task in the manufacturing system, but also managing machines and the whole system

Men are better at:

- Detecting small amounts of visual, auditory, or chemical energy
- Perceiving patterns of light or sound
- Improvising and using flexible procedures
- Storing information for long periods, and recalling appropriate parts
- Reasoning inductively
- Exercising judgment

Machines are better at:

- Responding quickly to control signals
- Applying great force smoothly and precisely
- Storing information briefly, erasing it completely
- Reasoning deductively
- Doing many complex operations at once

Fig. 1. The Fitts' MABA-MABA List, Abbreviated by Sheridan [3]

[14]. For example, Chef is preparing his specialty coincided with inspecting other cooks food in the restaurant; the driver is using cruise control system, while taking express way [15]. In the supervisory control, the system operator can shift efficiency process plan quickly when the process plan is exchanged by a customer. Most of current manufacturing environments are operated in terms of the supervisory control, so that the performance of the system is highly subject to the proper work allocations between manufacturing resources (e.g., human operators, machines)

2.2 Finite State Automata Representation of DES

One way of formalizing the logical behavior in discrete systems is based on theories of languages and automata. An automata theory is based on the notion that anything is possible to model with discrete states [16, 17]. This theory is an atomic mathematical model for finite state automata (FSA). Transitions of automata theory and a finite number of states is possible to model with predetermined rules. Transition functions generate transition between states. These functions of each transition determine which state to go to from a current state and a current input symbol. An FSA is a state and rule-based representing language based on well-defined rules which means an FSA is tractable [18]. A commonly FSA in practice is a deterministic finite automaton (DFA), which can be defined as a 5-tuple:

$\boldsymbol{M^{DFA}} = < \Sigma, Q, q_0, \delta, F, X_p, Z_q, J, W_{pq} >$, where the definitions of the components are as follows:

- J is a juxtaposition function such that $J : \boldsymbol{X} \times \boldsymbol{Z} \rightarrow \boldsymbol{W}_{pq}$;
- $\boldsymbol{X}_p$ is a set of affordances,
- $\boldsymbol{Z}_q$ is a set of effectivities (human capable actions),

- W_{pq} is a set of possible human actions,
- All other definitions of tuples are the same as those of $\mathbf{M}^{\mathbf{DFA}}$

3 Modeling of Human-Involved System

3.1 Formal Modeling of an Existing Semi-automated Manufacturing System: A Door-Part Injection and Handling

The process of modeling and simulation is conducted in four steps as shown in Fig. 2: (1) the criteria of MABA-MABA in an exemplary manufacturing process were investigated, (2) the formal automata model of affordance-based MPSG was built, (3) ABM-DES simulation model is implemented, and 4) the system was verified by simulations under different condition of human performances.

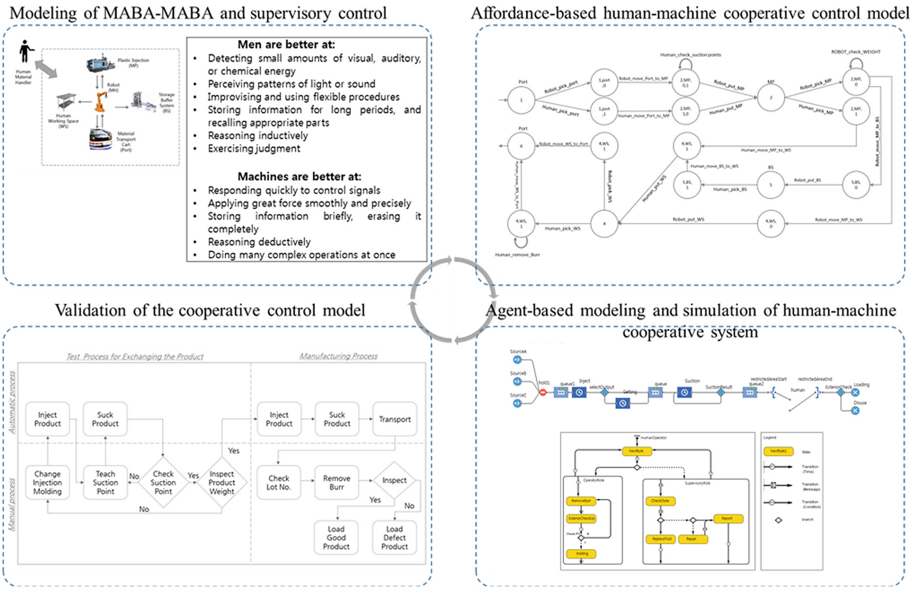

Fig. 2. Agent-based modeling of human-machine combined semi-automated manufacturing systems.

First, to represent the current process of a semi-automated manufacturing process (automobile door part injection and handling) using affordance-based MPSG, tasks and interactions need to be defined based on concepts of MABA-MABA and supervisory control as shown in Fig. 3. Identifying a key role of each task behavior in a human-involved manufacturing system starts from the analysis of the current process or a task assigned to a human. For instance, when a task is moving a rectangular box which has proper size and weight to a robot arm, this task is assigned to the robot. However, a moving route is complicated by obstacle positions, and varies according to the product option. Programming the path into the robot requires many sensors, then the necessary automation budget of the task, moving a rectangular box, is increased to operate without errors in the dynamic environment. Therefore, this task is better to a human operator than a robot.

We adopt an affordance-based MPSG presented by Kim et al., [9] as shown in Fig. 3. This formal modeling methodology distinguishes human potentially possible actions from human capable actions. In other words, a human can or cannot perform tasks due to physical limitations enforced by an environment or his/her cognitive recognition of tasks. Also, a human action is defined by the Boolean values with consideration of affordances. In their presented model, a module can generate possible transitions in terms of the MPSG that proves logical validation. Using affordance-based MPSG, the system can present a process without critical failures. The current process of the door part injection and handling system is modeled with the affordance-based MPSG (see Fig. 3) and verifies the logic and flow with a sequence diagram as shown in Fig. 4.

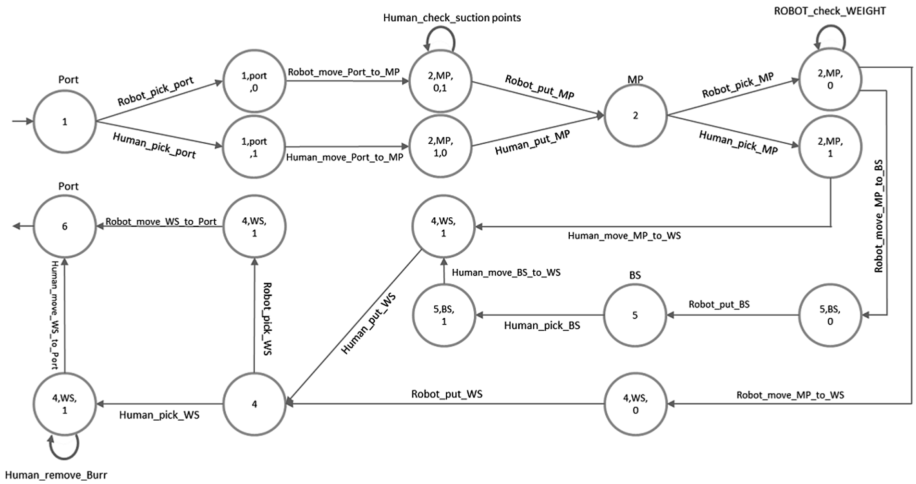

Fig. 3. Affordance-based MPSG of the door part injection and handling system

3.2 Simulation Modeling Using ABM

In regards to affordance-based MPSG, an operator is modeled as an agent instead of a machine in DES. A human operator mainly verifies the product quality after manufacturing process, where the performance of the human is affected by its characteristics. The human characteristics are dynamic and are affected significantly by factors like time, environment, or skilled level. To simulate a human considering dynamic characteristics, an ABM is better than DES.

Each behavior or task of a human operator consists of a stage and transition. Each stage also can have an internal stage to make a decision via defined rules. For example, the task of an operator is to remove a burr. This task stage is involved in the Operator

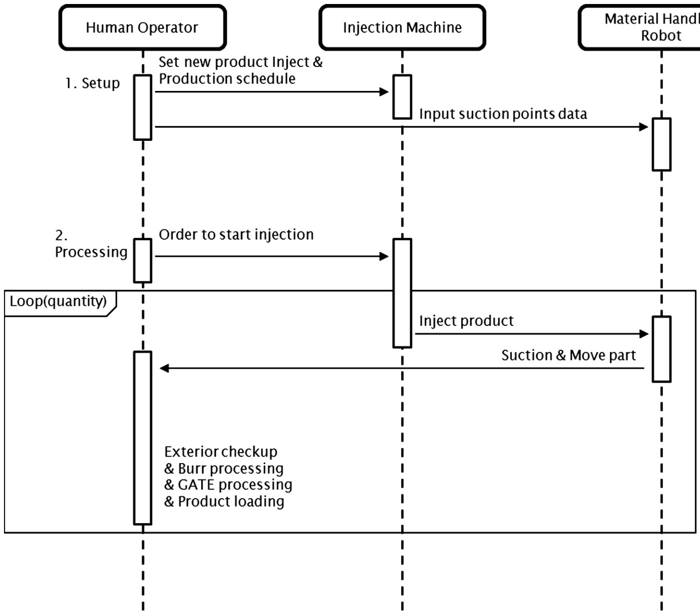

Fig. 4. The sequence diagram of the manufacturing process of the door part injection and handing [19].

Role group, and this group consists of three different stages. When the operator takes his/her task, the result of a task can be different depending on the product or other influence like fatigue or skilled level (see Fig. 5). The human operator also has supervisory role in this model. For instance, when a machine stops or the human operator finds out a problem in the process, the human operator checks the machine state and make decision whether a replace tool or repair. A dynamic characteristics of the human operator affect to decision-making. Depend on his working experience via skilled level, the human operator may repair the machine or report it based on a rule when the machine breaks down. For this reason, ABM easily presents the affordance-based MPSG. In the simulation, each operator is assumed to have a given level of skill. The skill level can be modeled as a function of the initial level of skill and total working time of the agent (experience) as shown in Fig. 5.

4 Simulation Implementation

4.1 Scenario of the Illustrative Example

The whole system process is modeled as DES, whereas each operator is modeled as an agent-based on task rules and task specifications. In this paper, plastic injection manufacturing line of an automobile door is used for simulation. The brief process is as follows: At first, raw material is injected in the injection machine. A robot arm transfers

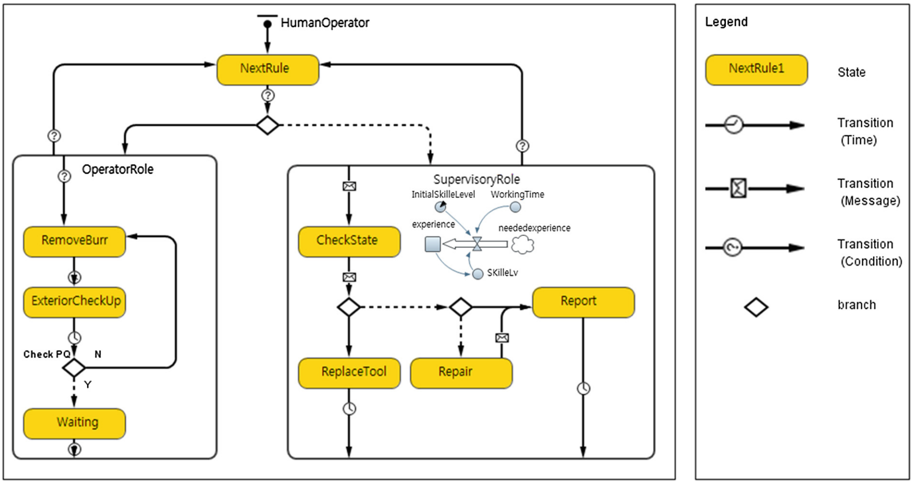

Fig. 5. State chart of a human operator in the semi-automated process of the door part manufacturing.

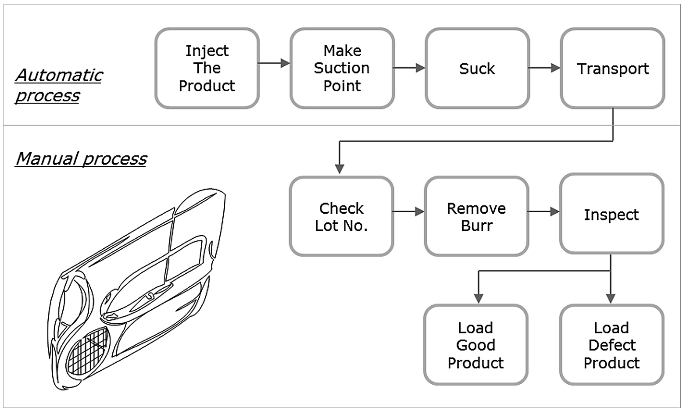

Fig. 6. Current process map of the semi-automated manufacturing system

the injected product from the machine to conveyer line. And the operator removes burrs on the product and then the operator inspects the product quality manually (see Fig. 6).

Figure 7 illustrates the simulation model of the current system. Raw material is source A, B and C. Each source is modeled as an agent and has different options like door trim size, color, or customer choice among selectable options. The setting is for machine adjust time when the source type is changed at some point. The restricted area is designated for operator tasks. Internal processes in the restricted area are similar to those shown in Fig. 5. Finally, the operator classifies and loads a product depending on the inspection standard.

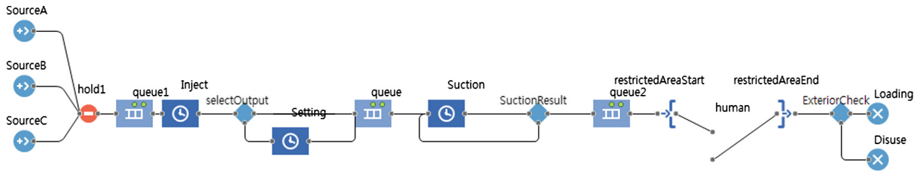

Fig. 7. Hybrid discrete event system and ABM modeling

4.2 Analysis of Simulation Results

For verifying the simulation result, the parameters of the manufacturing process are set as real data (see Table 1). The data are assumed to be the triangular distribution with mean values of actual process time. The parameter of operator's tasks is assumed as 0.95 % of which the human operator's skill level is high.

Table 1. Real process times in the manufacturing system and simulation inputs

	Process	Max. Process Time(sec)	Simulation Input(sec) (Triangular dist.)	Total Cycle Time (sec)
Set up Tasks	Injection machine	1200	(min,mean,max)	Max. 1800
	Robot arm	600		
Production Tasks	Injection	8	(6.4, 7.2, 8)	Max. 90
	Extra time for injection	22	(17.6,19.8,22)	
	Suction	10	(8,9,10)	
	Material moving	5	(4,4.5,5)	
	Human operator's tasks	15	Dependent on the operator's skill level & error rates	
	Final loading	30	(24,27,30)	

In the simulation results, the average cycle time (total time for one production) is calculated as 82.3 s (see Fig. 8). The simulation were conducted with 100 replications to analyze the variation of the data. The input parameters of the model are set with reference to the real production conditions for each manufacturing process (see Table 1). The unexpected errors occasionally cause delays on the processing times as shown in Fig. 8, it is still required to ensure realistic results of the simulation.

To show the effect of human error and operator's skill level, in the simulation the operator's skill level and error rate follows triangular distribution as follow :

$$processtime \sim Triangular(min, mean, max), \tag{1}$$

where: $mean$ = required process time × f(operator's skill level),
$min = mean \times error\ rate$, and
$max = mean \times error\ rate$

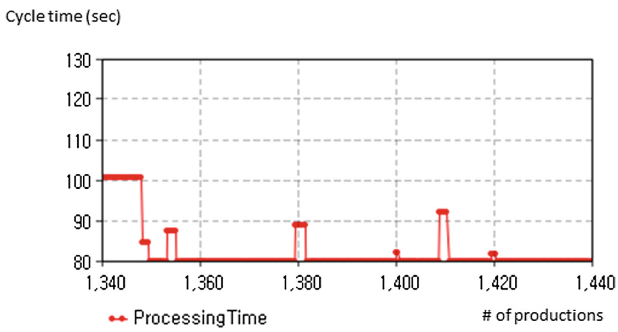

Fig. 8. Simulation test results of product time vs. the number of productions

The mean value of triangular distribution is assumed to be dependent on the operator's skill level such as that of novice, intermediate, expert cases. For the illustrative purposes, it is assumed to take 95 %, 90 %, and 85 % of the required process times for the novice, the intermediate, and the expert cases, respectively. The error rates for the cases are also assumed to have different values of min and max in the triangular distributions as shown in Fig. 9.

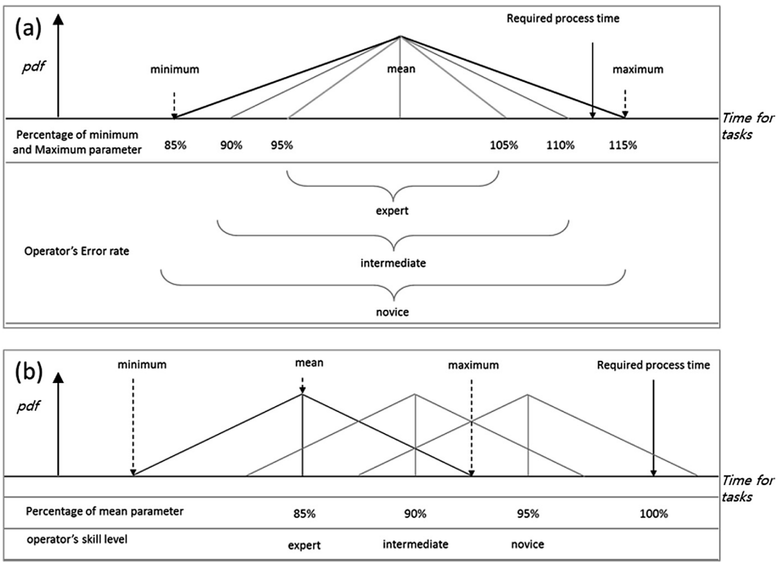

Fig. 9. The parameters of triangular distribution depend on the operator's skill level and error rate. (a) the minimum and maximum value depend on the error rate of an operator, (b) the mean value depend on the operator's skill level

The simulation results were analyzed by different error rates and the skill level assumed, by using ANOVA to illustrate how the human task variances affect the total processing time. The results show that the skill level, the error rate, and the interaction are all significant to the total process time in 95 % CI, because their p-values are all less than 0.05 (see Table 2). The error rate highly influences the process time when the operator's skill level is low, the case of novice, as shown in Fig. 10, which presents the effect of human involvement in the automated process. Thus, to identify the performance of the human-included manufacturing systems, the level of skills and error rates of the human agents should be modeled independently when the interactions among heterogeneous resources in the systems need to be considered and analyzed.

Table 2. Anova table of operator's skill level and error rate for process time

Source	DF	SS	MS	F	P
Skill level	2	3806.47	1903.24	672.39	0.00
Error rate	2	1108.98	554.49	195.90	0.00
Interaction	4	571.63	142.91	50.49	0.00
Error	891	2522.01	2.83		
Total	899	8009.09			

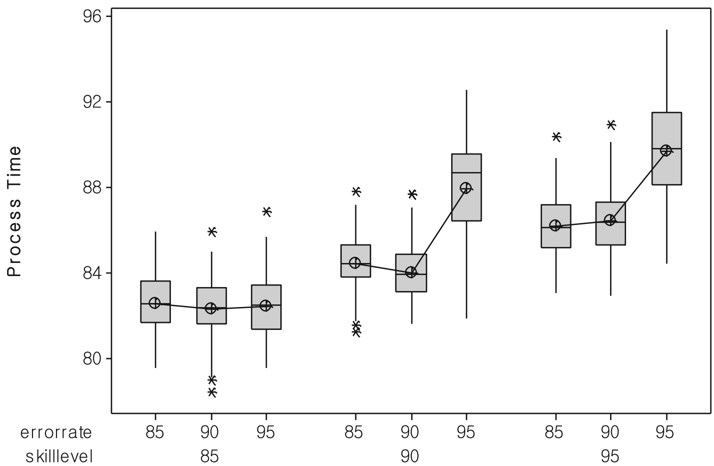

Fig. 10. Box plot of process time vs. error rate & skill level

5 Conclusion

The model presented in this paper provides a simulation implementation of an affordance-based MPSG in a real semi-automated manufacturing system. The affordance-based MPSG, the formal model methodology used in this paper, represents all possible interactions among system components in a human-involved manufacturing system. It also models human operators as components distinct from a machine or a robot. The affordance-based MPSG provides a reasonable modeling method for representing the human-involved manufacturing system. Thus, we provide the simulation and verification of the affordance-based MPSG in which an existing auto-part manufacturing system is simulated.

To make manufacturing processes plan and control the human-involved manufacturing system based on affordance-based MPSG, the simulation model combines DES and ABM. The combined simulation results of DES and ABM are implemented with real manufacturing data from a small auto part company. The simulation is modeled with the triangular distribution to obtain highly reliable data. And then, productivity and task efficiency are used for judgment of the simulation under dynamic situations, such as a different number of product types or urgent customer manufacturing orders. While the simulation model creates four types of products as an existing manufacturing system, the simulation results indicate that the minimum manufacturing time per product is four hours.

The effects of implementation of affordance-based MPSG still require further investigation with different manufacturing systems and extended environments. In addition, the affordance-based MPSG also needs to be extended to express the manufacturing process of human-machine collaboration in manufacturing systems.

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