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Smart control of the assembly process with a fuzzy control system in the context of Industry 4.0

Jiage Huo[1], Felix T.S. Chan[1,*], Carman K.M. Lee[1], Jan Ola Strandhagen[2], Ben Niu[3,*]

[1]*Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China.*

[2]*Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, NO-7491 Trondheim, Norway.*

[3]*College of Management, Shenzhen University, Shenzhen, China.*

Abstract: Assembly line balancing is important for the efficiency of the assembly process, however, a wide range of disruptions can break the current workload balance. Some researchers explored the task assignment plan for the assembly line balancing problem with the assumption that the assembly process is smooth with no disruption. Other researchers considered the impacts of disruptions, but they only explored the task re-assignment solutions for the assembly line re-balancing problem with the assumption that the re-balancing decision has been made already. There is limited literature exploring on-line adjustment solutions (layout adjustment and production rate adjustment) for an assembly line in a dynamic environment. This is because real-time monitoring of an assembly process was impossible in the past, and it is difficult to incorporate uncertainty factors into the balancing process because of the randomness and non-linearity of these factors. However, Industry 4.0 breaks the information barriers between different parts of an assembly line, since smart, connected products, which are enabled by advanced information and communication technology, can intelligently interact and communicate with each other and collect, process and produce information. Smart control of an assembly line becomes possible with the large amounts of real-time production data in the era of Industry 4.0, but there is little literature considering this new context. In this study, a fuzzy control system is developed to analyze the real-time information of an assembly line, with two types of fuzzy controllers in the fuzzy system. Type 1 fuzzy controller is used to determine whether the assembly line should be re-balanced to satisfy the demand, and type 2 fuzzy controller is used to adjust the production rate of each workstation in time to eliminate blockage and starvation, and increase the utilization of machines. Compared with three assembly lines without the proposed fuzzy control system, the assembly line with the fuzzy control system performs better, in terms of blockage ratio, starvation ratio and buffer level. Additionally, with the improvement of information transparency, the performance of an assembly line will be better. The research findings shed light on the smart control of the assembly process, and provide insights into the impacts of Industry 4.0 on assembly line balancing.

Keywords: Assembly line balancing; Re-balancing; Industry 4.0; Fuzzy control system.

* Corresponding authors: *E-mail address:* f.chan@polyu.edu.hk (Felix T.S. Chan).
E-mail address: drniuben@gmail.com (Ben Niu).

1. Introduction

An assembly line, which is essentially a continuous production line, consists of materials and workstations combined by conveyor belts, contacting workers and machines closely and efficiently [1]. The Assembly Line Balancing Problem (ALBP) focuses on assigning tasks to workstations, with the aim of satisfying the precedence relationships among the tasks and the workload limitations of workstations, with the aim of optimizing performance measures [2].

Most of the existing literature on ALBP assumes an environment that works smoothly without any disruption [3]. However, modifications in the input parameters, such as task adding or moving, changes in precedence relationships, increases and decreases in task times, and changes in the cycle time because of changing demand, necessitate a re-balancing [4]. Thus, an assembly line needs to be re-balanced rather than balanced, in practice [2], and assembly line balancing or the re-balancing problem should be considered in a dynamic environment with disruptions. There is some literature that deals with the re-balancing problem [4-6], however, the problem is still underdeveloped [7]. The existing research is based on the assumption that the re-balancing decision has been made already, and only addresses the task re-assignment problem without discussing how disruptions affect the current assembly plan and how to react to disruptions. Nevertheless, there is a trade-off between re-balancing the assembly line as soon as possible to reduce production losses, and keeping the stability of the assembly line to prevent bigger disruptions to the assembly line. How to make such a tradeoff is a problem faced by practitioners, and assembly planning and control are essential for managing the expanding product ranges, reducing delivery time, reducing costs and increasing profitability [8].

The majority of the literature on ALBP addresses the problem in the traditional context where it is manpower-intensive. Consequently, in a traditional assembly line, on-line monitoring of buffer levels, production performance of each workstation and processing times of tasks is unrealistic in practice. However, with the development of new technologies, automated assembly lines are attracting increasingly more attention, especially since the introduction of Industry 4.0, which is the fourth industrial revolution, in 2013.

Industry 4.0 aims to increase operational effectiveness and provide new definitions of business models, services and products [9, 10]. It introduces Internet technology to make factories more intelligent, improves adaptability, resource efficiency and ergonomics, and integrates customers and business partners into the product definition process and value and logistics chains, respectively [11]. According to ElMaraghy and ElMaraghy [12], Internet of things (IoT), which is a basic premise of Industry 4.0, refers to a networked interconnection of objects aiming to make all things communicable, and enables objects to exchange information on their status and condition. The advanced information and communication technology (e.g. wireless sensor network, and cyber-physical systems) enables the prevailing digital transformation, and enables products to evolve from the usual products to the smart, connected products (SCP) [13, 14]. SCP represents the third wave of IT-driven competition, with IT embedded in the products, and can collect, process and produce information [15].

Smart manufacturing resources embedded with IoT technologies (i.e. RFID, barcoding) can interact and communicate with each other intelligently, and smart machines in the era of Industry 4.0 have the ability to send their working status to a central cloud-based "manager" in real time [16]. Large amounts of real-time manufacturing data can be obtained, and different parts of an assembly line can communicate with each other and can get access to real-time information easily. Thus, Industry 4.0 will bring new attributes and opportunities for an assembly line, and will create a novel context for an assembly line, with real-time information on an assembly line. Nevertheless, there is sparse literature on on-line planning and control of an assembly line, taking the novel context into account. Furthermore, how to efficiently use the real-time data to make advanced decisions in a smart factory is an urgent problem to be solved [17].

Accurate analysis of an automotive assembly line is difficult because of the randomness and nonlinearity caused by unpredictable machine failures, asynchronousness among various sections in the assembly line, the coupling of sections through finite buffers, and coupling between the production and material handling system [18]. It is challenging to design a control system for a nonlinear system having unexpected events [19], and a mathematical model of such a control system is difficult to obtain. However, fuzzy controllers can provide a systematic and efficient framework for incorporating data obtained by sensors and human judgments, and it is always possible to design a fuzzy controller that is suitable for the nonlinear system by carefully choosing the parameters of the fuzzy controller [20]. Therefore, fuzzy controllers can be used to realize the smart control of an assembly line.

Although there are some explorations on ALBP with fuzzy theory, fuzzy theory is always used to deal with uncertain processing times, multiple goals, or improve the algorithm to solve ALBP [21-23]. To make balance control of the sewing operations on assembly lines, Hui et al. [24] used a fuzzy system to determine the number of operators to be moved in and out of a sewing section. This is an important exploration in that a fuzzy system is utilized to deal with the balance control of a manufacturing process. However, they restricted the balance control problem to apparel manufacturing and assumed that the machine downtime due to failure was insignificant. Thus, they did not consider possible disruptions in the manufacturing process, and did not discuss when disruptions can lead to assembly plan modifications.

Therefore, there is little literature that addresses ALBP, considering the novel context brought by Industry 4.0, where real-time information is accessible to workstations, and commands can be easily sent to machines to adjust their production rates to react to disruptions and achieve a better collaboration of workstations. Differing from the traditional production system, assembly lines in the era of Industry 4.0 will be more re-configurable and be re-balanced more frequently, thus, the assembly process to be controlled should be treated from a dynamic perspective. In this study, real-time information of an assembly line is analyzed by a fuzzy control system, and whether and how to re-balance the current assembly line and adjust the production rate of each workstation are determined. The number of open workstations will decrease or increase based on the availability of workstations and the 'decisions' of the fuzzy system, and task re-assignments will be implemented after the re-balancing decision is made. Consequently, an assembly line can be adjusted with the proposed fuzzy system to adapt to the dynamic environment, and to the best of our knowledge, this is the first study that deals with the on-line adjustment (layout adjustment and production rates adjustments) of an assembly line with a fuzzy system. The automated balance control of an assembly line is explored in a novel context created by Industry 4.0, and the link between disruptions and the corresponding reactions is created by the proposed fuzzy system. The research findings shed light on the smart control of the assembly process. Additionally, the performance of assembly lines with different levels of information transparency is compared to show the impact of high-level information transparency on the assembly process. Thus, the research findings also provide references for practitioners who are considering the adoption of new technologies involved in Industry 4.0.

The rest of the paper is structured as follows. The related literature is shown in section 2; The fuzzy control system is introduced in section 3; Section 4 shows the numerical experiments and results; Conclusions of the research findings and suggestions for future research are shown in section 5.

2. Literature review

2.1 Assembly line balancing and re-balancing

Assembly Line Balancing (ALB) is important for overall efficiency. Most of the ALB literature assumes an environment that works smoothly without any disruptions, however, manufacturing environments are often prone to disruptions [3]. A wide variety of modifications in the input parameters, such as task adding or moving, changes in precedence relationships, increases and decreases in task times, and changes in the cycle time because of the changing demand, necessitate a re-balancing [4]. Robust solutions can retain the initial task assignment to some extent without modifications, however, at some point, re-balancing of the line becomes inevitable [25]. Not surprisingly, Celik et al. [2] claimed that an assembly line needs to be re-balanced rather than balanced.

The re-balancing problems are quite different from the balancing problems since the existing configuration has to be taken into account, thus, the methods and solutions developed for line balancing problems cannot be directly used for re-balancing problems [25]. There are some researchers who have explored the re-balancing problems. Based on “Technique for Order Preference by Similarity to Ideal Solution” (TOPSIS), which is an integration of a multi-attribute decision-making procedure, Gamberini et al. [4] dealt with the assembly line re-balancing problem by considering minimizing the unit labor and expected unit incompletion costs and tasks re-assignment. Yang et al. [5] proposed a multi-objective genetic algorithm to address the re-balancing problem for a mixed-model assembly line with seasonal demands. Celik et al. [2] defined a U-line re-balancing problem with stochastic task times, and proposed a method based on ant colony optimization. Motivated by task improvements during the production process along an assembly line, Li [6] used an algorithm named ENCORE to solve the problem in the context of automatic assembly line systems. Sancı and Azizoğlu [3] considered the re-balancing problem in which tasks at least on the disrupted workstations should be reassigned to other workstations.

For the re-balancing problem, a quick resolution is more important than an optimal solution, and the aim is to react quickly to reduce negative impacts of any disturbing events and define a new solution that is close to the initial line balancing [26]. When dealing with the re-balancing problem, Celik et al. [2] proposed an algorithm to minimize the total cost of re-balancing which is the sum of task transposition costs, workstation opening/closing costs and operating costs of workstations for a particular planning horizon. Sancı and Azizoğlu [3] made a trade-off between the efficiency of the new balance and the stability, indicated by the differences between the initial and the new task assignments.

However, the re-balancing problem is still underdeveloped [7]. As discussed above, there are many factors resulting in re-balancing, but monitoring all these factors and combining them together to make a decision is difficult. Consequently, the re-assignment solutions are searched for with the assumption that the re-balancing decision has been made, however, there is sparse literature on when the re-balancing decision should be made, although this problem is faced by all practitioners. Because of the uncertainties, exact parameters of the production process are difficult to obtain before the process begins [27]. Thus, on-line solutions are needed to deal with uncertainties effectively.

2.2 Industry 4.0

Industry 4.0, as an industrial revolution, will reshape the ways things are made. Optimized cells will be integrated, automated and optimized to improve the efficiency and change the relationships among suppliers, producers and customers, and redefine the relationship between humans and machines [10]. Apart from providing great opportunities to reshape the future, Industry 4.0 aims to increase the operational effectiveness and new definitions of business models, services and products [9, 10]. With the latest advanced technologies, the smart factory in the context of Industry 4.0 is becoming a new manufacturing pattern [28].

According to Jazdi [29], we are experiencing Industry 4.0 in terms of Cyber-Physical Systems (CPS). With cyber technology, automated systems and equipment, internal logistics systems and operating supplies are connected, which enables direct access to the higher-level processes and services, optimal resource utilization and smart control [29].

The CPS connected to the Internet is often referred to as the Internet of Things (IoT), which is an information network that consists of physical objects which allows interaction and cooperation to reach common goals [30]. IoT is the basic premise for the implementation of Industry 4.0 [31]. It provides a version for the future Internet where physical things (such as Radio-Frequency Identification (RFID) tags, sensors, actuators and mobile phones) are connected [32]. What is more, its basic idea is the pervasive presence of large amounts and kinds of things or objects, allowing it to gain ground in the scenario of modern wireless telecommunications [30]. It gives access to information about the physical world and promotes innovative services to increase efficiency and productivity [32]. With the real-time data obtained by IoT, big data analysis can be used to make logistic decisions [33], and smart production [28], smart logistics [34] and smart cities [35] are possible. Meanwhile, advanced technologies enable better implementation of automated guided vehicles [36, 37], which supports smart warehouse. Additionally, big data analysis can be used to improve the speed and accuracy in maintenance decision making [38].

In the era of Industry 4.0, there will be vast changes in the assembly process. Different parts of an assembly line can communicate with each other, and with more easily accessible real-time information, it is expected to realize better collaboration between different parts. Smart assembly systems are needed to achieve more autonomy in communication between entities in the system and more adaptable control of assembly flow and better performance [12]. However, there are few studies dealing with assembly process control with the new attributes of an assembly line in the context of Industry 4.0 considered.

2.3 Fuzzy logic system

Researchers have used fuzzy logic when dealing with ALBP. Some use fuzzy logic to define the processing time of one task. For example, Zacharia and Nearchou [23] presented a fuzzy extension of the type 2 ALBP with fuzzy job processing times, and the processing times were formulated by triangular fuzzy membership functions. Some researchers use fuzzy theory to deal with multiple goals and heuristic algorithms improvements in ALBP. For example, fuzzy goal programming was used, and an appropriate genetic algorithm was developed by Cheshmehgaz et al. [21], to consider three criteria during the balancing: cycle time, overall workload and assembly worker postures. To solve a multi-objective ALBP, Simona [22] utilized a fuzzy controller for tuning inertia weight in particle swarm optimization.

There are few studies exploring the application of fuzzy controllers in workload balancing control of assembly lines, and real-time production rate adjustment in each workstation to decrease inventory and improve the overall production rate when there are uncertainties. However, fuzzy controllers are always applied in decision making. Tsourveloudis et al. [39] developed a line, assembly, and disassembly controller to adjust the processing rate of each production stage so that the workflow is balanced, and the extreme events of machine starving or blocking are reduced, and simulation results showed that the proposed approach outranks other control policies in keeping the WIP inventory low. Nakandala et al. [40] proposed a fuzzy-based decision support model for determining the chance of meeting on-time delivery in a complex supply chain environment. Fuzzy logic principles and a unitary structure-based supply chain model were integrated, and uncertainties associated with key inputs of on-time delivery performance for effective decision-making process were addressed, to minimize of business losses that result from penalties and customer dissatisfaction and the consequently reduced market share. Al-Ebbini et al. [41] presented a fuzzy lung allocation system to determine which potential recipients would receive a lung for transplantation in order to deal with the vagueness and fuzziness of the decision making of the medical experts, and the proposed decision process provided a more effective, time-efficient, and systematic decision support tool.

Thus, although there are some explorations on ALBP with fuzzy theory, there are few publications considering the impacts of Industry 4.0 on the assembly process, exploring the fuzzy control system to utilize the real-time information which is accessible to all workstations and adjusting the assembly line when necessary. In our study, a fuzzy control system is developed to deal with the disruptions to an assembly line and to adjust the assembly line to achieve better performance.

3. Problem statements and assumptions

Figure 1 shows the structure of an assembly line consisting of M workstations and $M-1$ buffers between these workstations, and this is the assembly line considered in this study. B_i denotes buffer i ($i = 0,1,2,...,M$).

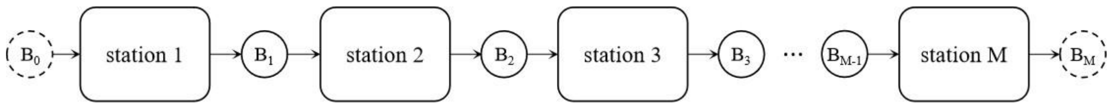

Figure 1. An assembly line with M workstations

The whole assembly process is divided into production cycles by assembly line re-balancing. After the preparation for assembly line re-balancing is completed, a new production cycle will begin, and P_i denotes the cumulative production in the i^{th} production cycle. Figures 2a and 2b are used to illustrate the related variables for two scenarios. Let P, D and T_d denote the cumulative production, the demand quantity of products and the delivery time left for the current production cycle, respectively. Let t_i ($i > 0$, $t_0 = 0$) denote the time when the preparation for the i^{th} re-balancing is completed and a new production cycle will begin. At t_i, D and T_d will be updated, and P will be initialized to be 0.

At first, $D = D_0$, and $T_d = T_{total}$. If there is no re-balancing since t_0, D and T_d will not be updated, and P is the cumulative production since t_0 (see Figure 2a). Let T_i ($i > 0$) denote the duration between $t_{i\text{-}1}$ and the beginning of the i^{th} re-balancing, and let T_{r_i} denote the preparation time for the i^{th} re-balancing. If assembly line re-balancing has been implemented for k times ($k > 0$),

$$D = D_0 - \sum_{i=1}^{k} P_k \,, \tag{1}$$

$$T_d = T_{total} - \sum_{i=1}^{k} \left(T_i + T_{r_i}\right), \tag{2}$$

and P is the cumulative production since t_k (see Figure 2b).

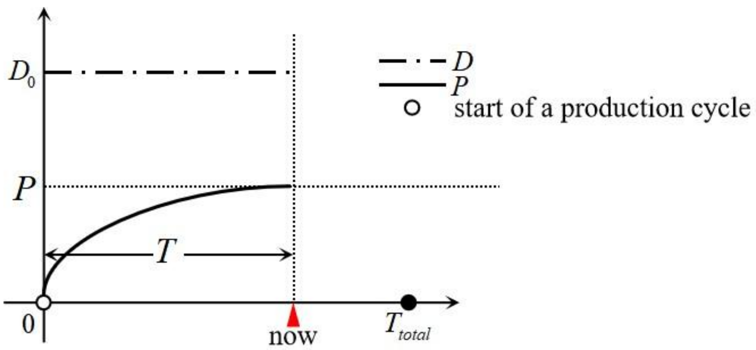

Figure 2a. Illustration of variables when no re-balancing has been conducted

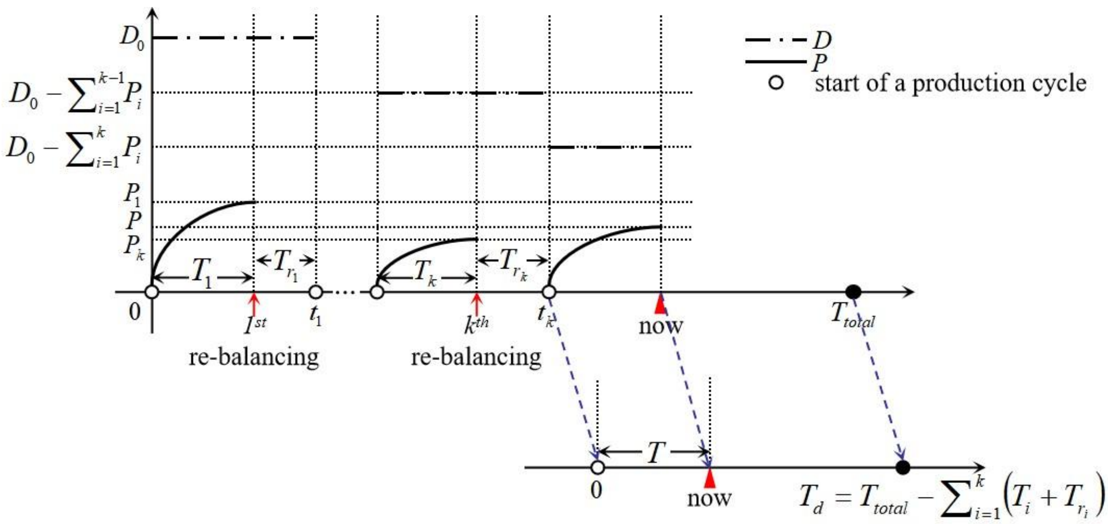

Figure 2b. Illustration of variables after an assembly line has been re-balanced

The main assumptions in this study are as follows:

(1) Let pr_i denote the production rate of workstation i ($pr_i \le pr_{\max}^i$), and $pr_{\max}^i$ is the largest production rate of workstation i. Thus, workstation i can operate at a minimum processing time $\frac{1}{pr_{\max}^i}$.

(2) B_i ($1 \le i \le M-1$) has finite capacity. B_0 is infinite source of raw material so that station 1 is never starved. B_M has infinite storage capacity so that station M is never blocked.

(3) D_0 is the demand quantity of products given at t_0.

(4) The financial cost for assembly line re-balancing is ignored in this study, but the time cost due to the preparation for all the re-assigned tasks is considered.

(5) Machines break down and are repaired randomly with different probabilities. The failure rates of all machines are λ, and the repair rates of all machines are μ. The uptimes and downtimes

of machines follow exponential distributions with the mean of $\frac{1}{\lambda}$ and $\frac{1}{\mu}$, respectively.

(6) The automated assembly line, where more automated technologies are adopted and the assembly tasks are done by robots rather than human workers, is considered in this study. According to Li [6], there are two characteristics of the automated assembly line in which robots are the primary agents in assembly tasks: learning automata, and control architecture and collaborative learning. The first characteristic means manufacturing techniques can be refined based on the prior manufacturing experience and this leads to task time reductions. As to the second characteristic, task time reductions of one robot can be realized by the other robots since the learned skills can be transferred to the other robots. In this study, the above learning effect is considered, and after the learning effect occurs, the processing ability of each workstation is improved. The processing time reductions of all tasks are assumed to occur simultaneously. The task time reduction rate of the task i is defined in equation (3):

$$r_i = \frac{t_i - t_i'}{t_i} \tag{3}$$

where t_i is the initial processing time of the task i, and t_i' is the decreased processing time of task i after a learning effect occurs.

(7) Blockage of workstation i occurs when it finishes one workpiece, but buffer i is full. Workstation i will be blocked until there is space in buffer i. Starvation of workstation i occurs when it is idle, but buffer $i-1$ is empty. The starvation will end when there is inventory in buffer $i-1$.

4. Fuzzy control model

4.1 Fuzzy control system

Figure 3 shows the fuzzy control system for the assembly line shown in Figure 1. FC_i denotes the i^{th} fuzzy controller. There are two types of fuzzy controllers in the fuzzy control system. Fuzzy controller FC_1 is used to deal with global information and make a decision on whether to re-balance the assembly line. Fuzzy controllers FC_2 to FC_{M+1} are used to process the local information and make decisions on how to adjust the production rate of each workstation when re-balancing is not needed.

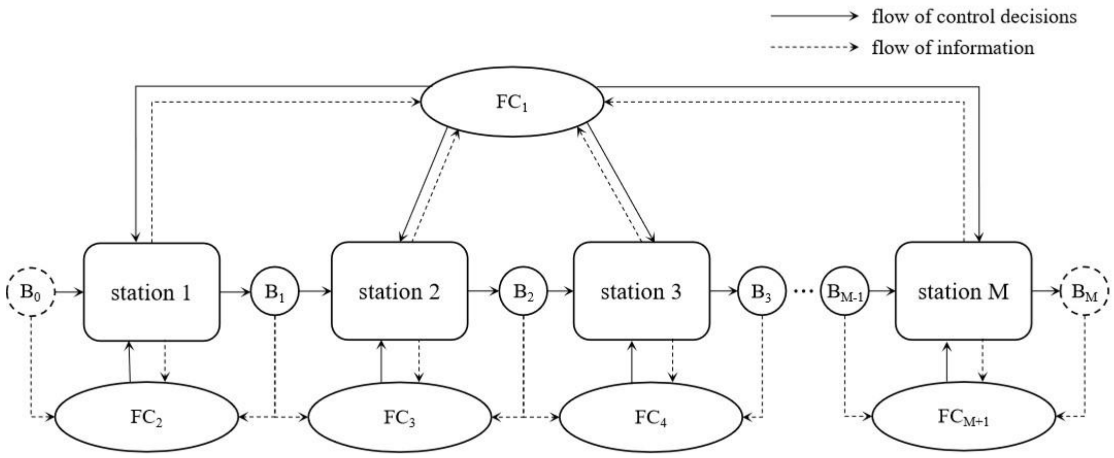

Figure 3. The framework of the fuzzy control system

4.2 Structures of two types of fuzzy controllers

A fuzzy controller is an inference system to mimic human thinking, which consists of a fuzzifier, some fuzzy IF-THEN rules, a fuzzy inference engine and a defuzzifier [41].

4.2.1 Fuzzification

In the fuzzification process, the input data set is converted into fuzzy sets by fuzzy membership functions. Each of the fuzzy subsets represents one linguistic term that allows its members to have different grades of membership.

4.2.2 Fuzzy inference engine and fuzzy rule base of type 1 fuzzy controller

Two factors, which are important in determining whether to re-balance the assembly line, are the inputs of the fuzzy controller, and the output is the necessity of assembly line re-balancing.

(1) Urgency of the assembly job, urg

To keep the stability of an assembly line and prevent overacting to disruptions, urgency of the assembly job is considered before a re-balancing decision is made. The assembly job urgency is defined in equation (4) as follows:

$$urg = \begin{cases} \dfrac{D \cdot \dfrac{T}{T_d} - P}{D \cdot \dfrac{T}{T_d}}, & D \cdot \dfrac{T}{T_d} \geq \dfrac{P}{2} \\ -1, & D \cdot \dfrac{T}{T_d} < \dfrac{P}{2} \end{cases} \tag{4}$$

where T is the assembly time used in the current production cycle. $D \cdot \frac{T}{T_d}$ is the amount of production that should be finished at present, and if it is larger than P, there is a risk that the demand cannot be satisfied. urg ranges from -1 to 1, and the fuzzy term set is {very small, small, medium, large, very large}.

(2) Time cost to re-balance the assembly line, T_c

Assembly line re-balancing should not be considered when there is not a large possibility that the production after re-balancing is more than that without re-balancing, even though it is quite urgent to increase production The cost of re-balancing is defined in equation (5):

$$T_c = \frac{pr_{ini} \cdot (T_{total} - T - T_m) - pr_{new} \cdot \left(T_{total} - T - T_r - \frac{1}{pr_{new}} \cdot n_{avail} \right)}{pr_{\max} \cdot (T_{total} - T)} \tag{5}$$

where T_m denotes the maintenance time of the assembly line, and is defined as

$$T_m = \max_{i \in T_A} \{ T_{m_i} \}. \tag{6}$$

T_A is a set consisting of the stations involved in the current assembly plan (some workstations may be closed for maintenance), and T_{m_i} is the maintenance time needed by station i. T_r designates the preparation time for re-balancing the assembly line and is defined as the sum of the preparation times of all the re-assigned tasks. The term pr_{ini} denotes the largest production ability according to the current assembly plan, defined as

$$pr_{ini} = \min_{i \in T_A} \{ pr^i_{\max} \}. \tag{7}$$

Besides, pr_{new} is the production rate after re-balancing, and $pr_{\max}$ designates the largest production rate that can be achieved by the current assembly line with all stations operative. n_{avail} denotes the number of stations used in the re-balancing plan. $T_r + \frac{1}{pr_{new}} \cdot n_{avail}$ denotes the shortest time from the beginning of the preparation for the re-balancing to obtaining one finished product. A small T_c less than 0 indicates that there is some possibility that the production, after re-balancing during the simulation time remaining, is increased. The smaller T_c is, the larger the possibility becomes. The fuzzy term set is {very small, small, medium, large, very large}.

(3) Output variable: the necessity of re-balancing, N

The set of fuzzy terms is {very small, small, medium, large, very large}. The necessity is between 0% and 100%, and the fuzzy terms of 'very small' and 'very large' indicate the range from 0% to 100%. Assembly line re-balancing is conducted when N is larger than a predetermined threshold.

Fuzzy rules are the base of the fuzzy inference engine, and they can be utilized to make decisions and generate control actions. The rules are in the form of if-then statements. There are 25 fuzzy rules for type 1 fuzzy controller (see Table 1). When there is a risk that the demand cannot be satisfied and T_c is smaller than 0, assembly line re-balancing may take place. Otherwise, re-balancing will not take place. Therefore, assembly line re-balancing takes place only when the necessity is large enough, so as to adjust the assembly line in time and prevent overreaction.

Table 1

Fuzzy rule base for the type 1 fuzzy controller

	T_c				
urg	VS	S	ME	L	VL
VS	S	S	S	VS	VS
S	L	ME	ME	VS	VS
ME	VL	VL	L	VS	VS
L	VL	VL	L	S	VS
VL	VL	VL	L	S	VS

Note: VS, S, ME, L and VL denote very small, small, medium, large and very large, respectively.

4.2.3 Fuzzy inference engine and fuzzy rule base of type 2 fuzzy controller

Three factors, which affect decision making on the production rate adjustment of a workstation, are the inputs of type 2 fuzzy controllers, and the output is the production rate adjustment of the corresponding workstation.

(1) Upstream buffer level $BL_{i\text{-}1}$ and downstream buffer level BL_i of workstation i

The upstream buffer of workstation i is B_{i-1}, and the downstream buffer is B_i. The buffer level of buffer i is defined in equation (8):

$$BL_i = \frac{w_i}{C_i}, \ \ i = 0,1,2,...,M \tag{8}$$

where w_i is the inventory of buffer i, and C_i is the capacity of buffer i. Buffer levels range from 0 to 1. The set of fuzzy terms is {very small, small, medium, large, very large}.

(2) Production surplus rate, S_i

The third factor that affects the production rate adjustment is the production surplus rate, which is defined in equation (9) as follows:

$$S_i = \begin{cases} \dfrac{\dfrac{P_{S_i}}{T} - d}{pr_{\max}^i - d}, & P_{S_i} \geq d \cdot T \\ \dfrac{\dfrac{P_{S_i}}{T} - d}{d}, & P_{S_i} < d \cdot T \end{cases} \tag{9}$$

where P_{S_i} is the cumulative production of workstation i. d denotes the demand production rate that is updated at the beginning of each production cycle. The production rate of workstation i should be around d to satisfy the demand.

If the percentage of the operative time of a workstation is $\dfrac{\frac{1}{\lambda}}{\frac{1}{\lambda}+\frac{1}{\mu}}$, the operative time of the whole assembly line is no larger than $T_{total} \cdot \dfrac{\mu}{\lambda+\mu}$. Thus, a relatively safe demand rate d at t_0 should be at least $\dfrac{D_0}{T_{total} \cdot \frac{\mu}{\lambda+\mu}}$. In addition, the re-balancing decision is made only when there is a risk that the demand cannot be satisfied, thus, after re-balancing, d is set to be a small value (it is 10^{-6} in this study) smaller than pr_{ini} in order to make up for the production loss due to assembly plan modification as soon as possible.

The surplus rate ranges from -1 to 1. When it is larger than 0, there is more inventory; Otherwise, there are backlogs. The fuzzy set of production surplus rate is {very small, small, medium, large, very large}.

(3) Output variable: production rate adjustment of workstation i, adj_pr_i

The output adj_pr_i is the adjustment suggestion for pr_i, and ranges from -1 to 1. The fuzzy terms set is {very small, small, medium, large, very large}. When adj_pr_i is larger than 0, pr_i should be increased toward $pr_{\max}^i$. Otherwise, pr_i should be decreased toward 0. The production rate after adjustment is defined in equation (10) as follows:

$$pr_i' = \begin{cases} pr_i + adj\_pr_i \cdot \left(pr_{\max}^i - pr_i\right), & adj\_pr_i \geq 0 \\ pr_i + adj\_pr_i \cdot \left(pr_i - 0\right), & adj\_pr_i < 0 \end{cases}. \tag{10}$$

There are 125 rules for the type 2 fuzzy controllers (see Table 2). When there is no risk of starvation or blockage, pr_i should be adjusted mainly based on S_i. Otherwise, since the adverse impact of starvation and blockage propagates throughout the assembly line, pr_i should be adjusted to eliminate starvation and blockage.

Table 2

Fuzzy rule base for type 2 fuzzy controllers

S_i=VS					
	BL_i				
BL_{i-1}	VS	S	ME	L	VL
VS	L	S	S	S	VS
S	VL	VL	VL	L	VS
ME	VL	VL	VL	VL	S
L	VL	VL	VL	VL	S
VL	VL	VL	VL	VL	ME
S_i=S					
	BL_i				
BL_{i-1}	VS	S	ME	L	VL
VS	L	S	S	VS	VS
S	VL	VL	L	L	VS
ME	VL	VL	VL	L	S
L	VL	VL	VL	L	S
VL	VL	VL	VL	L	ME
S_i=ME					
	BL_i				
BL_{i-1}	VS	S	ME	L	VL
VS	ME	S	VS	VS	VS
S	VL	ME	ME	ME	VS
ME	VL	L	ME	ME	S
L	VL	VL	ME	ME	S
VL	VL	VL	L	ME	ME
S_i=L					
	BL_i				
BL_{i-1}	VS	S	ME	L	VL
VS	S	VS	VS	VS	VS
S	ME	S	S	S	VS
ME	ME	S	S	S	VS
L	L	ME	S	S	S
VL	VL	L	L	ME	ME
S_i=VL					
	BL_i				
BL_{i-1}	VS	S	ME	L	VL
VS	VS	VS	VS	VS	VS
S	S	VS	VS	VS	VS
ME	ME	VS	VS	VS	VS
L	L	ME	VS	VS	VS
VL	VL	L	L	ME	ME

4.2.4 Defuzzification

The output generated by the fuzzy inference engine is a set of fuzzy membership values [40]. Fuzziness helps rule evaluation during the intermediate steps. However, the final desired output is generally a single number. Therefore, all the outputs are transferred into the final crisp value by a widely used defuzzification method: the centroid method, which assesses the center of gravity of the possible distribution of the fuzzy output [40], and is defined in equation (11) as follows [41]:

$$y = \frac{\sum_{r=1}^{R_l} A^{\alpha r} C_{A^{\alpha r}}}{\sum_{r=1}^{R_l} A^{\alpha r}} \tag{11}$$

where $A^{\alpha r}$ denotes the area of consequent's fuzzy subset, which is obtained by α membership determined by the r^{th} rule. $C_{A^{\alpha r}}$ is the center of area $A^{\alpha r}$. R_l designates the number of fuzzy rules.

5. Numerical experiments

5.1 Numerical experiments design

The assembly line used to test the fuzzy control system is defined by KILBRID (45 tasks), and the task times and precedence relationship information can be found in the SALBP data sets shown on https://assembly-line-balancing.de/salbp/benchmark-data-sets-1993/. Table 3 shows the original information of the task times and the precedence graph of the chosen instance. However, the total simulation time is set to be 1000, and in order to be consistent with this setting, all the task times in this study are made to be 100 times smaller so that $t_{\min}$, $t_{\max}$ and t_{avg} become to 0.03, 0.55 and 0.12267. The first column is the total number of tasks, and the second to the fifth columns are the minimal, maximal, total and average task times, respectively. The sixth column shows the order strength of the precedence graph, which is calculated by the ratio of the number of all precedence relations to $n \cdot (n-1)$. TV is the time variability ratio defined by $\frac{t_{\max}}{t_{\min}}$, and div and $conv$ are the degrees of divergence and convergence of the precedence graph.

Table 3

Original information of task times and the precedence graph of KILBRID

n	$t_{\min}$	$t_{\max}$	t_{sum}	t_{avg}	OS	TV	div	$conv$
45	3	55	552	12.267	44.55	18.33	0.67	0.69

There are 8 workstations in total, and the assembly line is balanced with all tasks assigned to these 8 workstations. Some workstations which need excessively long maintenance may be closed, and after the maintenance work is completed, whether a closed workstation should be opened again is based on the fuzzy control system. Although we only chose one instance from the SALBP data set, different characteristics of machine states and different production rates required by the demand will be considered to examine the effectiveness of the proposed fuzzy system. For each combination of parameters, there are ten random runs, and different seeds are used to guarantee the independent states of the machines.

Since the problem defined in this study is novel, there are no benchmark instances in the existing literature. In order to model different levels of information transparency and make comparisons, we set three kinds of comparative assembly lines. Table 4 shows the characteristics of the four kinds of assembly lines discussed in this study. The length of the time from the breakdown of the machine in station i to the recognition of the breakdown follows a normal distribution with a mean which is a multiple of T_{S_i}, which denotes the sum of the processing times of tasks assigned to station i. Since the real-time information is not only collected but also analyzed, the assembly line with the proposed fuzzy system (AS_1) achieves higher-level information transparency compared with the other three assembly lines. From AS_2 to AS_4, the level of information transparency decreases.

Table 4

Assembly lines to be compared in this study

Name	There is a fuzzy system	Production rate	Is there a maintenance delay	Description of the delay when it is applicable
AS_1	Yes	$0 \le pr_i \le pr_{\max}^i$	No	-
AS_2	No	$pr_i = pr_{\max}^i$	No	-
AS_3	No	$pr_i = pr_{\max}^i$	Yes, and it follows a normal distribution	the mean is $5T_{S_i}$ and the standard deviation is 3
AS_4	No	$pr_i = pr_{\max}^i$	Yes, and it follows a normal distribution	the mean is $10T_{S_i}$ and the standard deviation is 5

Figure 4 shows the assembly process with the proposed fuzzy system. FC_1 is used to determine whether to re-balance the assembly line. If it is decided to re-balance the assembly line, then the re-balancing solution is prepared and undertaken. Otherwise, FC_2 to FC_9 are activated to adjust the production rate of each workstation.

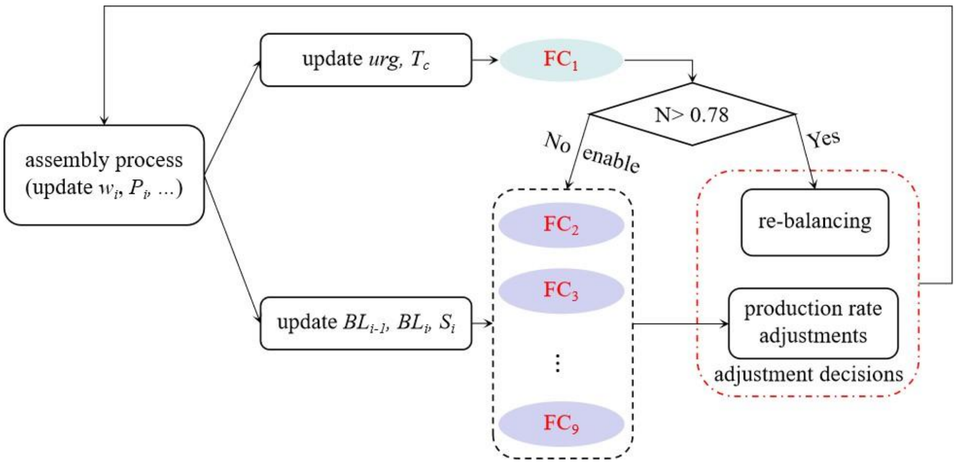

Figure 4. Assembly process with the proposed fuzzy system

As solution development for the assembly line re-balancing problem is not the main contribution of this study, the algorithm of ACO-BS developed by Huo et al. [42] to solve ALBP is used iteratively to generate the re-balancing solution, given the number of available workstations and the initial assembly plan. The framework of this method is shown in Figure 5. LB denotes the lower bound of cycle time, given the number of available workstations m^*, and is initialized to be $\max\left\{t_{\max}, \frac{t_{sum}}{m^*}\right\}$. tr_i denotes the sum of the preparation times of all the reassigned tasks for the solution s_i. The given cycle time is increased by 1 step by step to find all the possible cycle times, with all the available stations utilized. Finally, the re-balancing solution is obtained by considering both the cycle time and the corresponding preparation time for re-balancing.

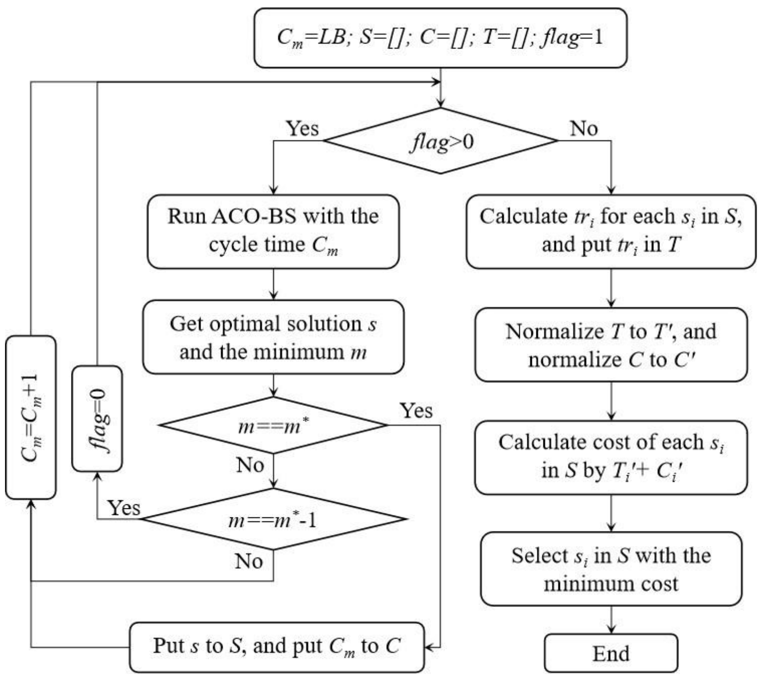

Figure 5. Framework of the method to generate the re-balancing solution

5.2 Numerical results

The numerical experiments were done with Simulink in MATLAB (R2016a). The learning effect was set to occur at a simulation time of 500. The task time reduction rate r_i was generated following the uniform distribution in the interval (0, 0.1), with mean 0.050, and standard deviation 0.027. For comparison reasons, the same setting related to the learning effect was used for all the cases. Additionally, all the buffer capacity of the buffer between workstations was set to be 25 units, and the preparation time for each task was set to be 0.01. The experiment stops when the simulation time is used up or the demand is satisfied.

There are 5 different combinations of λ and μ, 3 levels of d_0 (measured by $\frac{D_0}{T_{total}}$), and 4 different assembly lines. For each assembly line, there are 15 different cases to test, and for each case, the average values and the standard deviations of the ten random runs are calculated and shown in Tables 5a and 5b. For each experiment, six indicators are shown, that is, blockage ratio (ratio of the length of blockage to the total simulation time), average buffer level, starvation ratio (ratio of the length of starvation to the total simulation time), simulation time used, total production and number of times of assembly line re-balancing.

Table 5a

Results of the numerical experiments

λ	μ	μ/λ	No.	Mean and std	d_0=1						d_0=0.7						d_0=0.3					
					b_r	BL	st_r	t	P	no_r	b_r	BL	st_r	t	P	no_r	b_r	BL	st_r	t	P	no_r
0.1	0.5	5	AS_1	mean	0.000	0.347	0.047	949.409	1000.00	0.000	0.000	0.123	0.062	803.144	700.000	0.000	0.000	0.089	0.031	559.940	300.000	0.000
				std	0.000	0.064	0.008	21.739	0.000	0.000	0.000	0.018	0.012	9.844	0.000	0.000	0.000	0.002	0.004	5.607	0.000	0.000
			AS_2	mean	0.016	0.362	0.071	918.023	1000.00	0.000	0.011	0.327	0.083	671.585	700.000	0.000	0.007	0.244	0.119	315.004	300.000	0.000
				std	0.010	0.085	0.023	22.647	0.000	0.000	0.006	0.085	0.026	17.781	0.000	0.000	0.006	0.065	0.023	15.842	0.000	0.000
			AS_3	mean	0.053	0.428	0.118	1000.00	725.900	0.000	0.053	0.428	0.117	964.831	699.600	0.000	0.039	0.363	0.153	466.546	300.000	0.000
				std	0.017	0.075	0.035	0.000	31.370	0.000	0.017	0.078	0.029	22.982	1.265	0.000	0.020	0.086	0.032	30.299	0.000	0.000
			AS_4	mean	0.087	0.444	0.155	1000.00	512.900	0.000	0.079	0.430	0.153	1000.00	525.000	0.000	0.063	0.384	0.184	639.721	300.000	0.000
				std	0.032	0.077	0.036	0.000	39.159	0.000	0.023	0.057	0.032	0.000	27.793	0.000	0.025	0.062	0.026	29.157	0.000	0.000
0.01	0.1	10	AS_1	mean	0.003	0.285	0.090	967.039	999.200	0.333	0.000	0.126	0.062	863.241	700.000	0.000	0.000	0.095	0.041	594.412	300.000	0.000
				std	0.011	0.051	0.025	34.312	1.751	0.707	0.000	0.016	0.028	29.816	0.000	0.000	0.000	0.003	0.016	16.654	0.000	0.000
			AS_2	mean	0.067	0.435	0.098	911.229	1000.00	0.000	0.066	0.429	0.103	652.414	700.000	0.000	0.032	0.307	0.136	295.451	300.000	0.000
				std	0.024	0.089	0.032	44.328	0.000	0.000	0.022	0.080	0.029	26.334	0.000	0.000	0.036	0.123	0.036	25.368	0.000	0.000
			AS_3	mean	0.092	0.462	0.120	976.718	982.600	0.000	0.092	0.440	0.134	724.977	700.000	0.000	0.054	0.332	0.160	325.486	300.000	0.000
				std	0.029	0.101	0.036	27.294	33.662	0.000	0.030	0.094	0.034	37.823	0.000	0.000	0.050	0.139	0.038	37.421	0.000	0.000
			AS_4	mean	0.114	0.460	0.154	1000.00	904.400	0.000	0.111	0.454	0.145	777.045	700.000	0.000	0.088	0.367	0.186	372.435	300.000	0.000
				std	0.023	0.078	0.042	0.000	59.024	0.000	0.029	0.074	0.032	52.693	0.000	0.000	0.073	0.140	0.039	47.908	0.000	0.000
0.01	0.5	50	AS_1	mean	0.000	0.082	0.017	924.738	1000.00	0.000	0.000	0.088	0.017	835.108	700.000	0.000	0.000	0.085	0.022	590.860	300.000	0.000
				std	0.000	0.001	0.001	2.036	0.000	0.000	0.000	0.001	0.001	3.102	0.000	0.000	0.000	0.000	0.001	0.544	0.000	0.000
			AS_2	mean	0.000	0.138	0.029	727.136	1000.00	0.000	0.000	0.107	0.031	519.023	700.000	0.000	0.000	0.054	0.045	228.329	300.000	0.000
				std	0.001	0.027	0.006	3.864	0.000	0.000	0.000	0.028	0.006	6.212	0.000	0.000	0.000	0.027	0.014	5.763	0.000	0.000
			AS_3	mean	0.011	0.324	0.051	787.344	1000.00	0.000	0.009	0.265	0.067	572.001	700.000	0.000	0.001	0.143	0.088	254.766	300.000	0.000
				std	0.005	0.046	0.009	15.836	0.000	0.000	0.006	0.055	0.016	14.634	0.000	0.000	0.002	0.042	0.022	8.706	0.000	0.000
			AS_4	mean	0.041	0.408	0.077	861.475	1000.00	0.000	0.031	0.350	0.089	621.326	700.000	0.000	0.014	0.237	0.117	286.753	300.000	0.000
				std	0.015	0.056	0.015	22.755	0.000	0.000	0.013	0.072	0.020	18.745	0.000	0.000	0.011	0.065	0.027	12.734	0.000	0.000

Table 5b

Results of the numerical experiments

λ	μ	μ/λ	No.	Mean and std	d_0=1						d_0=0.7						d_0=0.3					
					b_r	BL	st_r	t	P	no_r	b_r	BL	st_r	t	P	no_r	b_r	BL	st_r	t	P	no_r
0.001	0.1	100	AS_1	mean	0.000	0.093	0.039	938.273	1000.00	0.000	0.000	0.091	0.028	840.511	700.000	0.000	0.000	0.086	0.024	594.759	300.000	0.000
				std	0.000	0.015	0.022	11.883	0.000	0.000	0.000	0.005	0.014	2.664	0.000	0.000	0.000	0.002	0.008	4.481	0.000	0.000
			AS_2	mean	0.011	0.203	0.048	750.031	1000.00	0.000	0.013	0.163	0.051	540.471	700.000	0.000	0.012	0.099	0.070	240.230	300.000	0.000
				std	0.010	0.097	0.024	29.281	0.000	0.000	0.013	0.080	0.034	31.280	0.000	0.000	0.022	0.088	0.066	29.834	0.000	0.000
			AS_3	mean	0.015	0.238	0.054	763.129	1000.00	0.000	0.016	0.182	0.059	553.254	700.000	0.000	0.014	0.113	0.078	243.959	300.000	0.000
				std	0.013	0.089	0.028	31.488	0.000	0.000	0.015	0.070	0.036	32.275	0.000	0.000	0.023	0.084	0.066	29.451	0.000	0.000
			AS_4	mean	0.023	0.280	0.060	781.053	1000.00	0.000	0.021	0.200	0.065	562.290	700.000	0.000	0.018	0.128	0.089	251.713	300.000	0.000
				std	0.015	0.092	0.033	34.417	0.000	0.000	0.017	0.067	0.038	32.991	0.000	0.000	0.031	0.084	0.077	36.822	0.000	0.000
0.001	0.3	300	AS_1	mean	0.000	0.081	0.017	933.622	1000.00	0.000	0.000	0.087	0.017	842.267	700.000	0.000	0.000	0.085	0.022	594.838	300.000	0.000
				std	0.000	0.000	0.001	2.134	0.000	0.000	0.000	0.000	0.000	1.353	0.000	0.000	0.000	0.000	0.000	0.095	0.000	0.000
			AS_2	mean	0.000	0.036	0.013	697.191	1000.00	0.000	0.000	0.026	0.012	494.844	700.000	0.000	0.000	0.013	0.018	214.962	300.000	0.000
				std	0.000	0.021	0.003	3.281	0.000	0.000	0.000	0.023	0.005	3.809	0.000	0.000	0.000	0.016	0.005	3.626	0.000	0.000
			AS_3	mean	0.000	0.090	0.020	709.865	1000.00	0.000	0.000	0.060	0.019	503.267	700.000	0.000	0.000	0.034	0.028	219.521	300.000	0.000
				std	0.000	0.051	0.004	6.178	0.000	0.000	0.000	0.038	0.007	5.083	0.000	0.000	0.000	0.031	0.011	6.124	0.000	0.000
			AS_4	mean	0.001	0.130	0.024	721.407	1000.00	0.000	0.001	0.108	0.029	516.427	700.000	0.000	0.001	0.061	0.038	225.219	300.000	0.000
				std	0.003	0.081	0.006	10.219	0.000	0.000	0.001	0.088	0.012	13.785	0.000	0.000	0.002	0.058	0.019	10.527	0.000	0.000

To show the findings of this study, the numerical results clustered by the performance indicators are shown in Figures 6a to 8. For each kind of assembly line, the performance of fifteen cases is shown. The demand rates are 1, 0.7 and 0.3 for cases 1 to 5, cases 6 to 10 and cases 11 to 15, respectively.

Figures 6a to 6c shows the average starvation ratio, blockage ratio and idle ratio (the sum of starvation ratio and blockage ratio). As these three figures (6a-6c) show, the assembly line with the proposed fuzzy system has significantly less blockage, less starvation and a higher level of machine utilization, and there is almost no blockage for all the cases. When machine breakdown is recognized more slowly, there is more idle time for an assembly line. Additionally, the idle time for AS_1 is the least, which indicates that the idle time is reduced further when actions are taken in time to deal with disruptions. Thus, there is less blockage, less starvation and a higher level of machine utilization when the level of information transparency is higher.

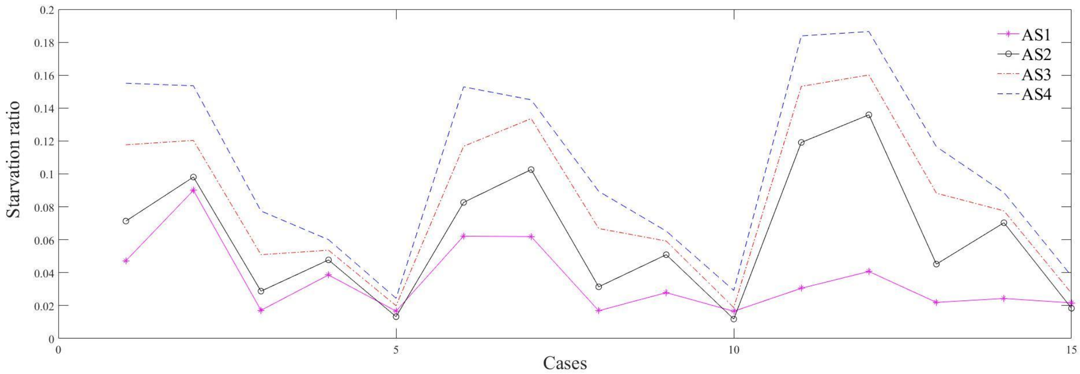

Figure 6a. Average starvation ratio for the four assembly lines

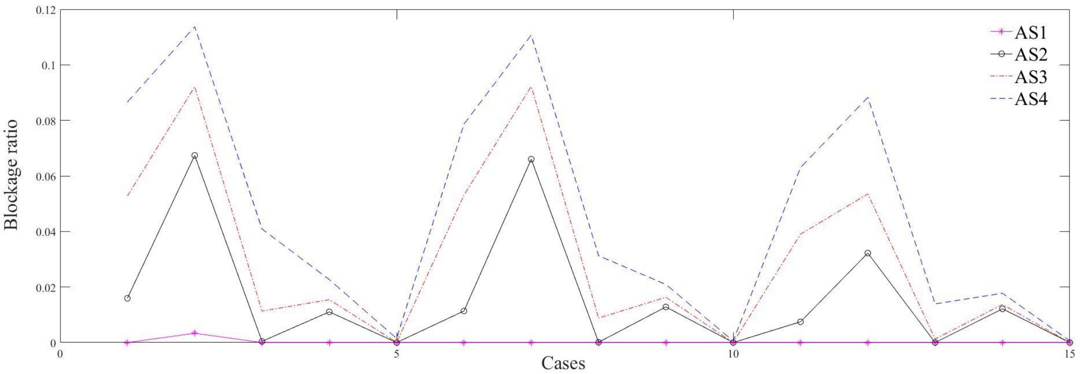

Figure 6b. Average blockage ratio for the four assembly lines

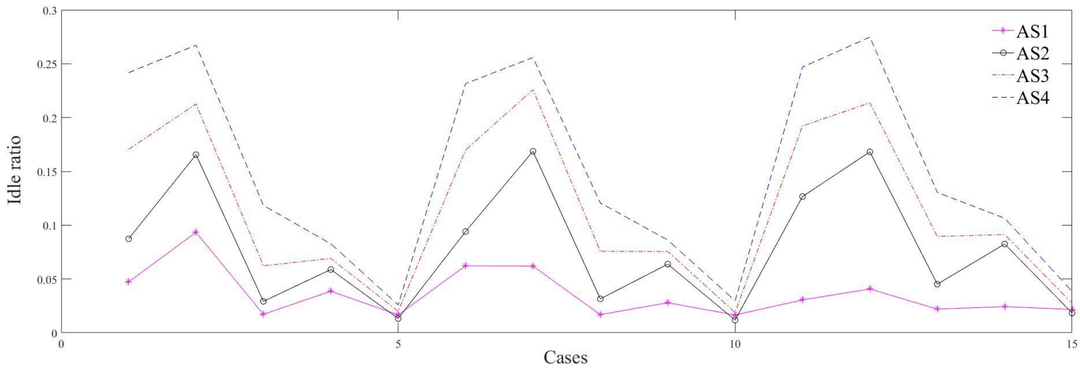

Figure 6c. Average idle ratio for the four assembly lines

Figure 7 shows the results related to the buffer level. For AS_1, except for the first two cases, the buffer levels are about 0.1. In general, the buffer level of AS1 is significantly lower than that of the other three assembly lines, and stays at a stable level. Not surprisingly, the buffer levels of AS_2, AS_3 and AS_4 rank the second, third and fourth, which indicates that the buffer level decreases significantly with the increase of information transparency level. Therefore, timely recognition of the disruptions and in-time adjustment of the assembly line are helpful to keep the WIP at a low level.

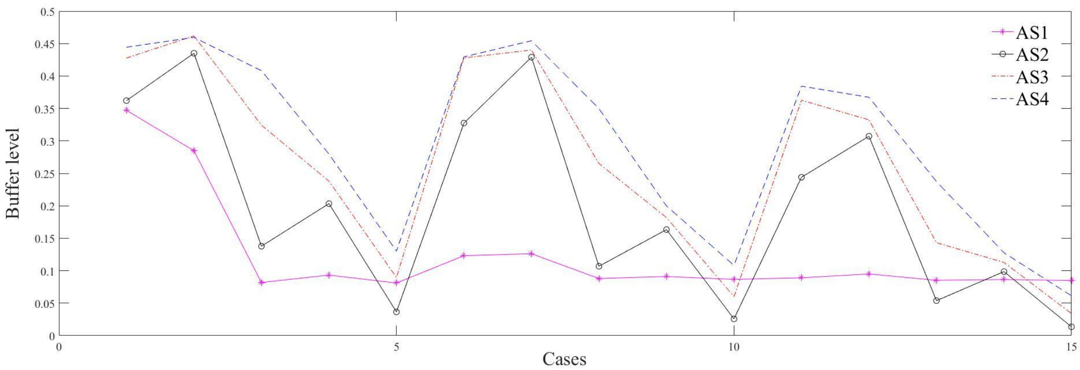

Figure 7. Average buffer levels for the four assembly lines

Figure 8 shows the total production information for the four assembly lines. For cases 1 to 5, the demand quantity is 1000 units, and there is a large backlog for AS3 and AS4. For cases 6 to 10, the demand quantity is 700 units, and there is a large backlog for only AS4. For cases 11 to 15, production of the four assembly lines satisfies the demand (300 units). AS3 and AS4 show worse production ability, which suggests that the information transparency positively affects the production ability of an assembly line. When disruptions are recognized and dealt with in time, production losses caused by disruptions can be reduced.

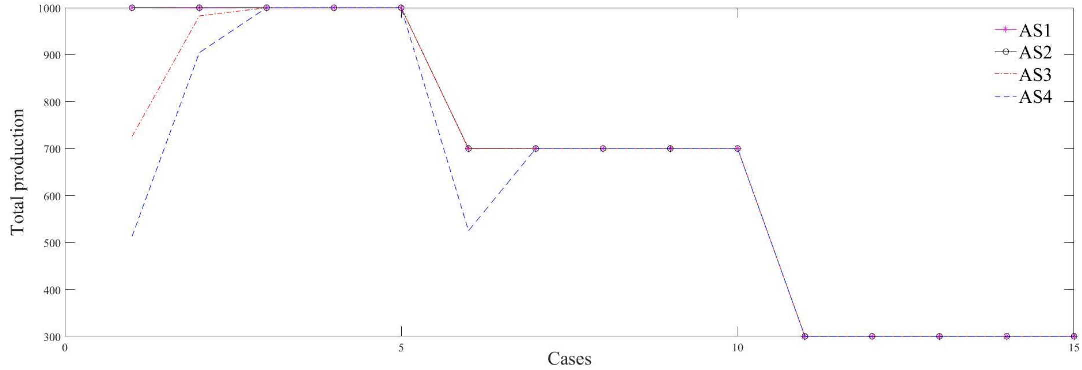

Figure 8. Average total production for the four assembly lines

Thus, the higher the information transparency level is, the better the performance of an assembly line becomes. For an assembly line with the proposed fuzzy system, real-time information can be analyzed, and in-time adjustments are undertaken accordingly. The performance is better due to the right decisions made by the proposed fuzzy system.

It can be seen from Tables 5a and 5b that assembly line re-balancing is conducted only for one case ($\lambda = 0.01$, $\mu = 0.1$, $d_0 = 1$). For ten runs in that case, assembly line re-balancing takes place in two runs. In order to explore the impact of the preparation time of each task when it is reassigned to another workstation, the preparation time is increased to 0.10 from 0.01, and the numerical results are shown in Table 6. This change does not affect the results of those cases without assembly line re-balancing, thus, only the results for the two special cases are discussed further. For AS_1 without FC_1, the production rates of the workstations are adjusted in time, but whether assembly line re-balancing is necessary is not examined.

Table 6

Numerical results of the two random cases where re-balancing are taken place

No.	random cases	Avg. b_r	Avg. BL	Avg. st_r	t	P	no_r
1	AS_1	0.000	0.314	0.074	999.620	997	2
	AS_1 (with increased T_r)	0.000	0.315	0.072	997.530	994	1
	AS_1 (without FC_1)	0.000	0.326	0.067	1000.000	986	0
	AS_2	0.105	0.482	0.060	902.590	1000	
	AS_3	0.124	0.517	0.074	979.800	1000	
	AS_4	0.131	0.561	0.085	1000.000	982	
2	AS_1	0.033	0.294	0.094	996.870	1000	1
	AS_1 (with increased T_r)	0.033	0.294	0.094	996.870	1000	1
	AS_1 (without FC_1)	0.000	0.260	0.127	1000.000	963	0
	AS_2	0.077	0.379	0.145	969.670	1000	
	AS_3	0.093	0.402	0.170	1000.000	945	
	AS_4	0.106	0.390	0.235	1000.000	799	

As seen in Table 6, when the preparation time for each task is increased to 0.10 from 0.01, there are no significant changes in the performance of AS_1. For the first special case, the total production is 986 units when there are production rate adjustments but no assembly line re-balancing, and the production increases to 997 units when both production rate adjustments and re-balancing are allowed. There is a relatively large difference between the total production of AS_4 and the demand quantity. Although the production for AS_2 and AS_3 can satisfy the demand within the simulation time, the buffer levels are 153.503% and 164.650% of the buffer level of AS_1, and the utilization of the machines for AS_2 and AS_3 are also significantly smaller than for AS_1. Similar rules are found for the second special case.

6. Conclusions

Disruptions break the initial balance of an assembly line, and negatively affect the collaboration between workstations and lead to worsening performance. In this study, the assembly process is discussed in a dynamic environment, where there are task time reductions due to the learning effect, maintenance due to machine failures, starvation and blockage. A fuzzy control system is developed to deal with the unpredictable disruptions. Based on the results of the fuzzy control system proposed in this study, an assembly line is re-balanced with tasks re-assigned to the available workstations so as to decrease the adverse impact of failed workstations on the whole assembly line. Meanwhile, since starvation and blockage can propagate throughout the assembly line, the production rate of each workstation is monitored and controlled by a fuzzy controller. Consequently, the production rate of each workstation tends to be maximum when there is no risk of blockage or starvation, and is adjusted when it is necessary.

To examine the effectiveness of the proposed fuzzy control system, the performance of four kinds of assembly lines (AS_1, AS_2, AS_3 and AS_4) are compared. We can see from the numerical results that with the increase of information transparency level, the performance of an assembly line is better. Not surprisingly, AS_1 performs much better in terms of blockage ratio, starvation ratio and the buffer level, with the satisfaction of demand considered. Thus, information transparency positively affects the performance of an assembly line, and Industry 4.0 will lead us to a more intelligent and efficient era. Practitioners should devote more effort to the adoption and application of new advanced technologies to improve the information transparency level and the intelligence level of the assembly process.

There are some limitations in this study. Although a promising fuzzy control system is used to deal with the disruptions of an assembly line, only a straight assembly line is considered. The more complex assembly lines will be discussed in the next stage. Besides, it is assumed that the production rates of the workstations do not change without adjustment. However, the production rate of one workstation will not remain constant even without adjustment, since the health state of machines will not be always the same. This will be considered in future research.

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