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Intelligent workload balance control of the assembly process considering condition-based maintenance

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Abstract: Balancing the workloads of workstations is key to the efficiency of an assembly line. However, the initial balance can be broken by the changing processing abilities of machines because of machine degradation, and at some point, re-balancing of the line is inevitable. Nevertheless, the impacts of unexpected events on assembly line re-balancing are always ignored. With the advanced sensor technologies and Internet of Things (IoT), the machine degradation process can be monitored continuously, and condition-based maintenance can be implemented to improve the health state of each machine. With the technology of robotic process automation, workflows of the assembly process can be smoothed and workstations can work autonomously together. A higher level of process automation can be achieved. Real-time information of the processing abilities of machines will bring new opportunities for automated workload balance via adaptive decision-making. In this study, a fuzzy control system is developed to make real-time decisions to balance the workloads based on the processing abilities of workstations, given the policy of condition-based maintenance. Fuzzy controllers are used to decide whether to re-balance the assembly line and how to adjust the production rate of each workstation. The numerical experiments show that the buffer level of the assembly line with the proposed fuzzy control system is lower than that of the assembly line without any control system and the buffer level of the assembly line with another control system is the lowest. The demand can always be satisfied by assembly lines except the one with another control system since there is too much production loss sacrificed for the low buffer level. The sensitivity analysis of the control performance to the parameter settings is also conducted. Thus, the effectiveness of the proposed fuzzy control system can be demonstrated, and intelligent automation can improve the performance of the assembly process by the fuzzy control system since real-time information of the assembly line can be used for adaptive decision-making.

Keywords: Assembly line re-balancing; Machine degradation; Condition-based maintenance; Fuzzy control system; Intelligent automation; Robotic process automation

1 Introduction

Assembly line balancing problem (ALBP) is key to the efficiency of the assembly process. However, the assembly process is prone to disruptions. Disruptions associated with workstations, buffers or raw materials can affect the assembly process negatively, and the adverse impact can

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propagate along the assembly line. Thus, the assembly process should be monitored and controlled in real time to smooth the workflow. Industry 4.0, the fourth industrial revolution, brings new possibilities for the assembly systems. Internet of Things (IoT), as the basic premise for the implementation of Industry 4.0 [1], has a significant influence on the developments of smart workshop [2]. Cyber-Physical Systems (CPS), which is another key technology of Industry 4.0, can manage the integration of data collected from a factory, and enables information to be monitored and synchronized between the physical world and the cyber environment [3]. With the real-time information obtained, the production process can be optimized and re-optimized, thus, intelligent manufacturing, which will bring revolutionary changes [4], is possible. Smart systems such as smart robotic mobile fulfillment system [5], warehouse management system for smart logistics [6], smart product-service systems [7, 8], smart active maintenance system [4], smart suite for smart factory towards re-industrialization [9] and smart home system [10] have been proposed based on the advanced technologies of Industry 4.0.

With the development of information and communication technologies (ICT), information technology is embedded in normal products and transforms them to smart, connected products so that information can be generated [11]. IoT brings internet to all kinds of devices so that they can not only collect and send information but also receive information. Additionally, IoT can significantly affect the tracking applications [2], therefore, the work-in-progress during the production process can be tracked more easily and accurately. Due to the digital transformation enabled by ICT, physical products can be digitized in the virtual space and interconnected [12]. As a result, a workstation of an assembly line can 'communicate' with its upstream and downstream workstations and buffers to get access to both local information and global information. Then, information barriers between different parts of an assembly line can be broken, and centralized and decentralized decision-making are possible. Robotic process automation (RPA), a new technology that consists of software agents that mimic the manual routine decisions via various computer applications, has attracted attention in Industry and academia [13]. It is enabled by the advanced information technologies, and brings new possibilities to the assembly process: workstations can work autonomously with each other to satisfy the demand, and can collaborate with each other to deal with unexpected events and decrease work-in-progress. Since the benefits brought by the advanced technologies can be fused by the automation with analytics and decision-making via tools of artificial intelligence, traditional automation of the assembly process can be improved to be intelligent automation [14]. Therefore, an intelligent control system of the assembly process enabled by the latest technologies of Industry 4.0 is possible, and it is necessary to decrease the negative impacts of unexpected events and increase the line efficiency.

Machine degradation can affect the duration of job processing, and will negatively affect the workload balance of an assembly line. Thus, the degradation process and machine state should be monitored so that workloads of workstations can be balanced with the real-time processing abilities of workstations. With the development of sensor technologies, it is possible to monitor the machine degradation process, and the information collected can be used to build and optimize the schedule of condition-based maintenance, which is to implement maintenance operations based on the online measurements of machine degradation level [15]. Besides, IoT enables real-time information collection to be possible, and helps establish efficient maintenance strategies at low cost with the related information [10]. The findings of Ghaleb et al. [16] indicated that significantly increase savings could be obtained when the accurate information of machines' degradation process were incorporated in the condition-based maintenance strategies. Thus, smart machines can send their working status to a central cloud-based "manager" [17], and real-time degradation information can be levered to implement condition-based maintenance and improve the health state of each machine at the right time.

Some researchers explored the production scheduling problems and modeled the impact of deterioration effect on job processing time with a linear or non-linear function of start time (e.g. [18, 19]) or the position of the job (e.g. [20, 21]). However, the link between the extent of machine degradation and production re-scheduling was not discussed by these studies. With respect to assembly line re-balancing, to react quickly to the disruptions to the assembly process, Belassiria et al. [22] and Girit and Azizoğlu [23] explored the assembly line re-balancing solution with methods based on genetic algorithm and both exact and tabu search algorithm, respectively. Meanwhile, to respond quickly to changes, Moghaddam et al. [24] utilized reconfigurable manufacturing systems with modular reconfigurable machine tools to adjust production capacity of the system. However, these researches focused on searching the re-optimization solutions with the assumption that the re-balancing decision has been made already, and when to re-balance the assembly line was still not examined.

The link between the extent of disruptions and the decision-making process of assembly line re-balancing is examined by only a few researches. Suwa [25] and Valledor et al. [26] proposed the periodic re-scheduling policy, and whether to implement re-scheduling was determined based on the condition at the predetermine inspection times. However, the effectiveness of such policies would inevitably depend on the predetermined inspection interval, and the real-time decision-making was not possible. In our previous work [27, 28], a fuzzy control system was proposed to determine when to re-balance the workloads and manage the inventory level of work-in-progress. Nevertheless, it was assumed that no maintenance activities would be conducted until machines of an assembly line broke down. Therefore, it is necessary to build a real-time control system and develop a link between the extent of disruptions and the re-balancing decision, and real-time information of the machine degradation process should be utilized to implement condition-based maintenance.

Due to the randomness and non-linearity caused by unpredictable disruptions, accurate analysis of the assembly line is difficult. However, fuzzy controllers provide an efficient architecture to incorporate the linguistic information from the knowledge of experts to the final automated decisions. Thus, fuzzy control theory is chosen to design the control system of the assembly process, and is used to determine the trigger point of assembly line re-balancing in a novel way. To fill the above research gaps, this study integrates the fuzzy logic principles and the assembly line monitoring and control mechanism, and enables the effective decision-making process of how to manage the inventory level of the work-in-progress and when to re-balance the assembly line, which is of great importance to the efficiency of assembly lines but always ignored in the current literature. During the control process, fluctuations of processing abilities of machines due to machine degradation and condition-based maintenance are considered. A fuzzy control system is proposed to analyze the real-time information collected from the assembly process and balance the workloads by not only adjusting the production rates of workstations but also re-balancing the workloads by task re-assignments when necessary. Two kinds of assembly line re-balancing strategies are used so that two levels of modifications of the initial assembly plan can be implemented to the assembly line. The machine degradation process is assumed to be monitored continuously in real time so that the changing processing abilities of workstations can be considered in the decision-making process. This study explores the smart balance control of an assembly line with the consideration of the information brought by the advanced technologies in Industry 4.0. The research findings will shed light on the intelligent control of the assembly process and contribute to the smart manufacturing theory.

The remaining sections of this paper are organized as follows. In section 2, literature on production scheduling considering the deterioration effect and the real-time control of the production process is reviewed. Section 3 shows the problem definition and the proposed fuzzy control system. The results of the numerical experiments are shown in section 4. Section 5 presents the conclusions of this study.

2 Literature review

2.1 Production scheduling considering the deterioration effect

In the traditional production scheduling problems, it is assumed that the processing time of a job is constant. However, due to the deterioration effect, the duration of job processing increases with the increase of the total operation time; The duration decreases if the learning effect is considered.

The impact of machine degradation on job processing is modeled by a linear increasing function of the job's starting time by some researchers. For example, Woo and Kim [29] explored a parallel machine scheduling with time-dependent deterioration and multiple rate-modifying activities, and the deterioration was modeled by a linear function. Li et al. [30] proposed a new algorithm to deal with a parallel batching distributed flow-shop problem, and the considered deterioration effect was linear and time-dependent. Zhang et al. [31] studied linear deteriorated jobs and maintenance activities under the potential disruption parallel machines, and the linear time-dependent deterioration effect was considered. Meanwhile, the nonlinear time-dependent deterioration was considered in a single machine scheduling problem by Wang and Wang [32]. Additionally, some researchers consider the deterioration and learning effects simultaneously so that the processing time could fluctuate rather than be constant. In simple assembly line balancing problems, Toksarı et al. [18] considered both linear and non-linear time-dependent deterioration effects and the learning effect. Soleimani et al. [19] incorporated the impacts of start-time-related deterioration and position-related learning and sequence-related setup times on the processing time of each job simultaneously in an unrelated parallel machine scheduling problem, with the objectives of minimize the mean weighted tardiness and power consumption.

Compared with the studies considering the start-time-related deterioration effect, there are only a few studies considering the position dependent deterioration effect. Many researchers studied the scheduling problems considering only special cases, however, Mosheiov [20] introduced a polynomial time solution for the multi-machine scheduling problem, and studied the general, non-decreasing, job-dependent and position-dependent deterioration effect. Yin et al. [33] considered job deterioration as well as learning effects so that the processing time of a job was determined by both the total processing time of all the job already and the scheduled position. Lee et al. [34] studied the joint optimization of maintenance and multi-machine scheduling with deterioration effects, which was position dependent. To minimize the makespan and the total completion times, Rustogi and Strusevich [35] introduced a general model for single machine scheduling problems, with the processing times subject to positional and time-dependent deterioration and learning effects considered. Arık and Toksarı [21] investigated the fuzzy parallel machine scheduling problems under fuzzy job deterioration and learning effects, and considered the linear and non-linear position-related deterioration effect with different types of models. Wang et al. [36] investigated a due date assignment and multitasking scheduling problem, with position-dependent deterioration effect and efficiency promotion considered.

In addition, some researchers try to divide the machine degradation process into small intervals with different degradation levels, and the processing time in different intervals shows different characteristics. For example, Mosheiov [37] explored makespan minimization of step-wise deteriorating jobs, and the step functions, featured by a sharp change in processing time at the deadline points, was used to model the effect of machine degradation on processing time. Ghaleb et al. [16] explored the joint optimization of production scheduling and maintenance planning in a single-machine production environment. They modeled the machine degradation process as a Markov chain so that the process was a multi-state degradation process, and the impact of machine degradation on the processing time of each state was modeled.

Therefore, although the above studies explored the production scheduling problems considering the impact of machine deterioration on the variations of processing times, real-time impact of the machine degradation process on the assembly process was not discussed. With the increase of machine degradation level, a serious workload imbalance of workstations will occur and assembly line re-balancing may be inevitable. As a result, it is essential to examine the relationship between assembly line re-balancing and the extent of machine degradation.

2.2 Real-time control of the production process

Assembly lines are prone to disruptions caused by task time changes, cycle time changes, technological changes and workstation breakdowns [23]. The effects of such disruptions on the production process cannot be overlooked, since the negative effects can propagate along the assembly line. To response quickly to the disruptions, some researchers explored the re-balancing solutions with mathematical models and the corresponding algorithms. For example, To quickly react to the disruption due to demand changes, Belassiria et al. [22] proposed a method based on the genetic algorithm to re-balance the assembly line, and the objective was to maximize the line efficiency and allocate the idle time into workstations evenly. Girit and Azizoğlu [23] developed both exact algorithm and tabu search algorithm to re-balance the assembly line by making a trade-off between the fairness measure and the stability measure. On the other hand, Moghaddam et al. [24] developed two new mathematical formulations for the reconfigurable manufacturing systems, in which the modular reconfigurable machine tools were used and production capacity of the system is adjusted by removing or adding modules, to respond quickly to changes in the market. Nevertheless, these studies assumed that the re-scheduling decision had been made already and explored the re-scheduling solutions without discussing how such decision was related to the disruptions.

Real-time monitoring and controlling of the production process are important to the final output and work-in-progress inventory. Some researchers studied the production rate adjustment of each machine in order to deal with disruptions and smooth the workflows in real time [38, 39]. Tamani et al. [40] proposed a supervisory-based control system. Besides the distributed fuzzy controllers to adjust the production rates of machines, three global control objectives were proposed to utilize the global information. As a result, the global control could modify the local control if necessary. Zou et al. [41] examined the bottlenecks in the production process in real time in order to increase the responsiveness to the disruptive events.

Only limited researches explore the impacts of disruptions on re-scheduling in the production process. Suwa [25] proposed a re-scheduling policy for the single-machine system. The rescheduling would be implemented when the cumulative task delay caused by unexpected events exceeded a predetermined threshold, and the current schedule was always modified at the planned times. With the disruptions of new job arrivals, machine breakdowns and processing time changes considered, Valledor et al. [26] proposed a periodic predictive-reactive rescheduling strategy to minimize the makespan, total weighted tardiness and stability, and a new method was used to obtain the reactive schedule at each point of rescheduling. However, periodic policies are designed in both studies, so that rescheduling cannot be implemented dynamically based on the real-time situations of the manufacturing systems.

In our previous works of Huo et al. [27] and Huo et al. [28], the fuzzy control system was proposed to balance the workloads in real time. Local fuzzy controllers were used to the adjust the production rates of machines, and a global fuzzy controller was designed to determine when to re-balance the assembly line. However, although machines were assumed to be failure-prone, maintenance activities (e.g. condition-based maintenance) which could improve the health state of each machine were not considered until the machine broke down. This setting differs from the practical situation, since condition-based maintenance, which is always implemented based on the degradation level of each machine in practice, is ignored. Therefore, to manage the work-in-progress inventory level and re-balance the assembly line based on the real-time information, it is necessary to develop an intelligent control system to monitor and adjust the assembly process, with the machine degradation process considered.

3 Problem statement

Figure 1 shows the structure of the assembly line considered in this study. B_i denotes buffer i. Buffers B_1 to B_{M-1} have finite capacity, and B_0 and B_M have infinite capacity since they are used to store raw materials and the finished products.

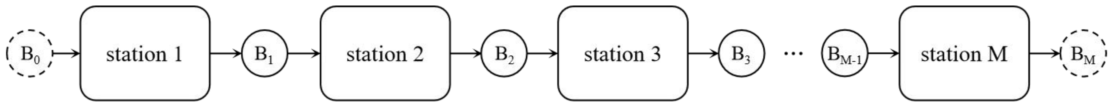

Figure 1 The structure of the assembly line.

Machine degradation can affect the processing time of a job [16]. Thus, information of machine degradation is useful to retain the workload balance of an assembly line. It is assumed that machine deterioration is monitored continuously. Let X_t and X'_t be the real deterioration level and the observed level at time t, respectively. Then, $X'_t = X_t + \varepsilon$, and ε denotes the observation error and follows a Gaussian distribution $N(0,\sigma^2)$ with the standard deviation of σ [42]. According to Xiang et al. [43], the degradation increment is positive in practice so that the degradation level is positive and strictly increasing. Therefore, in this study, the degradation process is represented by gamma processes with shape parameter a and scale parameter b.

With the real-time information of machine degradation, condition-based maintenance can be conducted to improve the machine condition. The thresholds of preventive maintenance and failure can be predetermined, and are denoted by A and L, respectively. Following the condition-based maintenance policy of Huynh et al. [44] and Zhao et al. [45], preventive maintenance (PM) is conducted when the deterioration level is higher than A, and corrective repair (CR) is conducted when the deterioration level is higher than L. PM and CR are assumed to be perfect so that machines become as-good-as-new after PM or CR.

Besides the failure caused by the increasing degradation level, random failures caused by random events are considered. Following Huynh et al. [44] and Zhao et al. [45], the occurrence of such random events is modeled by a non-homogeneous Poisson process with changing intensity. When the degradation level is lower than the predetermined threshold, A', the intensity is $r_1(t)$; Otherwise, the intensity is $r_2(t)$. The two failure modes are mutually exclusive.

Ghaleb et al. [16] divided the degradation process into discrete health states so that the processing times of different health states follow different characteristics. Although it was assumed that the degradation level is monitored continuously, Nguyen et al. [42] used state discretization to divide the machine degradation process into several stages based on the degradation level so as to facilitate decision-making. Thus, in this study, to facilitate decision-making, it is assumed that there are finite health states during the deterioration process of each machine, and the machine degradation process is divided into several stages based on the degradation level as shown in figure 2. The health state $s \in \{1,2,\ldots,n_1\}$ is defined by the degradation interval of $[(s-1)l, sl)$, with $l = \frac{A}{n_1}$. The health state $s \in \{n_1+1, n_1+2,\ldots,n_1+n_2\}$ is defined by the degradation interval of $[A+(s-1-n_1)l', A+(s-n_1)l')$, with $l' = \frac{L-A}{n_2}$.

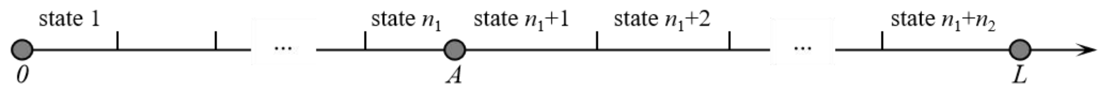

Figure 2 The state division of the machine degradation process.

Some researchers have developed methods of real-time remaining time prediction [46]. Thus, the remaining time before a health state can be predicted with high accuracy when there are enough observations, and it is assumed that the remaining time before PM can be predicted since the beginning of state n_1. The prediction of the remaining time is assumed to follow a normal distribution with mean of r and standard deviation of $0.1r$, where r is the real remaining time. Before state n_1, the remaining time is set to be a big value to show that PM is far away.

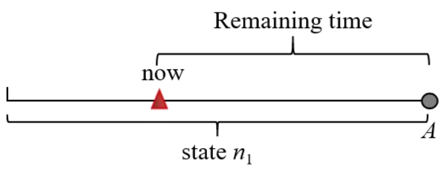

Figure 3 The remaining time of state n_1.

The changing processing performance of a workstation is always assumed to follow the normal distribution [47, 48]. Thus, for each health state of a machine, the corresponding production rate of workstation i is assumed to follow a normal distribution with the mean of pr_i^h and standard deviation of $0.1pr_i^h$, where $h \in \{1,2,...,n_1+n_2\}$ and pr_i^h denotes the average production rate of workstation i at state h. Let α_h denote the production rate increment index at state h due to machine degradation. Then, $er = (\alpha_1, \alpha_2, \ldots, \alpha_{n_1+n_2})$ designates the processing time extension rates of different health states. Furthermore, $\alpha_h > 1$ and $pr_i^h = \alpha_h pr_i^1$.

4 A real-time assembly line balancing method

With the consideration of machine degradation and condition-based maintenance, processing abilities of machines fluctuate with the changing health state. Thus, it is necessary to monitor the assembly process and balance the workloads of workstations based on the real-time information of machines' processing abilities. In this study, a fuzzy control system is proposed to monitor and adjust the workload of workstations in real time. Assembly line re-balancing will be conducted to reduce the production loss caused by unexpected events, and production rates of workstations are adjusted to improve the collaboration of workstations. Fuzzy controllers are developed to utilize the available information and support decision-making.

Assembly line re-balancing and production rate adjustment are used as two methods to balance the workloads. Two strategies of re-balancing are considered. The first is conservative: the task sequence will not be changed, and workloads are changed by changing the assignments of workstations. There are limited possible task re-assignments with this strategy, thus, the solution is easy to implement and the preparation time is usually short. This re-balancing strategy is more suitable to the situation where the duration of a disruption is short. The second is a re-optimization considering the production rate after re-balancing and the preparation time for re-balancing. Since there is no restriction on task re-assignments, the production rate of the assembly line after re-balancing with this strategy tends to be higher, but the preparation time tends to be longer. This strategy is more suitable to the situation where there is an urgent need to speed up the production progress to satisfy the demand.

Figure 4 shows the fuzzy control process of the assembly line with two types of fuzzy controllers.

Type 1 fuzzy controllers are used to support the decision-making of whether it is necessary to implement a re-balancing solution. For type 1’ fuzzy controller, solutions obtained with two different re-balancing strategies, rather than a re-balancing solution and situation of not re-balancing, are compared. This is the only difference between type 1 fuzzy controller and type 1’ fuzzy controller. Type 2 fuzzy controllers are used to adjust the production rates of workstations. S_{re1} and S_{re2} denote the best solutions found with the first and the second re-balancing strategy, respectively.

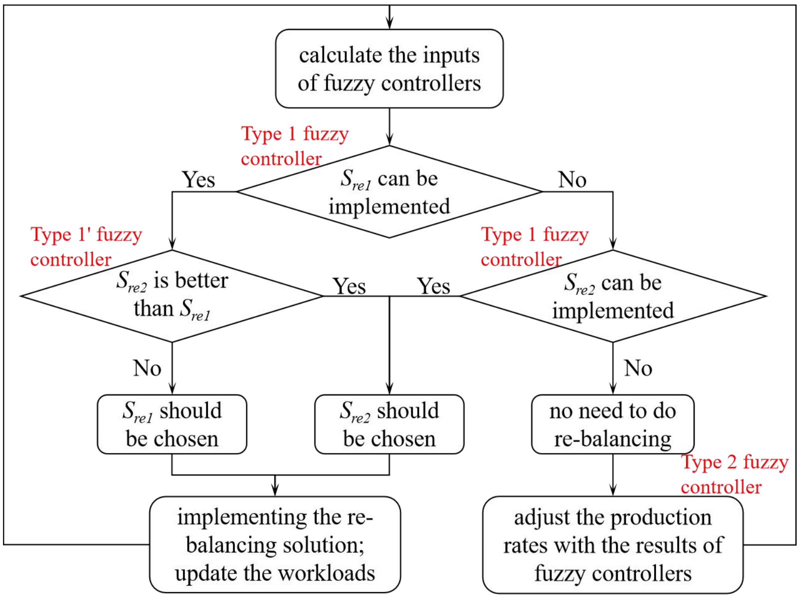

Figure 4 Fuzzy control process of the assembly line

4.1 Assembly line re-balancing model

The inputs of the type 1 and type 1’ fuzzy controllers:

(1) The urgency of increasing production to satisfy the demand is defined as follows:

$$urg = \begin{cases} \dfrac{D - P \cdot \dfrac{T_{total}}{T}}{D}, P \cdot \dfrac{T_{total}}{T} \le 2D \\ -1, P \cdot \dfrac{T_{total}}{T} > 2D \end{cases} \tag{1}$$

where D is the total quantity of demand, and P denotes the cumulative production. T denotes the time passed and T_{total} is the total available time. Assume D_0 is the given demand quantity, and T_0 is the given time before the delivery date. At the beginning, $D = D_0$, $P = 0$, $T = 0$ and $T_{total} = T_0$. When the assembly line is re-balanced, D and T_{total} are updated:

$D = D - P$ and $T_{total} = T_{total} - T$. Then, P and T are re-initialized by 0. $D - P \cdot \frac{T_{total}}{T}$ denotes the difference between the demand and the predicted total production according to the current progress. The larger the difference is, the more urgent increasing the production to satisfy the demand is. urg is between -1 and 1, and the fuzzy term set is {VS, S, ME, L, VL}. VS, S, ME, L and VL denote very small, small, medium, large and very large, respectively.

(2) The production increase after re-balancing compared with the production without re-balancing is defined as follows:

$$P_{incre} = \begin{cases} \dfrac{pr_{new}\left(\Delta t - T_r\right) - P}{D\dfrac{\Delta t}{T_{\text{total}}}}, A \neq \phi, B \neq \phi \\ \dfrac{pr_{new}\left(\Delta t - T_r\right) - P}{D\dfrac{\Delta t}{T_{\text{total}}}}, A \neq \phi, B = \phi \\ -1, A = \phi \end{cases} \tag{2}$$

where pr_{new} denotes the production rate after re-balancing. A and B are the sets of available and down workstations, respectively. t_i^{rt} denotes the predicted remaining time of workstation i before PM, and t_j^d designates the down time of workstation j. P is the production without re-balancing, and is calculated by the method used in Huo et al. [28]. T_r designates the considered period and preparation time for the re-balancing plan, respectively. When the first re-balancing strategy is used, T_r is defined by $T_r = \sum_{k \in RT} t_k^r$, where RT is the set of the reassigned tasks in the re-balancing plan and t_k^r denotes the preparation time of task k. When the second re-balancing strategy is used, T_r is defined by $T_r = \sum_{k \in RT} t_k^r + \frac{|A|}{pr_{new}}$, where $|A|$ is the cardinal of set A. Δt is defined as follows:

$$\Delta t = \begin{cases} \min\left(\min_{i \in A} t_i^{rt}, \min_{j \in B} t_j^{d} \right), A \neq \phi, B \neq \phi \\ \min_{i \in A} t_i^{rt}, A \neq \phi, B = \phi \\ 0, A = \phi \end{cases} \tag{3}$$

The production increase after re-balancing with the second strategy compared with the production with the first re-balancing strategy is defined as follows:

$$P_{incre} = \begin{cases} \dfrac{pr_{new2}\left(\Delta t - \sum_{k \in RT_2} t_k^r - \dfrac{|A|}{pr_{new2}} \right) - pr_{new1}\left(\Delta t - \sum_{k \in RT_1} t_k^r \right)}{D \dfrac{\Delta t}{T_{\text{total}}}}, A \neq \phi, B \neq \phi \\ \dfrac{pr_{new2}\left(\Delta t - \sum_{k \in RT_2} t_k^r - \dfrac{|A|}{pr_{new2}} \right) - pr_{new1}\left(\Delta t - \sum_{k \in RT_1} t_k^r \right)}{D \dfrac{\Delta t}{T_{\text{total}}}}, A \neq \phi, B = \phi \\ -1, A = \phi \end{cases} \tag{4}$$

where pr_{new1} and pr_{new2} denote the production rate after re-balancing with the first and the second strategy, respectively. RT_1 and RT_2 designate the sets of reassigned tasks in the re-balancing plans by the first and the second strategy, respectively. Equation (4) is used to determine whether pr_{new2} is significantly higher than pr_{new1}, which will be used in type 1' fuzzy controller.

P_{incre} is between -1 and 1, and the fuzzy term set is {VS, S, ME, L, VL}.

The output of the type 1 and type 1' fuzzy controllers:
The output is the necessity of implementing assembly line re-balancing, and ranges from 0 to 100%. If the output is larger than the given threshold, then re-balancing will be conducted.

4.2 Production rate adjustment model

Inputs of type 2 fuzzy controller:

(1) Upstream and downstream buffer levels

Let BL_j denote the buffer level of buffer j. BL_j is defined by ratio of the inventory to the capacity of buffer j. BL_j is between 0 to 1, and the fuzzy term set is {VS, S, ME, L, VL}.

(2) Production surplus rate

The production surplus rate is defined as follows:

$$S_i = \begin{cases} \dfrac{\frac{P_i}{T} - d}{d}, P_i < 2dT \\ 1, P_i \geq 2dT \end{cases} \tag{5}$$

where P_i is the cumulative production of workstation i in the current production cycle. d denotes the production rate required by the demand, and it is defined by $\dfrac{D}{T_{total}}$. S_i varies from -1 to 1, and the fuzzy term set is {VS, S, ME, L, VL}.

The output of type 2 fuzzy controller:

The output ad_i is used to adjust the production rate of station i, and varies from -1 to 1. The output ranges from 0 to 1, and the fuzzy term set is {VS, S, ME, L, VL}.

The production rate at each health state is assumed to follow a normal distribution, and the average production rate is adjusted to balance the workloads. Let pr_i denote the current average production rate of workstation i. At first, pr_i is initialized by pr_i^h. Then, pr_i is updated by the following equation:

$$pr_i = \begin{cases} \min\{pr_i^h, pr_i + pr_i^h ad_i\}, ad_i > 0 \\ \max\{0, pr_i + pr_i^h ad_i\}, ad_i \leq 0 \end{cases} \tag{6}$$

The real-time production rate is then generated following the normal distribution with the mean of pr_i and standard deviation of $0.1pr_i$.

4.3 Fuzzy rules

The fuzzy IF-THEN rules of type 1 fuzzy controller are shown in table 1. Assembly line re-balancing will be conducted only when it is urgent to speed up the progress and it is possible to increase the production rate significantly by re-balancing.

Table 1

Fuzzy rules of type 1 fuzzy controller.

urg	P_{incre}				
	VS	S	N	L	VL
VS	VS	VS	VS	S	N
S	VS	VS	S	N	L
N	VS	VS	N	L	L
L	VS	S	N	L	VL
VL	VS	S	N	VL	VL

The fuzzy IF-THEN rules of type 2 fuzzy controller are shown in table 2. When there is no obvious sign of blockage or starvation in the adjacent buffers of a workstation, the machine should work at the high speed; otherwise, the production rate should be adjusted to prevent blockage and starvation.

Table 2

Fuzzy rules for the type 2 fuzzy controller.

S_i=VS					
BL_{i-1}	BL_i				
	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-1}	BL_i				
	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-1}	BL_i				
	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-1}	BL_i				
	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-1}	BL_i				
	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

5 Numerical results

5.1 Numerical experiments

The task times and precedence relationship of the assembly line are initialized by an instance of assembly line balancing problem: KILBRID (45 tasks). The processing times of tasks and precedence relationship are in the SALBP data sets shown on https://assembly-line-balancing.de/salbp/benchmark-data-sets-1993/. In order to differentiate the output of different assembly lines, the processing times used in the numerical experiments are set to be 100 times smaller than the initial ones.

Since the problem defined in this study is novel, there is no benchmark instances. To illustrate the effectiveness of the proposed fuzzy control system, the performance of three different assembly lines is compared. The features of the three assembly lines (AS_1, AS_2 and AS_3) are shown in table 3. As to AS_2, the production rates vary only with the health state of machines. AS_1 and AS_3 are monitored and controlled by the fuzzy control system proposed in this study and the control system proposed in Tamani et al. [40], respectively. The reason that the control system in Tamani et al. [40] was chosen is that the structure of our fuzzy control system is similar to that of the control system in Tamani et al. [40]. For AS_3, distributed controllers are used to adjust the production rates of workstations, and the local action is augmented by the supervisory action determined by the values of global objectives. Thus, similar to this study, both local information and global information are used in decision-making. Different from this study, it is the ratio of the current production rate to the maximum production rate that is adjusted by the fuzzy controller, since it is assumed that the maximum production rate is constant and each machine produces at a rate less than the maximum rate. In order to apply the control system to the problem defined in this study, the maximum production rate should be set to pr_i^h. Let ad_i' be the output of the fuzzy controller which is used to control station i. The production rate after adjustment follows the normal distribution with the mean of $pr_i^h ad_i'$ and the standard deviation of $0.1 pr_i^h ad_i'$.

Table 3

The three assembly lines considered in this study.

No.	With a control system	Description of the control system if applicable
AS_1	Yes	The fuzzy control system proposed in this study
AS_2	No	-
AS_3	Yes	The control system proposed by Tamani et al. [40]

The numerical experiments with the following parameter settings are conducted:

(1) The total number of workstations is set to be $M = 4$ so that the number of operative workstations ranges from 0 to 4.

(2) Following Huynh et al. [44] and Zhao et al. [45], the failure threshold L and the threshold for preventive maintenance A are chosen by $L = 30$ and $A = 16$, and the degradation level after which the failure rate changes is set to be 20.

(3) The standard deviation of the degradation measurement errors indicates the inspection quality. The higher the inspection quality, the smaller the variance of measurement errors. Based on the standard deviation of the degradation measurement errors in Nguyen et al. [42], the standard deviation of measurement errors in this study is set to be $\sigma = 0.5$.

(4) Following Peng and van Houtum [15], the duration of preventive maintenance is set to be a fixed value, that is, $D_{pm} = 3$; the duration of corrective maintenance follows a gamma distribution, with shape parameter $a' = 2$ and scale parameter $b' = 0.3$.

(5) The number of states is set with $n_1 = 2$, and $n_2 = 1$ so that a three-state degradation process is considered [49]. Following Yan et al. [50], a machine is treated as failed when the processing time is thirty percent longer than the expectation. Thus, the production rate increment indexes are chosen by $\alpha_1 = 1$, $\alpha_2 = 1.15$ and $\alpha_3 = 1.3$.

(6) The preparation time for a re-assigned task is generated by the uniform distribution $Uniform\left(1, \frac{\sum_{i=1}^{n} t_i}{n}\right)$, where n is the total number of tasks and t_i denotes the processing time of task i on a machine at state 1.

Since this study focuses on the machine degradation process, random instances are created to model the different possible degradation scenarios. To consider different degradation velocities which can be indicated by the mean (m) and variance (δ^2) of the degradation levels, machine degradation process is modeled by the gamma process with parameters of $a = 0.05$ and $b = 0.1$ ($m = 0.5$, $\delta^2 = 5$), $a = 0.025$ and $b = 0.1$ ($m = 0.25$, $\delta^2 = 2.5$), and $a = 0.02$ and $b = 0.2$ ($m = 0.1$, $\delta^2 = 0.5$), respectively. Failure rates are set to be $r_1(t) = r_1 = 0.01$ and $r_2(t) = r_2 = 0.05$, and $r_1(t) = r_1 = 0.05$ and $r_2(t) = r_2 = 0.3$. Consequently, the real-time machine condition is generated based on a , b , r_1 and r_2 . The maximum production rate of the assembly line is 0.7246, which is the reciprocal of the operation time of each station (1.38). Consequently, the demand production rate is set to be 0.5 (high demand rate), 0.3 (middle demand rate) and 0.1 (low demand rate). Therefore, there are 18 random instances in total (shown in table 4), and six different machine condition levels (MC_1, MC_2, MC_3, MC_4, MC_5 and MC_6) are considered for each demand level. There are ten random runs for each instance, and the numerical results are means of the ten runs.

Table 4

Parameters of the 18 random instances.

No.	d	a	b	r_1	r_2
1	0.5	0.05	0.1	0.01	0.05
2		0.025	0.1	0.01	0.05
3		0.02	0.2	0.01	0.05
4		0.05	0.1	0.05	0.3
5		0.025	0.1	0.05	0.3
6		0.02	0.2	0.05	0.3
7	0.3	0.05	0.1	0.01	0.05
8		0.025	0.1	0.01	0.05
9		0.02	0.2	0.01	0.05
10		0.05	0.1	0.05	0.3
11		0.025	0.1	0.05	0.3
12		0.02	0.2	0.05	0.3
13	0.1	0.05	0.1	0.01	0.05
14		0.025	0.1	0.01	0.05
15		0.02	0.2	0.01	0.05
16		0.05	0.1	0.05	0.3
17		0.025	0.1	0.05	0.3
18		0.02	0.2	0.05	0.3

Assembly line re-balancing will be conducted when at least one of the outputs of type 1 and type 1’ fuzzy controllers are larger than 0.76. The normal re-balancing solution is found by the algorithm in our previous work Huo et al. [28]. As to the re-balancing solution with the task sequence not changed, another method is used. At first, if there are machines under PM or CM, the assignments in such workstations will be moved to the neatest available station, and the processing times of workstations are updated accordingly. Then, the workloads of workstations are adjusted further with the method shown in figure 5 to improve the efficiency of the assembly line. During the solution searching process, a task is not allowed to be reassigned more than once. Let T_{s1} denotes the average operation time of the bottleneck, and let T_{s2} denotes the updated operation time of adjacent station to which a task in the bottleneck is reassigned. The feasible move can be obtained when $T_{s2} < T_{s1}$.

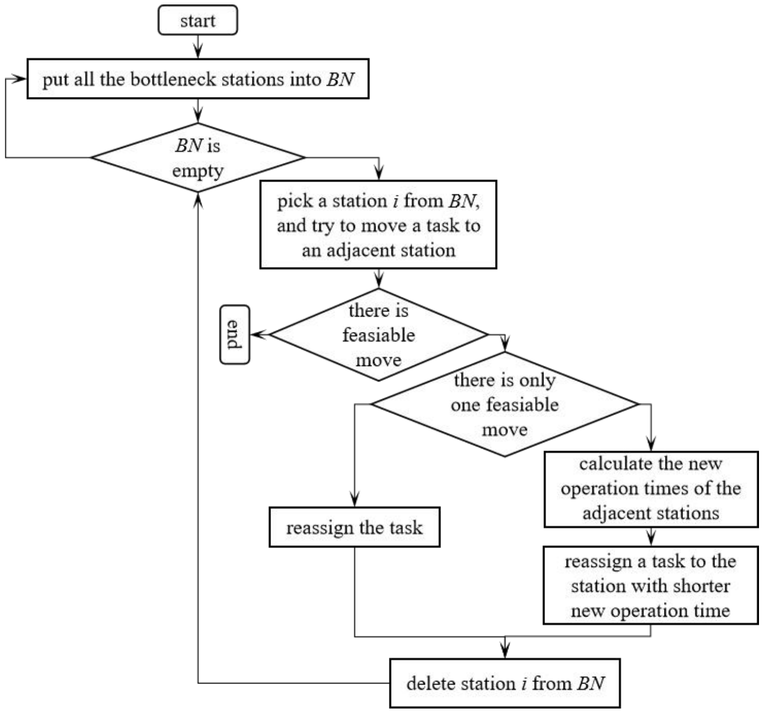

Figure 5 The method to generate the re-balancing solution with the first re-balancing strategy.

5.2 Comparative results

Simulink in Matlab (R2016a) is used to conduct all the numerical experiments. The total simulation time is set to be 1000 time units, and the control system is used to support decision-making every 1 time unit. The numerical experiment will end when the demand is satisfied or when the simulation time is used up.

Table 5 shows the numerical results of the 18 instances, and means of ten random runs are reported. AS_i-MC_j denotes the assembly line AS_i with the machine condition level of MC_j (the explanation can be found in section 5.1). For each level of demand rate, there are five performance indicators reported: the average blockage ratio (BR), the average starvation ratio (SR), the average buffer level (BL), the total simulation time used (T) and the corresponding total production (P).

Table 5

Numerical results of the 18 instances

Assembly lines	d=0.5					d=0.3					d=0.1				
	BR	SR	BL	T	P	BR	SR	BL	T	P	BR	SR	BL	T	P
AS$_1$-MC$_1$	0.000	0.018	0.171	934.888	500.000	0.000	0.022	0.096	882.546	300.000	0.000	0.175	0.058	849.348	100.000
AS$_2$-MC$_1$	0.000	0.018	0.129	817.355	500.000	0.000	0.025	0.103	496.394	300.000	0.000	0.051	0.060	169.946	100.000
AS$_3$-MC$_1$	0.000	0.029	0.072	1000.000	275.700	0.000	0.031	0.059	1000.000	194.600	0.000	0.067	0.038	1000.000	77.100
AS$_1$-MC$_2$	0.000	0.011	0.126	923.941	500.000	0.000	0.018	0.103	873.906	300.000	0.000	0.054	0.072	846.696	100.000
AS$_2$-MC$_2$	0.000	0.021	0.177	780.419	500.000	0.000	0.029	0.140	473.175	300.000	0.000	0.057	0.055	163.044	100.000
AS$_3$-MC$_2$	0.000	0.032	0.076	1000.000	284.400	0.000	0.035	0.062	1000.000	201.200	0.000	0.069	0.040	1000.000	78.100
AS$_1$-MC$_3$	0.000	0.013	0.147	929.088	500.000	0.000	0.019	0.099	879.415	300.000	0.000	0.123	0.064	862.988	100.000
AS$_2$-MC$_3$	0.000	0.018	0.162	803.557	500.000	0.000	0.026	0.134	486.416	300.000	0.000	0.052	0.067	169.616	100.000
AS$_3$-MC$_3$	0.000	0.031	0.076	1000.000	281.100	0.000	0.034	0.061	1000.000	197.800	0.000	0.069	0.041	1000.000	77.800
AS$_1$-MC$_4$	0.000	0.013	0.138	927.348	500.000	0.000	0.020	0.101	877.086	300.000	0.000	0.091	0.068	856.105	100.000
AS$_2$-MC$_4$	0.000	0.021	0.187	796.012	500.000	0.000	0.029	0.138	481.775	300.000	0.000	0.057	0.076	166.234	100.000
AS$_3$-MC$_4$	0.000	0.033	0.085	1000.000	279.500	0.000	0.038	0.068	1000.000	196.400	0.000	0.071	0.043	1000.000	78.200
AS$_1$-MC$_5$	0.000	0.009	0.119	916.201	500.000	0.000	0.017	0.106	867.458	300.000	0.000	0.056	0.072	846.548	100.000
AS$_2$-MC$_5$	0.000	0.017	0.169	753.091	500.000	0.000	0.024	0.119	456.894	300.000	0.000	0.049	0.049	157.743	100.000
AS$_3$-MC$_5$	0.000	0.026	0.080	1000.000	286.400	0.000	0.031	0.064	1000.000	201.500	0.000	0.064	0.038	1000.000	78.400
AS$_1$-MC$_6$	0.000	0.011	0.127	923.474	500.000	0.000	0.017	0.104	873.722	300.000	0.000	0.074	0.070	852.182	100.000
AS$_2$-MC$_6$	0.000	0.020	0.196	779.887	500.000	0.000	0.026	0.144	471.706	300.000	0.000	0.055	0.079	162.674	100.000
AS$_3$-MC$_6$	0.000	0.030	0.087	1000.000	275.600	0.000	0.035	0.069	1000.000	192.900	0.000	0.068	0.044	1000.000	76.800

In order to better illustrate the results of the 18 random instances (information of each instance is shown in Table 4), the average buffer levels and total outputs are shown in Figures 6 and 7.

There are significant differences among the buffer levels of AS$_1$, AS$_2$ and AS$_3$. For each assembly line, the average buffer level decreases significantly when the demand rate decreases, and tends to be relatively stable under the same demand level. This rule is even more obvious for the assembly lines with a control system (i.e. AS$_1$ and AS$_3$). Therefore, compared with other parameters, the buffer level seems to be more sensitive to the demand level. In general, the buffer level of AS$_1$ is less than that of AS$_2$ for 83.3 percent of instances. Specifically, compared with the buffer level of AS$_2$, the buffer level of AS$_1$ decreases by 16.1 percent and 20.9 percent for the demand levels of 0.5 and 0.3, respectively; The buffer level of AS$_1$ is close to that of AS$_2$ when the demand level is 0.1. In addition, it is clearly shown in figure 6 that the buffer level of AS$_3$ is the lowest among the three assembly lines. Meanwhile, compared with the buffer level of AS$_2$, the buffer level of AS$_3$ decreases by 52.9 percent, 50.3 percent and 35.4 percent for the demand levels of 0.5, 0.3 and 0.1, respectively.

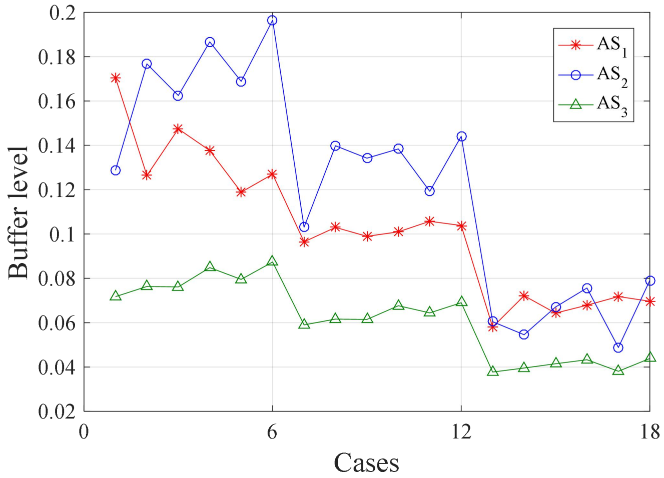

Figure 6 Average buffer levels of the three assembly lines (AS_1 is controlled by the proposed fuzzy control system in this study, AS_2 is without any control system, and AS_3 is controlled by the control system in Tamani et al. [40]).

However, interestingly, as figure 7 shows, the demand cannot be satisfied for all the instances for AS_3, while the demand can be satisfied within the simulation time for AS_1 and AS_2. For each demand level, the final output of AS_3 is around 55 percent of the demand, which indicates that there is too much production loss sacrificed for the low buffer level. Compared with Tamani et al. [40], this study considers the impact of machine degradation on the processing times of tasks. Consequently, the production rate adjustment rules that work in Tamani et al. [40] may not work properly in the problem considering processing ability change of machines with the health state of machines. By contrast, the fuzzy control system developed in this study can support decision-making by retaining lower buffer level and processing at a proper speed to satisfy the demand.

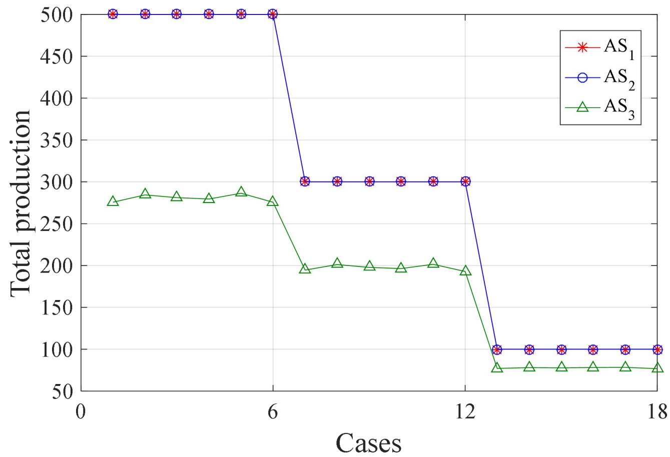

Figure 7 Total production of the three assembly lines within the simulation time.

5.3 Sensitivity analysis

As shown in Figure 6, the buffer levels under the same demand level are close. In order to further examine the changes of the performance of the proposed fuzzy control system to the parameter settings, sensitivity analysis is conducted for the parameters of interest as follows: (1) number of states of the degradation process; (2) degradation velocity and the shock failure rates; (3) degradation threshold of preventive maintenance; (4) duration of preventive maintenance and corrective maintenance; (5) the prediction error of the observations of machine degradation level; (6) processing time extension rates for different health states. The sensitivity analysis is done considering the value variation of one parameter at a time, with the rest parameters set at the baseline values [15]. The baseline values are $n_1 = 2$, $n_2 = 1$, $a = 0.025$, $b = 0.1$, $r_1(t) = r_1 = 0.01$, $r_2(t) = r_2 = 0.05$, $A = 16$, $D_{pm} = 3$, $a' = 2$, $b' = 0.3$, $\sigma = 0.5$ and $er = [1, 1.15, 1.3]$. The results of sensitivity analysis are shown in table 6. In order to show the performance variations, for each demand production rate d , the buffer level obtained with the baseline values is set to be benchmark and is denoted by B_d . Then, Δ_i ($i = 1,2,3$) is calculated by $\Delta_i = \frac{BL_d^p - B_d}{B_d} \cdot 100\%$, where BL_d^p denotes the buffer level with the parameter set of p under the demand production rate of d . Similarly, Δ is calculated by $\Delta = \frac{\sum_d BL_d^p - \sum_d B_d}{\sum_d B_d} \cdot 100\%$.

Table 6

Results of sensitivity analysis

Variable names	Parameters	d=0.5 BL	d=0.5 Δ_1 (%)	d=0.3 BL	d=0.3 Δ_2 (%)	d=0.1 BL	d=0.1 Δ_3 (%)	Δ (%)
Degradation threshold of PM	A=12	0.137	8.602	0.101	-1.797	0.072	-0.538	2.863
	A=16	0.126	0.000	0.103	0.000	0.072	0.000	0.000
	A=20	0.123	-2.913	0.105	1.672	0.072	-0.206	-0.699
	A=24	0.119	-6.034	0.106	2.480	0.072	-0.210	-1.732
Duration of PM	D_{pm}=1	0.118	-6.646	0.106	2.613	0.072	-0.136	-1.926
	D_{pm}=2	0.122	-3.635	0.105	1.680	0.072	-0.200	-0.998
	D_{pm}=3	0.126	0.000	0.103	0.000	0.072	0.000	0.000
	D_{pm}=4	0.138	9.123	0.102	-1.440	0.072	-0.046	3.321
Duration of CM	a'=3, b'=0.3; m=10, δ^2=33.33	0.128	1.649	0.103	0.412	0.072	-0.073	0.814
	a'=2, b'=0.3; m=6.67, δ^2=22.22	0.126	0.000	0.103	0.000	0.072	0.000	0.000

	a’=1, b’=0.5; m=2, δ^2=4	0.127	0.549	0.104	0.787	0.072	0.016	0.503
	a’=0.18, b’=0.09; m=2, δ^2=22.22	0.126	-0.684	0.103	0.281	0.072	-0.069	-0.207
Standard deviation of observation errors	σ=0.1	0.126	-0.013	0.103	-0.314	0.072	-0.259	-0.175
	σ=0.5	0.126	0.000	0.103	0.000	0.072	0.000	0.000
	σ=1	0.129	1.670	0.103	0.459	0.071	-1.082	0.598
	σ=1.5	0.132	4.417	0.103	0.070	0.069	-3.916	0.938
Gamma process of machine degradation	a=0.0125, b=0.05; m=0.25, δ^2=5	0.115	-9.349	0.106	3.271	0.072	-0.655	-2.958
	a=0.025, b=0.1; m=0.25, δ^2=2.5	0.126	0.000	0.103	0.000	0.072	0.000	0.000
	a=0.05, b=0.1; m=0.5, δ^2=5	0.171	34.896	0.096	-6.326	0.058	-19.599	7.775
	a=0.02, b=0.2; m=0.1, δ^2=0.5	0.147	16.629	0.099	-3.931	0.064	-10.870	3.026
	a=0.01, b=0.1; m=0.1, δ^2=1	0.118	-6.876	0.106	2.778	0.072	-0.172	-1.974
Shock failure rates	r1=0.001, r2=0.005	0.132	4.146	0.102	-1.005	0.072	-0.078	1.376
	r1=0.003, r2=0.015	0.132	4.213	0.102	-0.679	0.072	-0.661	1.376
	r1=0.01, r2=0.05	0.126	0.000	0.103	0.000	0.072	0.000	0.000
	r1=0.05, r2=0.3	0.119	-5.954	0.106	2.668	0.072	-0.509	-1.706
	r1=0.1, r2=0.5	0.119	-5.919	0.106	2.524	0.072	-0.014	-1.622
Number of health states	**n1=2, n2=1; er=[1,1.15,1.3]**	0.126	0.000	0.103	0.000	0.072	0.000	0.000
	n1=2, n2=2; er=[1,1.1,1.2,1.3]	0.123	-2.943	0.104	1.181	0.072	-0.190	-0.876
	n1=3, n2=1; er=[1,1.1,1.2,1.3]	0.133	5.319	0.102	-1.019	0.072	-0.025	1.876
	n1=3, n2=2; er=[1,1.075,1.15,1.225,1.3]	0.125	-0.800	0.103	-0.164	0.072	-0.402	-0.487
	n1=4, n2=1; er=[1,1.075,1.15,1.225,1.3]	0.135	7.108	0.101	-2.392	0.066	-8.419	0.147
	n1=4, n2=2; er=[1,1.05,1.1,1.15,1.2,1.25,1.3]	0.130	3.233	0.103	-0.224	0.072	0.094	1.301
Processing time extension rates	er=[1,1.1,1.3]	0.123	-2.343	0.105	1.531	0.072	-0.092	-0.481
	er=[1,1.15,1.3]	0.126	0.000	0.103	0.000	0.072	0.000	0.000
	er=[1,1.2,1.3]	0.134	5.886	0.102	-1.067	0.070	-2.384	1.532

The degradation threshold of preventive maintenance, A, ranges from 12 to 24. With the increase of A, the buffer levels tend to decrease. Since other parameters, especially the velocity of the degradation process and processing time extension rates, are fixed, the larger A is, the later the processing speed of a machine is unacceptable. Thus, the results indicate that the buffer levels tend to be lower when the machines can maintain good processing performance for more time. It is also noted that the buffer levels varies significantly when the demand production rate is relatively high ($d = 0.5$) and no significant variation is shown for the other two demand rates. When high production rate is required, the real production rates of machines will be closer to the maximal production abilities of machines, which tend to be larger when A is larger.

As to the duration of PM and CM, different impacts on the buffer levels are observed when these two parameters varies. Specifically, when D_{pm} increases from 1 to 4, the buffer levels increase significantly. However, no significant variations are shown with the changes of the parameters related to the duration of CM. This can be explained by the fact that the total number of CM is quite small and PM is often conducted in time before machine breakdown since machine degradation level is continuously monitored.

The observation error of the degradation level is considered in this study. There is only a slight increase of the average buffer level, with the increase of standard deviation of observation errors from 0.1 to 1.5. This indicates that the higher the inspection quality of the real-time machine degradation process, the better control performance of the proposed fuzzy control system. Nevertheless, the increase rate of average buffer level is less than one percent, which suggests the robustness of the performance to the observation error.

For the gamma process of machine degradation, parameters are chosen with different means and variances. When the mean is fixed and the variance increases, the average buffer level will decrease. However, when the variance is fixed, the average buffer level will increase with the increase of the mean. Besides, with the increase of shock failure rates, the average buffer level shows a slight decrease tendency. Meanwhile, it is interesting to note that the buffer level tends to be constant when changes to the shock failure rates are not large enough.

With the variations of the number of health states, the corresponding processing time extension rates are modified accordingly with the same variation ratio. When the total number of health states is fixed, the average buffer level tends to increase with the increase of n_1. When $n_2 = 2$, the average buffer level will increase with the increase of n_1. However, no tendency is shown when $n_2 = 1$, with the increase of n_1.

As to the extension rate of the processing time at different health states, different variation ratios are set for comparison. When the variation ratio from the first state to the second increases, larger impact of machine degradation on the duration of processing times can be expected and the buffer levels tend to increase. Also, compared with the other two demand scenarios, more significant changes are shown under the demand production rate of 0.5.

It is shown that Δ ranges from about -3.0% to approximate 7.8%. Besides, the buffer levels are between 0.058 and 0.07, between 0.096 and 0.106, and between 0.115 and 0.171 under the demand production rates of 0.1, 0.3 and 0.5, respectively. There is relatively large variation of buffer levels for the demand production rate of 0.5, but the buffer levels are pretty low. Among all the parameters discussed, the parameter changes of the gamma process of machine degradation have the largest impact on the performance of the proposed fuzzy control system, and the parameter changes of the duration of CM have the smallest effect on the control performance.

6 Conclusions

In this paper, machine degradation process is modeled by the gamma process so that the degradation level is strictly increasing. The impact of machine degradation on the duration of task processing is considered. The degradation process is divided into several stages, and the processing abilities of machines vary with their health state. In order to balance the workloads of workstations based on the real-time processing abilities associated with the health state of machines, a fuzzy control system is proposed. Global controllers are used to determine whether it is necessary to re-balance the assembly line, and one local controller is used to adjust the production rate of each workstation. To examine the effectiveness of the proposed fuzzy control system, the performance of AS_1, AS_2 and AS_3 is compared. As the numerical results show, although AS_3 achieves lowest buffer level, there is too much production loss that the demand cannot be satisfied. However, for AS_1, the buffer level is much lower than that of AS_2 for most instances. Importantly, the demand can always be satisfied by AS_1. Therefore, the proposed fuzzy control system can support decision-making effectively. Besides, according to the results of sensitivity analysis, the proposed fuzzy control system can sustain good performance with the variations of parameters. The performance is the most sensitive to the changes of parameters related to the gamma process of machine degradation, and is the most robust to the changes of parameters associated with the duration of CM.

During the decision-making process, real-time information of machine degradation is utilized to examine the processing abilities of machines and the remaining time before condition-based maintenance. Based on the comparative results of the two assembly lines with a control system (AS_1 and AS_3), it can be concluded that the machine degradation information can be used to improve the efficiency of an assembly line by improving the quality of decisions during the assembly process. Thus, workload balance of an assembly line can be done in a more intelligent and efficient way with the real-time information enabled by advanced technologies. It can also be concluded that the performance of the assembly line can be improved when intelligent automation is implemented to smooth the workflows of the assembly process.

There are some limitations in this research, although good performance of the assembly line is shown when the proposed fuzzy control system is used. First, it cannot be guaranteed that the optimal re-balancing solution can be found with the methods used in this study. This will affect the performance of the assembly line negatively. In the future research, the more effective re-balancing algorithm will be explored to improve the quality of re-balancing solution. Second, at present, to simplify the problem, condition-based maintenance is implemented based on the given condition-based maintenance policy. The joint planning of maintenance and assembly process will be explored to improve the performance of the assembly line further.

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