



# Multi-state decision of unreliable machines for energy-efficient production considering work-in-process inventory

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## Abstract

Energy-efficient operation of manufacturing systems is critical for industrial enterprises in current environmentally conscious society. Decreasing the idle time of a machine is one of the main methods to achieve energy-efficient production. From the system level, when and how long a machine can be turned into standby state with lower energy consumption is still a difficult problem for unreliable manufacturing systems considering less throughput loss. In this paper, a novel multi-state decision method based on fuzzy logic is proposed to switch a machine into different sleep states considering real-time work in process inventory of buffers. Three basic modules and their corresponding fuzzy controllers are presented to construct complex manufacturing systems with disassembly and assembly workstations. The fuzzy rules for machine state decision are generated based on the expert/production knowledge. By means of simulation experiments, the effectiveness of the proposed method is illustrated for an unreliable complex manufacturing system.

**Keywords** Machine state decision · Fuzzy logic · Energy-efficient production · Unreliable manufacturing system

## 1 Introduction

Global warming is a big threat to the earth. The 2015 United Nations Climate Change Conference in Paris has reached an agreement that countries should make efforts to cut down the greenhouse gas emissions. According to Bruzzone et al. [1], about 31% of primary energy consumption and 36% of carbon dioxide (CO<sub>2</sub>) emissions are attributed to manufacturing industry sector. Globally, it is important to control the production process both from the aspects of productivity and energy consumption for a sustainable development [2]. In China, almost 50% of the national electric energy is consumed by manufacturing industry [3]. Chinese government has legislated to decrease the CO<sub>2</sub> emissions and encourage green

manufacturing. More and more Chinese manufacturing enterprises pay attention to the energy cost and environmental influence of their production processes.

In discrete manufacturing industry, many non-bottleneck machines have a lot of idle time. Reducing idle time is a good approach to realize energy-efficient production [4]. In an aircraft small-parts supplier, the idle periods accounted for 16% of the total production time, and about 13% of the total energy consumption could be saved if the idle machines were switched off [5]. Supposing that the short periods of all non-productive time were identified beforehand, almost 50 to 60% of energy consumption could be reduced by turning the standby machines into energy-saving states [6]. In the vision of Industry 4.0, the Internet of Things (IoT) technologies enable networked manufacturing system to be smarter and more digitalized based on the real-time monitoring of the production processes [7]. Many real-time production data, such as machine states, real-time buffer levels, and energy consumption of equipment, can be collected from the shop floor. More and more new equipment, such as CNC machines and industrial robots, have multiple energy-saving modes instead of traditional ON and OFF modes [8]. The equipment can be switched into energy-saving mode by turning off some auxiliary components such as actuators, hydraulic system, and pneumatic.

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In a general discrete manufacturing system, machines/workstations and buffers are usually main components. They are diversely connected to form complex structures, such as serial lines, parallel lines, and assembly and disassembly lines. Due to different cycle times and unreliability of machines, the idle periods of machines in a highly dynamic production system are not easily determined in advance [6]. The methods are scarce but indispensable for deciding when, where, and how long the machines should execute energy-saving actions in manufacturing systems. In this study, a novel fuzzy logic-based method was proposed to decide machine states in a multi-stage complex manufacturing system with disassembly and assembly workstations. Machines could be switched into different standby states according to real-time levels of their adjacent buffers by fuzzy logic reasoning.

The paper is organized as follows. Related works of energy-efficient manufacturing are reviewed in the “[Related works](#)” section. The “[Problem statements and assumptions](#)” section describes the problem and some assumptions. In the “[Multi-state fuzzy decision of machines for energy saving production](#)” section, a machine state fuzzy decision method is proposed for energy-saving operation of unreliable complex manufacturing systems. In the “[Simulation study](#)” section, a manufacturing system with disassembly and assembly workstations is controlled to illustrate the effectiveness of the method. In the “[Discussions](#)” section, the influence of different thresholds and decision cycles of the controllers on machine/system performances are discussed. The conclusions and future works are presented in the “[Conclusions](#)” section.

## 2 Related works

Recently, energy-efficient manufacturing has been a very hot research issue with the increasing environmental consciousness all over the world [9–12]. Approaches to achieve energy-efficient manufacturing can be classified as equipment, process, and system levels. The new advanced machines with less energy consumption can be applied in the shop floor at the equipment level [13]. For the same kind of machines, an eco-efficiency process can make production greener at the process level [14]. At the system level, many researches focused on energy-aware production scheduling [15] and various kinds of scheduling optimization algorithms were reviewed in [16]. The method proposed in this paper is related to the real-time machine control at the system level based on policies, rules, models, and algorithms in order to achieve energy-efficient operation. The related works are reviewed as follows.

### 2.1 Operation policies for machine state control at system level

Policies or rules can express the human knowledge of machine control purpose. In order to shorten the idle time of machines, many researchers defined policies or rules to

switch the machine state for energy saving during production process. Mouzon et al. [17] described different switch-off dispatching rules to minimize the total system energy consumption in a one-buffer and one-machine system. Simulation results illustrated that there were 80% energy saving when a non-bottleneck machine was shut off during the production process. The key point to apply these rules was that the inter-arrival time between jobs should be accurately predicted, which was a very difficult problem in practical situation because of the randomness of the manufacturing system.

By extending a M/M/1 model to a serial production line based on queuing theory, a simple control policy was proposed to reduce energy consumption of idle states [18]. Machines were switched into low power idle modes when the idle time exceeded the predefined threshold value. In a pallet-constrained flow shop, the schedule for the loading of the part set was given. Mashaei and Lennartson [19] proposed a control policy for switched-off machines to reduce energy consumption considering design constraints and two idle modes with deterministic warm-up durations. However, machine failures were not considered when the control policies were used in above two studies.

In a single machine system with stochastic inter arrival times of parts, some control policies, such as N-policy, Upstream Policy, Downstream Policy, and Upstream & Downstream Policy, were defined to switch the machine off when the conditions of the policies were satisfied [20]. The policies were evaluated based on energy consumption and optimized with the general arrival distribution of parts. The authors stated that the parameters of the control policies were hard to be determined when the method was used for energy-efficient production [21].

The control policies of machine states in current literatures for energy-efficient manufacturing were described in quantitative statements. It is obvious that some uncertain and imprecise knowledge are hard to be described quantitatively. The limited quantity of policies cannot cover all complex situations of manufacturing systems and the application of the policy method is restricted.

### 2.2 Analytical method of energy consumption control at system level

During the production process, it is important to make real-time decision of machine state for energy-saving control of a manufacturing system. Chang et al. [22] proposed a concept of opportunity window, which was the time length of the machine’s shutdown period without affecting the system throughput. The opportunity window was predicted based on an approximate analytical model with real-time control algorithm considering random downtime events of a serial automotive manufacturing line.

For serial manufacturing systems, Sun and Li [23] presented analytical opportunity estimation for energy control considering buffer utilization and machine stochastic failure. Their simulation results showed that the simple shutdown policy was not an optimal one. The optimal power level within estimated opportunity window should be identified in the future. They also developed a Markov decision process model to describe the evolution process of system states and make energy control decisions [24]. A near-optimal solution of machine state evolution was generated by a real-time approximate algorithm for energy-saving operation.

In Bernoulli serial lines, Jia et al. [25] proposed mathematical models to calculate the power of transient/steady state, as well as the system production rate, by switching the machine on/off. For a serial line with two Bernoulli machines, Su et al. [26] described an integrated model to evaluate energy consumption and productivity. They carried out analytical investigation to discover the conditions when energy consumption could be minimized with and without the workforce constraints or machine processing capability.

For a multi-stage serial-parallel manufacturing system, Li et al. [27] proposed an algorithm to estimate energy-saving opportunity window to improve system energy efficiency. An event-based analysis method was used to calculate the opportunities and a supervisory method was adopted to take the opportunity windows periodically. Zou et al. [28] developed a stochastic analytical model to predict the shutdown time and recovery time of machines based on discrete-time Markov chain for stochastic parallel production systems. A profit function was also described to balance energy cost and potential throughput loss based on real-time production data. Hibino and Yanaga [29] defined a normal idle state and an energy-saving idle state for facilities. The idle-time prediction model, selection algorithm, and transition model of idle state were implemented in Witness to decide the proper idle state without affecting the productivity.

Analytical method of energy consumption control at system level usually depends on fixed structures of manufacturing systems and specific reliability model of machines. The analytical models in [22–26] could only be used in serial lines. The reliability model of machines was limited to Bernoulli distribution in [25, 26]. For the parallel lines, some corrections must be made to energy-saving windows in [28] for unreliable manufacturing systems because of the errors coming from the aggregation method. The simulation method in [29] was time-consuming and not suitable for practical application. There is no literature of energy-efficient operation for assembly and disassembly manufacturing systems.

### 2.3 Fuzzy logic control of manufacturing systems

Fuzzy logic control has already played a significant role in current manufacturing systems and been widely used in

production planning, scheduling, and process control [30, 31], for it can easily integrate human linguistic knowledge into the control process. Compared with conventional method, fuzzy logic method applied more expert knowledge and relied less on mathematical model of a manufacturing system [32].

Based on arithmetic fuzzy interval, Tamani et al. [33] proposed a supervisory mechanism to implement a stable multiple objective real-time scheduling of a production system. By adjusting processing rates of machines, limited production capacity was allocated and the specified global performances were guaranteed within acceptable limits. In single and multiple parts type production lines with finite buffers and unreliable machines, Tsourveloudis et al. [34, 35] developed fuzzy controllers to adjust the processing rate of machines. Their controllers kept machine cycle time and work-in-process at low levels so that work flow was balanced; thus, starvations or blockages of machines were reduced. Yuniarto and Labib [36] proposed a fuzzy logic module to optimize the production rate of an unreliable machine with varying product demands. Their controller provided a YES/NO decision on production and then specified the production rate of machines. Homayouni et al. [37] designed a genetic distributed and supervisory fuzzy controller for a complex multi-part-type production system, where two controllers were used to minimize the production cost and surplus considering backlog costs and work-in-process level.

By decomposing a serial line into several basic modules with one-machine and two-buffers, Wang et al. [38] proposed a fuzzy decision method to decrease the duration of idle states by switching off/on the machine based on real-time information of production lines. The single-machine control and multiple-machine control simulations showed that the method decreased the system energy consumption while the throughput loss was not noticeable. But, only shutdown and normal idle state of machine were considered in their work, which was not practical to frequently shutdown machine in consideration of lifetime. The sensitivities of the parameters were also unknown.

Much progress has been made on energy-efficient operation of manufacturing systems for serial and parallel lines [22–28, 38]. The performances of manufacturing system with assembly and/or disassembly workstations are difficult to be evaluated and controlled [39], and the energy-saving operation of this kind of manufacturing system has never been studied in previous literatures, which is going to be discussed in this paper. By extending our previous work [38], a fuzzy decision method for multi-state decision of unreliable machines was proposed for energy-efficient system operation. Based on fuzzy reasoning and threshold decision, machines were switched into lower energy standby state, i.e., light sleep state or deep sleep state, instead of normal idle state with higher energy consumption. Our simulation experiments showed that the proposed method efficiently decreased the

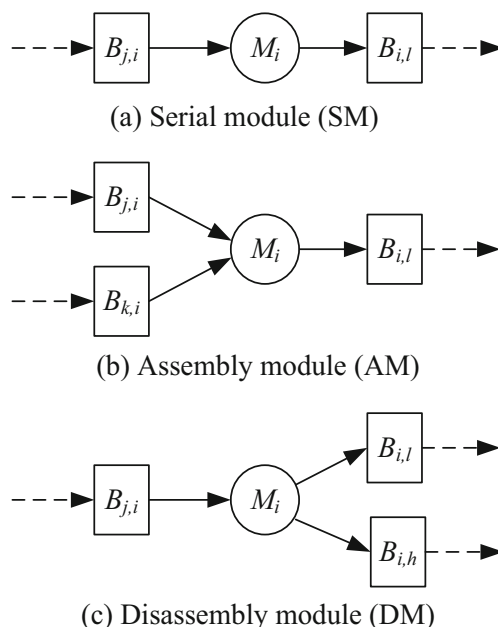
system energy consumption, although slightly sacrificing the system throughput. It was proved that the energy consumption of per product could be reduced effectively.

### 3 Problem statements and assumptions

It is known that the idle states in the manufacturing system come from the unbalanced workability and uncertain failures of machines. The random breakdowns of machines make the job quantity in buffers change frequently. The buffer level, i.e., work in process, is the original source of idle states. The full level of a buffer makes its upstream machine blocked and an empty buffer causes the starvation of its downstream machine. This phenomenon propagates throughout the whole manufacturing system. Our contribution mainly lies in deciding a suitable machine state based on fuzzy logic with a goal of reducing the overall system energy consumption and maximizing the system throughput.

Complex manufacturing systems with  $n$  unreliable machines and a certain number of limited capacity buffers can be decomposed into several basic modules. In our previous research [38], the serial module was discussed. Hereby, the three basic modules (Fig. 1), i.e., serial module (SM), assembly module (AM), and disassembly module (DM), were described uniformly to construct complex production systems for energy-efficient operation.

Each basic module was made up of one machine and its upstream and downstream buffers. For different kinds of basic modules, the quantity of upstream and downstream buffers



**Fig. 1** Three basic modules for complex manufacturing systems. **a** Serial module (SM). **b** Assembly module (AM). **c** Disassembly module (DM)

was varied as shown in Fig. 1. In this study, only two upstream buffers in AM and two downstream buffers in DM were considered. The proposed method can be extended to modules with more buffers. Three basic modules can constitute various system structures if connected to each other. It should be noted that the AM and DM module are different from traditional merging/branching workstations of a parallel line, in which the number of downstream/upstream buffer is only one.

In our study, the discrete time was used to model the production process. For a general manufacturing system composed by three basic modules, the following assumptions were made.

- (1) A machine,  $M_i$ ,  $i = 1, 2, \dots, n$ , had a deterministic known cycle time. The cycle times were equal or different.
- (2) Each machine had two standby states, i.e., light sleep (LS) state and deep sleep (DS) state. These two standby states consumed lower energy than the traditional normal idle (ID) state.
- (3) A power-on machine consumed different kinds of energy, such as electricity, gas, fuel, and compressed air, while a buffer would not. In each state, a machine consumed deterministic energy which was collected from the shop floor.
- (4) Mean time between failure (MTBF) and mean time to repair (MTTR) of machines were supposed to follow probability distribution. Time-dependent failures were assumed for the machines.
- (5) The buffers,  $B_{j,i}$ ,  $B_{k,i}$ ,  $B_{i,l}$ ,  $B_{i,h}$ , had real-time buffer level  $b_{j,i}(t)$ ,  $b_{k,i}(t)$ ,  $b_{i,l}(t)$ ,  $b_{i,h}(t)$  at the beginning of each discrete time slot.
- (6) It was assumed that there was a buffer with unlimited capacity at the beginning of the system and the first machine was never starved.
- (7) It was assumed that there was a buffer with unlimited capacity buffer at the end of the system and the last machine was never blocked.
- (8) The machine in one disassembly module outputs two different parts after operation. Each downstream buffer in a disassembly module got one part respectively.
- (9) The machine in one assembly module consumed two parts for every operation. Each upstream buffer in the assembly module fed one part to the machine respectively.

## 4 Multi-state fuzzy decision of machines for energy-saving production

### 4.1 The controller of basic modules for energy-saving operation

For machines with several idle power states, i.e., normal idle, light sleep, and deep sleep in this paper, the aim of the fuzzy decision was to switch the machines into suitable states based

on the real-time data of manufacturing systems. The most commonly used fuzzy inference method, the Mamdani scheme [40], was adopted to construct the controller of the basic modules.

The structure of the proposed fuzzy controller for basic modules was shown in Fig. 2. Each controller had four components, i.e., fuzzification, fuzzy inference, defuzzification, and state decision. The  $f_i(t)$  was a real number after defuzzification. The output of the controller  $c_i(t)$  was a decision signal sent to machine  $M_i$ , which represented the controlled state for the next time slot after its current state. For each basic module, there were different input variables as follows.

- (1)  $b_{j,i}(t)$ , the real-time level of upstream buffer  $B_{j,i}$  in three modules
- (2)  $b_{k,i}(t)$ , the real-time level of upstream buffer  $B_{k,i}$  in AM module
- (3)  $b_{i,l}(t)$ , the real-time level of downstream buffer  $B_{i,l}$  in three modules
- (4)  $b_{i,h}(t)$ , the real-time level of downstream buffer  $B_{i,h}$  in DM module
- (5)  $s_i(t)$ , the current up or failure state of machine  $M_i$

### 4.2 Fuzzification of the production and state data

Fuzzy logic is based on the concept of fuzzy sets, whose elements are not clearly quantified. A fuzzy set contains elements with partial degrees of membership (usually between 0

and 1). The membership function (MF) is defined to map the degrees of membership to each element. Fuzzification process is to classify numerical data of the system into fuzzy sets.

In each basic module, the real-time level of a buffer during production process, i.e.,  $b_{j,i}(t)$ ,  $b_{k,i}(t)$ ,  $b_{i,h}(t)$ , and  $b_{i,l}(t)$ , was expressed in linguistic terms with certain MF. In this paper, the linguistic value of a buffer level was formulated as the fuzzy set  $BL = \{Empty, Almost\ Empty, Normal, Almost\ Full, Full\}$ . Several types of MFs were usually used in literatures for different purpose, e.g., triangular function, trapezoidal function, Gaussian function, and bell function. The triangle membership functions (Fig. 3) were adopted in this paper for linguistic values of buffer levels. The reason is that the buffer level increases or decreases one by one and the overall trend appears to be an oblique line. The advantage of triangle membership function is its simplicity and ease of implementation [41].

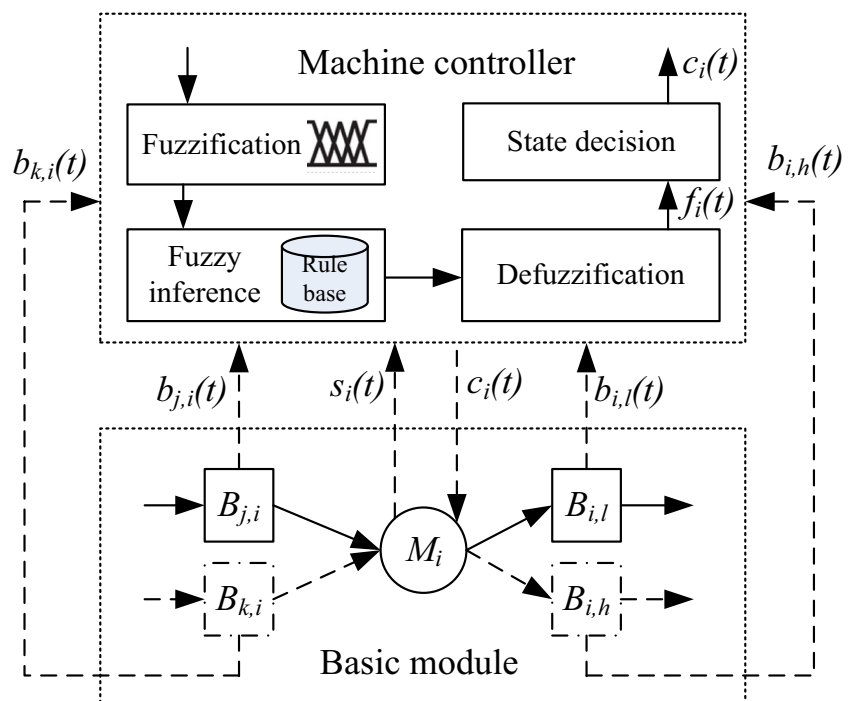
The machine state  $s_i(t)$  can be 1 (up) or 0 (failure) and consequently had the term set  $MS = \{Up, Down\}$ , which indicated power-on or failure (FL) state of machines.

The output value of the fuzzy logic  $e_i(t)$  took from the fuzzy set  $OS = \{Deep\ sleep, Light\ sleep, Processing\}$ . The output linguistic value was assigned with a triangle membership function in this paper (Fig. 4).

### 4.3 Fuzzy rules and inference for energy-saving operation of machines

In order to avoid the possible normal idle state with higher energy consumption, the fuzzy rules were defined in this paper to infer the suitable machine states based on the real-time

Fig. 2 The fuzzy controller of basic modules



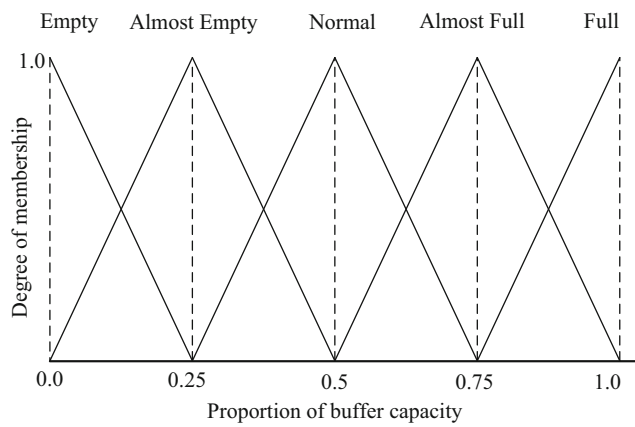
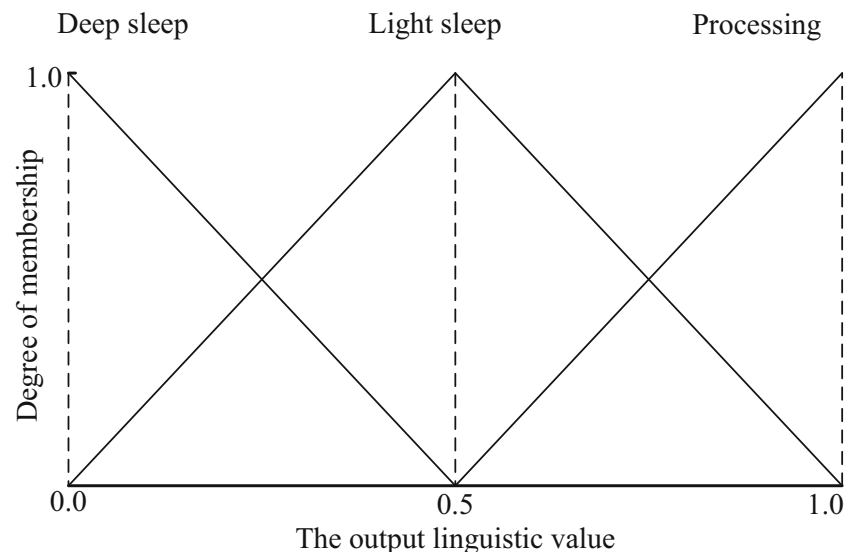


Fig. 3 Membership functions of a buffer level

level of its upstream and downstream buffers. A fuzzy rule is a linguistic statement which presents the relationship between the input and output of a fuzzy system. The IF-THEN expression is the simplest and most widely used for its computational efficiency [40]. The IF-part of a rule is the conditions under which the rule is applicable and forms the composition of the inputs. The THEN-part of a rule is the conclusion which should be drawn under these conditions. The number of rules depends on the total number of linguistic variables. The fuzzy rules are defined based on production knowledge of experts and/or experiments.

In order to avoid normal idle state, the defined fuzzy rules should switch a machine into deep sleep or light sleep state based on the real-time buffer level so that the buffers were neither full nor empty. If a machine is going to be starved or blocked according to the real-time level of its connected buffers, the machine will be switched into different sleep states to avoid normal idle state. If a machine will starve/block its downstream/upstream machine according to the

Fig. 4 Membership functions of controlled machine states



real-time level of its connected buffers, the machine will be waken up to avoid the idleness of other machines. This practice takes full advantages of the buffer capacity and keeps the overall throughput within acceptable ranges.

The above knowledge was formulated as fuzzy rules for each basic module. For the fuzzy controllers of SM, AM, and DM basic modules, the fuzzy rules of the Mamdani type were defined respectively:

$$\begin{aligned} &\text{IF } b_{j,i}(t) \text{ is } BL^{(g)} \text{ AND } b_{i,l}(t) \text{ is } BL^{(g)} \\ &\text{AND } s_i(t) \text{ is } MS^{(g)} \text{ THEN } e_i(t) \text{ is } OS^{(g)} \end{aligned} \quad (1)$$

$$\begin{aligned} &\text{IF } b_{j,i}(t) \text{ is } BL^{(g)} \text{ AND } b_{k,i}(t) \text{ is } BL^{(g)} \\ &\text{AND } b_{i,l}(t) \text{ is } BL^{(g)} \text{ AND } s_i(t) \text{ is } MS^{(g)} \\ &\text{THEN } e_i(t) \text{ is } OS^{(g)} \end{aligned} \quad (2)$$

$$\begin{aligned} &\text{IF } b_{j,i}(t) \text{ is } BL^{(g)} \text{ AND } b_{i,l}(t) \text{ is } BL^{(g)} \\ &\text{AND } b_{i,h}(t) \text{ is } BL^{(g)} \text{ AND } s_i(t) \text{ is } MS^{(g)} \\ &\text{THEN } e_i(t) \text{ is } OS^{(g)} \end{aligned} \quad (3)$$

Some rules with  $s_i(t) = 1$  were shown in Table.1. It should be noted that the fuzzy controllers of the basic modules had a decision cycle. A machine would be switched into a controlled state after its current state within a decision cycle. Fuzzy inference process formulates a mapping from a given input to an output based on fuzzy logic. Mamdani is a direct inference method which determines the outputs from the rules by min-max operations directly. As a standard procedure, the fuzzy reference process can be found in [40] and will not be detailed here.

#### 4.4 Defuzzification and machine state decision

Defuzzification is the process which generates a real number value from the inference result. The most frequently

**Table 1** Some fuzzy rules for three basic modules

Module	Inputs				Output
	$b_{j,i}(t)$	$b_{k,i}(t)$	$b_{i,i}(t)$	$b_{i,h}(t)$	
SM	Empty	–	Full	–	Deep sleep
	Almost empty	–	Almost full	–	Deep sleep
	Almost empty	–	Almost empty	–	Low sleep
	Normal	–	Almost empty	–	Working
	Almost full	–	Normal	–	Working
	Full	–	Almost full	–	Low sleep
AM	Almost empty	Normal	Almost empty	–	Low sleep
	Almost empty	Almost full	Almost full	–	Deep sleep
	Normal	Almost empty	Almost full	–	Deep sleep
	Normal	Normal	Normal	–	Working
	Normal	Almost full	Almost full	–	Low sleep
	Almost full	Almost empty	Almost full	–	Deep sleep
	Almost full	Almost full	Normal	–	Working
	Full	Almost empty	Normal	–	Low sleep
DM	Full	Almost full	Empty	–	Working
	Almost empty	–	Empty	Almost full	Deep sleep
	Almost empty	–	Almost empty	Normal	Low sleep
	Normal	–	Almost empty	Normal	Working
	Normal	–	Normal	Almost full	Low sleep
	Normal	–	Almost full	Almost full	Deep sleep
	Almost full	–	Almost empty	Almost empty	Working
	Almost full	–	Almost full	Normal	Low sleep
	Full	–	Normal	Full	Deep sleep
	Full	–	Almost full	Almost empty	Low sleep

used defuzzification strategy, the center of gravity method [40], was adopted. The output of the defuzzification  $f_i(t)$  in Fig. 2 is a real number between 0 and 1.

In order to decide the next controlled state of machine  $M_i$ , i.e., deep sleep, light sleep, or processing, two real threshold numbers between 0 and 1,  $d_i$  and  $w_i$ , were defined to divide the interval [0,1] into three sub-interval. If the  $f_i(t)$  was less than  $d_i$ , the final decision was to switch the machine into deep sleep state at the end of its current state. If the  $f_i(t)$  was larger than  $w_i$ , the final decision was to switch the machine into processing state at the end of its current state. Otherwise, the controller switched the machine into light sleep state at the end of its current state. The output of the controller was represented as a signal sent to the machine as follows, where the number 0, 1, and 2 means deep sleep, light sleep, and processing respectively.

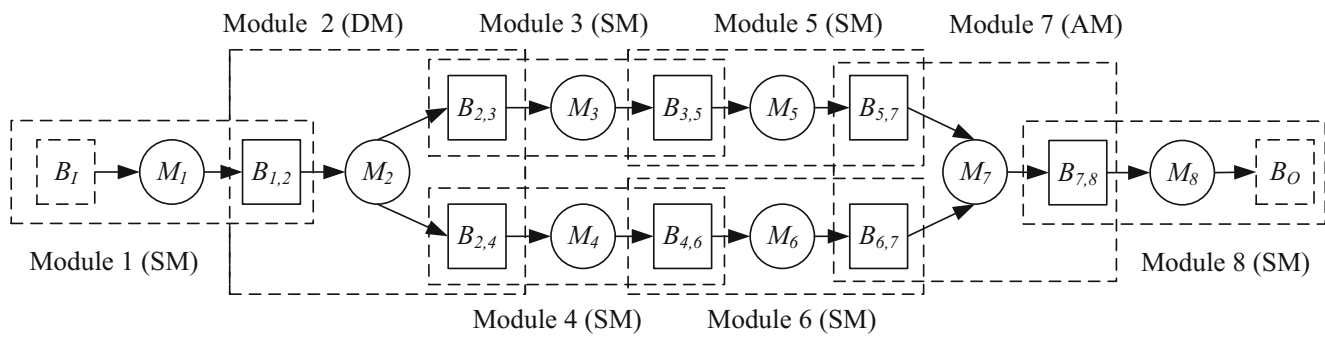
$$c_i(t) = \begin{cases} 0, & \text{if } f_i(t) < d_i \\ 1, & \text{if } d_i \leq f_i(t) \leq w_i \\ 2, & \text{other} \end{cases} \quad (4)$$

## 5 Simulation study

Simulation is an important tool for energy-efficient manufacturing research [42, 43]. In this section, a typical complex manufacturing system with assembly and disassembly workstations was used to validate the proposed method based on simulation experiments. Fuzzy Logic Toolbox of MATLAB and SIMULINK were used to build models. All the scenarios were repeated 20 times for an 8-h shift. The failure modes of machines were supposed to follow exponential distribution.

### 5.1 A manufacturing system

Figure 5 shows a manufacturing system with 8 machines and 8 buffers. Two virtual buffers were added to the beginning and ending of the system in order to have a uniform expression. There were 8 basic modules including 6 serial modules, 1 disassembly module, and 1 assembly module. Each module had a fuzzy controller for machine state decision.



**Fig. 5** A complex manufacturing system with assembly and disassembly stations

The parameters of machines, i.e., cycle time, MTBF, MTTR, buffer's capacity, and initial level, were listed in Tables 2 and 3. It is known that the energy consumed by normal idle state is usually 15 to 30% lower than that consumed by processing (PR) state [44], and the energy required in sleep state is somewhat lower than that required in normal idle state, depending on how many components are turned off [45]. To guarantee the generality of our study, the assumptions about the energy consumption based on the processing power  $P_{pr}$  of a machine were made as follows:

The normal idle power  $P_{id}$  was 70% of  $P_{pr}$ . The deep sleep power  $P_{ds}$  was 30% of  $P_{pr}$ . The light sleep power  $P_{ls}$  was 50% of  $P_{pr}$ . When a machine woke up from the sleep state, the wake-up time was 4 s for light sleep state and 6 s for deep sleep state. The wake-up power was 110% and 120% of  $P_{pr}$  for these two different sleep states respectively.

## 5.2 Simulation experiments

Three scenarios were simulated and the results were analyzed. The first scenario (S1) was a baseline production without any control. One machine was controlled in the second scenario (S2) and more machines were controlled in the third scenario (S3).

For S1, the machine throughput (MTP), the time duration of each machine states was shown in Table 4. It was observed that about 6.30% downtime (242.08 min) of all machines led to blockage/starvation in the system, which resulted in over 21.09% idle (blockage/starvation) time (810.02 min) of all machines during the production process. According to the blockage and starvation data,  $M_3$  and  $M_4$  were identified as

**Table 2** Machine data of the manufacturing system

Machine	$M_1$	$M_2$	$M_3$	$M_4$	$M_5$	$M_6$	$M_7$	$M_8$
Cycle time(min)	1	1	2	2	2	2	1	1
MTBF (min)	100	60	80	115	132	158	108	100
MTTR (min)	8	3	9	13	10	7	6	5
Processing power (kW)	12	5	10	9	17	16	6	5

the system throughput (STP) bottlenecks based on the methods in [39].

In S2, the disassembly machine  $M_2$  or the assembly machine  $M_7$  was controlled to validate the effectiveness of the controller for energy-saving operation. The effects of various threshold values on system performances were discussed in the next section. The thresholds of fuzzy controllers in S2 were  $w_2=0.5$ ,  $d_2=0.48$  for  $M_2$  and  $w_7=0.3$ ,  $d_7=0.28$  for  $M_7$ . In S3, all machines excluding bottlenecks  $M_3$  and  $M_4$  were controlled at the same time with the thresholds  $w_1=0.8$ ,  $w_2=0.8$ ,  $w_5=0.3$ ,  $w_6=0.3$ ,  $w_7=0.2$ ,  $w_8=0.2$ , and  $d_i$  of all machines was 0.02 lower than  $w_i$ . The system performances of the three scenarios, measured in energy consumption of system (ECS) and energy consumption of unit (ECU), were shown in Table 5. The energy-saving control cycle of the machines was 5 min, which means the production data was collected and the energy-saving decision was made every 5 min.

As Table 5 showed, the system throughput remained the same when only  $M_2$  was controlled. The simulation results showed that the control of  $M_2$  did not affect the working process of  $M_3$  and  $M_4$ . The normal idle time of controlled  $M_2$  was zero and its total sleep time was about 232.20 min. The system's total normal idle time, i.e., the total normal idle time of other machines, was 633.07 min. Compared with S1, the total normal idle time of all machines decreased 21.85%. When only  $M_7$  was controlled, the system throughput loss was 1.53% of that in S1 because the control of  $M_7$  aggravated the starvation of  $M_8$ , whose starving time length increased from 213.07 to 216.82 min. For the energy consumption, the ECS decreased by 1.3% and 1.4% respectively when only  $M_2$  or  $M_7$  was controlled compared with S1. When  $M_7$  was controlled, the ECU was higher because of the system throughput loss.

In S3, six machines ( $M_1$ ,  $M_2$ ,  $M_5$ ,  $M_6$ ,  $M_7$ ,  $M_8$ ) were controlled simultaneously. From Table 5, the total normal idle

**Table 3** Buffer capacity and initial level

Buffer	$B_{1,2}$	$B_{2,3}$	$B_{2,4}$	$B_{3,5}$	$B_{4,6}$	$B_{5,7}$	$B_{6,7}$	$B_{7,8}$
Capacity	60	80	85	25	40	35	40	45
Initial level	28	40	50	10	15	12	18	10



**Table 4** Statistical data of machines and throughputs in S1

Machine	Processing (min)	Blockage (min)	Starvation (min)	Failure (min)	Energy consumed (kW)	MTP (unit) (95% CI)
M1	283.50	161.88	0.00	34.62	79.36	283.50 ± 3.96
M2	252.30	204.25	0.00	23.45	32.94	252.30 ± 4.16
M3	434.10	0.00	0.00	45.90	72.35	217.05 ± 3.49
M4	436.90	0.00	0.00	43.10	65.54	218.45 ± 4.50
M5	445.40	0.00	4.12	30.48	127.01	222.70 ± 4.34
M6	456.20	0.00	5.62	18.18	122.70	228.10 ± 3.68
M7	234.65	0.00	221.09	24.26	38.94	234.65 ± 4.51
M8	244.85	0.00	213.07	22.09	32.83	244.85 ± 4.24
Total	2787.90	366.13	443.89	242.08	571.68	–

time of all machines notably decreased to 32.54 min, which reduced 96% of that in S1. The sleep time went up to 911.65 min for all controlled machines, which accounted for 31.65% of the shift time of controlled machines. The system throughput loss was 2.25%. The ECS of S3 decreased by 8% and the ECU also went down from 2.33 to 2.20, compared with S1. Figure 6 shows the MTP loss, energy reduction, and sleep time of each machine in S3. All controlled machines lost their throughput and had different durations of sleep time. The energy consumption of each controlled machine also decreased with different degrees. But the working process of the bottlenecks was not affected.

## 6 Discussions

It was obvious that the input parameters of fuzzy controllers affected the system throughput and the energy consumption of machines. In this section, the influence of different thresholds and decision cycles of the controllers on machine/system performances were discussed.

### 6.1 Threshold values of the controllers

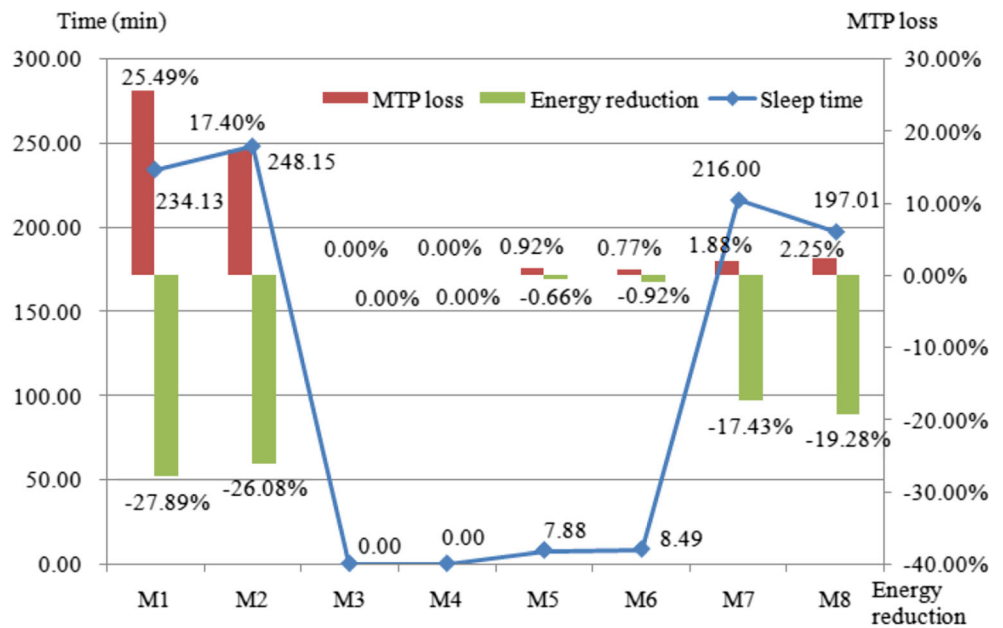
The effects of threshold value were tested with the same decision cycle in S2. M<sub>2</sub> or M<sub>7</sub> was solely controlled based on different thresholds and the decision cycle was constant as 5 min. According to formula (4), the first threshold  $w_i$  was used to decide the processing state or sleep state of machine

and the second threshold  $d_i$  was used to decide the light sleep or deep sleep state of machine. The larger the threshold value  $w_i$  is, the more easily a machine enters the sleep state. The closer the threshold value  $d_i$  is to  $w_i$ , the more easily a machine enters the deep sleep state. Apparently, the controller always turns a machine into sleep state if  $w_i = 1$ . While, it has no effect on the machine if  $w_i = 0$ . The simulation experiments also showed the same results with  $w_i = 0.9$  and  $w_i = 0.1$  respectively. The numerical value of  $d_i$  did not affect the system throughput because the machine was in sleep state, no matter whether it is in light or deep sleep state. The numerical value of  $d_i$  only influenced preference of selecting light sleep and deep sleep state, thus leading to different total energy consumption. If  $d_i$  was close to  $w_i$ , the deep sleep state would be more easily decided and more energy saving would be achieved. According to our experiments, the machine did not have deep sleep state if  $d_i$  was 0.1 smaller than  $w_i$ . In order to have more energy saving, larger  $d_i$  should be assigned. Therefore, we used  $d_2 = 0.48$  and  $d_7 = 0.28$  in our simulations, which was 0.02 smaller than  $w_2 = 0.5$  and  $w_7 = 0.3$  respectively in S2. The system performance, i.e., throughput and energy saving, was shown in Table 5. There were only 1.53% loss of throughput and 1.4% reduction of energy consumption per unit. The assigned threshold value generated better system performance. However, since the selectable ranges of threshold values were very large, the optimized values were not discussed in the paper. Figure 7 shows the system and machine performances of different thresholds.

**Table 5** Performances comparison of three scenarios

Scenario	Machine controlled	Total sleep time (min) (95% CI)	Total idle time (min)	STP (unit) (95% CI)	STP loss (%)	ECS/ECU (kW)
S1	–	–	810.02	244.85 ± 4.24	–	571.68/2.33
S2	M <sub>2</sub>	232.20 ± 2.84	633.07	244.85 ± 4.24	0.00	564.23/2.30
	M <sub>7</sub>	221.20 ± 3.79	596.27	241.10 ± 3.89	1.53%	563.67/2.34
S3	M <sub>1</sub> ,M <sub>2</sub> ,M <sub>5</sub> , M <sub>6</sub> ,M <sub>7</sub> ,M <sub>8</sub>	911.65 ± 18.90	32.54	239.35 ± 3.91	2.25%	525.86/2.20

Fig. 6 The performance of all machines in S3



From Fig. 7, larger threshold resulted in longer sleep time and more throughput loss of machines and system. When only M<sub>2</sub> was controlled, the STP loss was zero even with the different threshold values. From the simulation experiments, the control of M<sub>2</sub> did not affect the working process of the downstream bottlenecks M<sub>3</sub>, M<sub>4</sub>, and all machines after the bottlenecks. If M<sub>7</sub> was controlled, larger threshold value caused more MTP of M<sub>7</sub>, and the MTP loss of M<sub>7</sub> caused more starvation time of M<sub>8</sub> and the STP decreased slightly.

The above experiments showed that threshold values of machines should be properly chosen according to the positions of machines in the system with the aim of not sacrificing the system throughput while achieving more energy-saving time. For machines before bottlenecks, it is apparently that the threshold should be as high as possible in order to obtain more energy-saving time, as long

as it does not lead to the starvation of the bottlenecks. For machines after bottlenecks, the threshold should be lower in order not to sacrifice the throughput and not to block the bottlenecks as well.

### 6.2 Decision cycle time of the controller

An appropriate decision cycle time of a controller should be decided considering the cycle time of the machines. The decision cycle time influences the real-time buffer levels and determines the data collection frequency. A smaller decision interval means a more frequent data-collection from the shop floor and imposes more burdens on system management. A smaller decision interval also means that the buffer level has slighter change and the controller output almost remains constant. When a larger

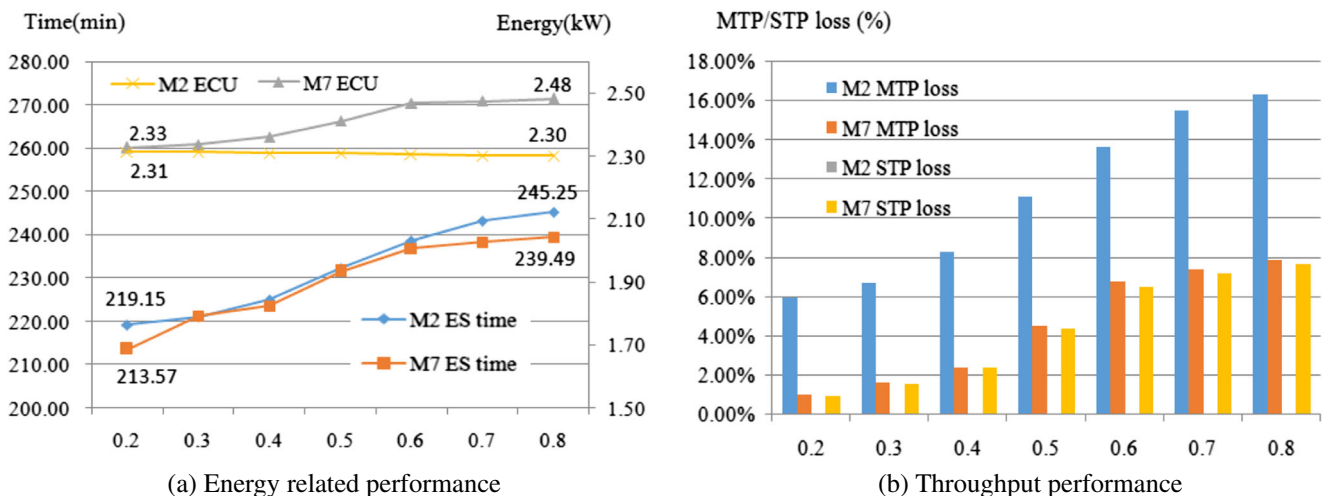


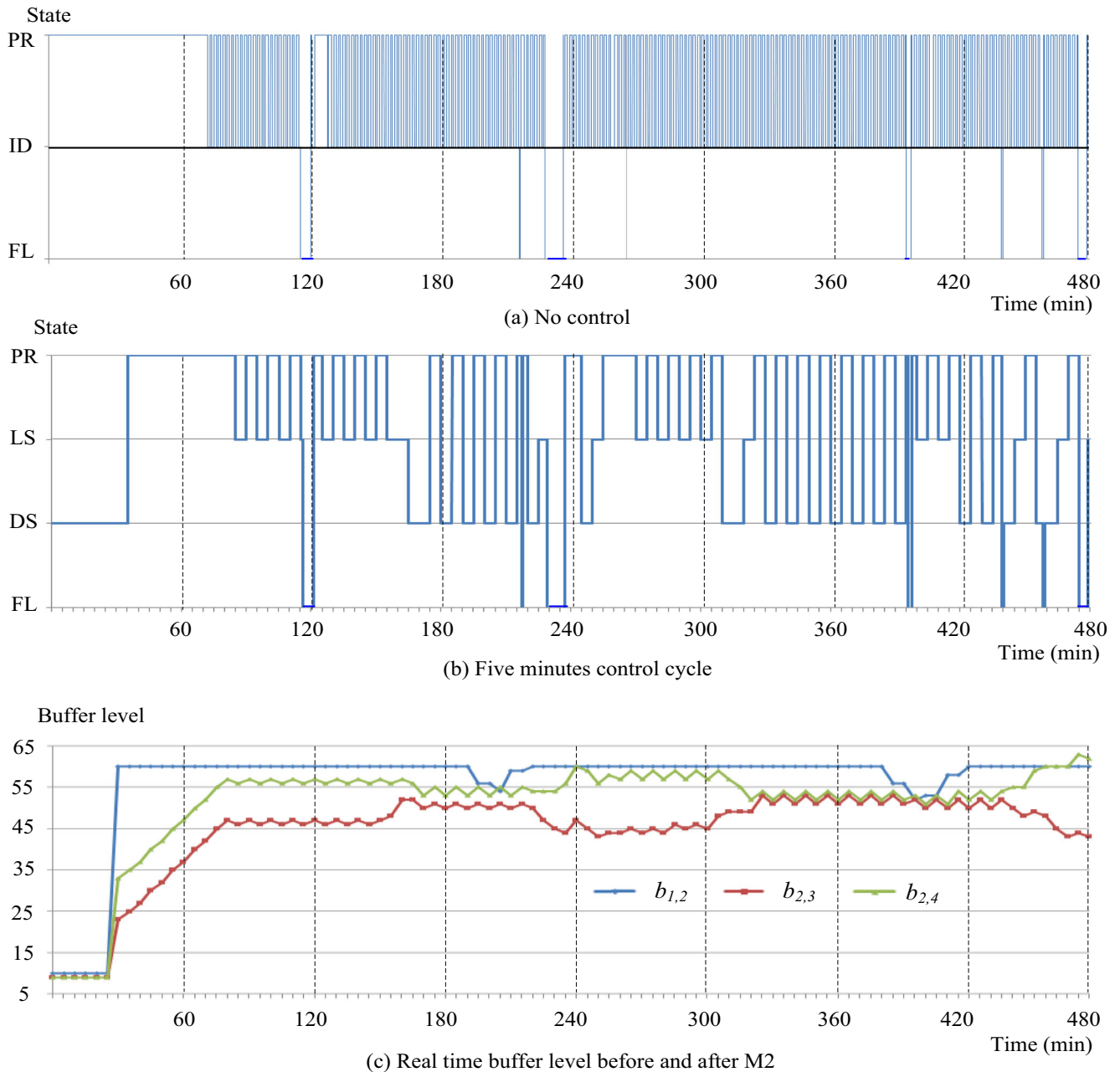
Fig. 7 System and machine performances with different threshold in S2. a Energy-related performance. b Throughput performance

**Table 6** Performance comparison with different decision cycle in S3

Decision cycle (min)	Total ES time (min) (95% CI)	STP (95% CI)	STP loss (%)	ECS/ECU (kW)
No	–	244.85 ± 4.24	–	571.68/2.33
2	901.94 ± 20.33	241.65 ± 3.93	1.31%	531.41/2.20
5	911.65 ± 18.90	239.35 ± 3.91	2.25%	525.86/2.20
10	901.17 ± 21.11	234.75 ± 4.83	4.12%	523.17/2.23

decision interval is used, the decision of a controller takes longer time on machines. The full or empty buffer state is easier to be formed and the throughput loss will increase.

The effects of the different decision cycle times in S3 were thoroughly studied in simulation experiments with the same threshold (Table 6).



**Fig. 8** Machine state trajectory of  $M_2$  and real-time buffer level before/after  $M_2$ . **a** No control. **b** Five minutes control cycle. **c** Real-time buffer level before and after  $M_2$

From Table 6, it was observed that the total energy-saving time did not have a rising trend with a longer decision cycle. The system throughput loss was larger when a longer decision cycle was adopted, which indicated that the controller could not catch system transient state if the decision cycle was too long. Then, energy-saving opportunities were missed and more normal idle time of machines occurred. An acceptable decision cycle interval can be decided based on the cycle time of machines and validated by simulation with data collected from real manufacturing scenarios.

### 6.3 The trajectory of machine states during production

To get a clear change process of a machine state, the trajectory of the machine states and the buffer levels was recorded. Figure 8 shows a state trajectory of  $M_2$  and the buffer levels before/after  $M_2$  in a random experiment of S2. The warm-up states after the sleep and failure states were not shown due to their short durations.

From Fig. 8, there were many frequent state changes between PR state and ID states because of the blockage of  $M_2$  without control. Therefore, many normal idle states with short time consumed huge amount of energy. When the fuzzy controller took into effect, the machine  $M_2$  was turned into light sleep or deep sleep state if there was a tendency of blockage or starvation. For example, the decision at 155 min made  $M_2$  switch into LS state with the buffer level data  $\{b_{12} = 60; b_{23} = 47; b_{24} = 57\}$ . Five minutes later, the decision result was also LS with buffer level data  $\{b_{12} = 60; b_{23} = 48; b_{24} = 56\}$ . At 165 min, the decision result was DS state for  $M_2$  with the buffer level data  $\{b_{12} = 60; b_{23} = 52; b_{24} = 57\}$ . During this shift, there were 20 times LS decisions and 28 times DS decisions. The total sleep time of  $M_2$  was 232.20 min as shown in Table 5 and  $M_2$  has no normal idle state.

In summary, the proposed fuzzy method has obvious advantages to achieve energy-efficient operation of complex manufacturing system with assembly and disassembly workstations by applying energy-saving knowledge representation and reasoning in machine state decision. The new IoT-based manufacturing system control automation can be easily realized based on the knowledge other than complex mathematical models. Single or multi-machine can be selected flexibly to achieve energy-efficient production at the system level. The easy design and realization of the method makes it more practical for shop floor manufacturing systems control. On the other hand, the previous researches of energy-saving operation usually depended on specified failure modes [20, 22–28]. While in our study, the buffer level other than failure mode is used as the input of the controller and the energy-saving decision would be simplified, which is not restricted to complicate failure modes of machines.

## 7 Conclusions

For complex manufacturing systems with serial, disassembly, and assembly workstations, a multi-state fuzzy controller was proposed in this paper to switch the machines into sleep state at an appropriate opportunity for energy-saving operation. Three basic modules were constructed to generate the system structure. The real-time data of machines and buffers were collected and used as controller inputs. The components of the controllers were described in detail to show the decision process of energy-efficient operation. A large number of simulation experiments were conducted and the results illustrated the feasibility and effectiveness of the fuzzy method for energy-efficient manufacturing. In the current study, the machines were in distributed control based on local real-time data. Future study will focus on a supervisory control considering real-time system throughput. The energy-saving operation of manufacturing system with re-entrant line will also be carried out.

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## References

1. Bruzzone AAG, Anghinolfi D, Paolucci M, Tonelli F (2012) Energy-aware scheduling for improving manufacturing process sustainability: a mathematical model for flexible flow shops. *CIRP Ann-Manuf Technol* 61(2):459–462
2. Fysikopoulos A, Pastras G, Alexopoulos T, Chryssolouris G (2014) On a generalized approach to manufacturing energy efficiency. *Int J Adv Manuf Technol* 73(9–12):1437–1452
3. Zhang XP, Cheng XM (2009) Energy consumption, carbon emissions, and economic growth in China. *Ecol Econ* 68(10):2706–2712
4. Dufloy JR, Sutherland JW, Dornfeld D, Herrmann C, Jeswiet J, Kara S, Hauschild M, Kellens K (2012) Towards energy and resource efficient manufacturing: a processes and systems approach. *CIRP Ann-Manuf Technol* 61(2):587–609
5. Twomey J, Yildirim M B, Whitman L, Liao H, Ahmad J (2008) Energy profiles of manufacturing equipment for reducing energy consumption in a production setting. Working paper, Wichita State Univ., Wichita, KS
6. Weinert N, Mose C (2014) Investigation of advanced energy saving stand by strategies for production systems. *Proced CIRP* 15(15):90–95

7. Wang B, Cao Z, Yan Y, Liu W, Wang Z (2011) Fundamental technology for RFID-based supervisory control of shop floor production system. *Int J Adv Manuf Technol* 57(9–12):1123–1141
8. Peng T, Xu X (2014) Energy-efficient machining systems: a critical review. *Int J Adv Manuf Technol* 72(9–12):1389–1406
9. Seow Y, Rahimifard S (2011) A framework for modeling energy consumption within manufacturing systems. *CIRP J Manuf Sci Technol* 4(3):258–264
10. Jia S, Tang R, Lv J, Yuan Q, Peng T (2016) Energy consumption modeling of machining transient states based on finite state machine. *Int J Adv Manuf Technol* 88(5–8):1–16
11. Zhou Z, Yao B, Xu W, Wang L (2017) Condition monitoring towards energy-efficient manufacturing: a review. *Int J Adv Manuf Technol* 91(9–12):3395–3415
12. Apostolos F, Alexios P, Georgios P, Panagiotis S, George C (2013) Energy efficiency of manufacturing processes: a critical review. *Proced CIRP* 7:628–633
13. Feng SC, Senthilkumaran K, Brown CU, Kulvatunyou B (2014) Energy metrics for product assembly equipment and processes. *J Clean Prod* 65(4):142–151
14. Ma J, Ge X, Chang SI, Lei S (2014) Assessment of cutting energy consumption and energy efficiency in machining of 4140 steel. *Int J Adv Manuf Technol* 74(9–12):1701–1708
15. Zhang L, Li X, Gao L, Zhang G (2013) Dynamic rescheduling in FMS that is simultaneously considering energy consumption and schedule efficiency. *Int J Adv Manuf Technol* 87(5–8):1–13
16. Giret A, Trentesaux D, Prabhu V (2015) Sustainability in manufacturing operations scheduling: a state of the art review. *J Manuf Syst* 37:126–140
17. Mouzon G, Yildirim MB, Twomey J (2007) Operational methods for minimization of energy consumption of manufacturing equipment. *Int J Prod Res* 45(18–19):4247–4271
18. Prabhu VV, Jeon HW, Taisch M (2012) Modeling green factory physics - an analytical approach. *Proceedings of the 8th IEEE International Conference on Automation Science and Engineering*, August 20–24, Seoul, Korea, pp 20–24
19. Mashaei M, Lennartson B (2013) Energy reduction in a pallet-constrained flow shop through on–off control of idle machines. *IEEE Trans Autom Sci Eng* 10(1):45–56
20. Frigerio N, Matta A (2015) Energy-efficient control strategies for machine tools with stochastic arrivals. *IEEE Trans Autom Sci Eng* 12(1):50–61
21. Su HT, Frigerio N, Matta A (2016) Energy saving opportunities and value of information a trade-off in a production line. *Proc CIRP* 48:30–306
22. Chang Q, Xiao GX, Biller S, Li L (2013) Energy saving opportunity analysis of automotive serial production systems. *IEEE Trans Autom Sci Eng* 10(2):334–342
23. Sun Z, Li L (2013) Opportunity estimation for real time energy control of sustainable manufacturing systems. *IEEE Trans Autom Sci Eng* 10(1):38–44
24. Li L, Sun Z (2013) Dynamic energy control for energy efficiency improvement of sustainable manufacturing systems using Markov decision process. *IEEE Trans Syst Man Cybern* 43(5):1195–1205
25. Jia Z, Zhang L, Arinez J, Xiao G (2016) Performance analysis for serial production lines with Bernoulli machines and real-time wip-based machine switch-on/off control. *Int J Prod Res* 54(21):1–17
26. Su W, Xie X, Li J, Zheng L (2016) Improving energy efficiency in Bernoulli serial lines: an integrated model. *Int J Prod Res* 54(11):1–15
27. Li Y, Chang Q, Ni J, Brundage MP (2016) Event-based supervisory control for energy efficient manufacturing systems. *IEEE Trans Autom Sci Eng* 99:1–12
28. Zou J, Arinez J, Chang Q, Lei Y (2016) Opportunity window for energy saving and maintenance in stochastic production systems. *J Manuf Sci Eng-Trans ASME* 138(12):121009
29. Hibino H, Yanaga K (2017) Decision support for energy-saving idle production facility operations in a production line based on an M2M environment. *Proc CIRP* 61:399–403
30. Azadegan A, Porobic L, Ghazinoory S, Samouei P, Kheirkhah AS (2011) Fuzzy logic in manufacturing: a review of literature and a specialized application. *Int J Prod Econ* 132(2):258–270
31. Sharma S, Agrawal N (2012) Application of fuzzy techniques in a multistage manufacturing system. *Int J Adv Manuf Technol* 60(1–4):397–407
32. Precup RE, Hellendoorn H (2011) A survey on industrial applications of fuzzy control. *Comput Ind* 62(3):213–226
33. Tamani K, Boukezzoula R, Habchi G (2011) Application of a continuous supervisory fuzzy control on a discrete scheduling of manufacturing systems. *Eng Appl Artif Intell* 24(7):1162–1173
34. Tsourveloudis NC, Dretoulakis E, Ioannidis S (2000) Fuzzy work-in-process inventory control of unreliable manufacturing systems. *Inf Sci* 27:69–83
35. Tsourveloudis NC, Doitsidis L, Ioannidis S (2007) Work-in-process scheduling by evolutionary tuned fuzzy controllers. *Int J Adv Manuf Technol* 34(7–8):748–761
36. Yuniarto MN, Labib AW (2005) Optimal control of an unreliable machine using fuzzy-logic control: from design to implementation. *Int J Prod Res* 43(21):4509–4537
37. Homayouni SM, Hong TS, Ismail N (2009) Development of genetic fuzzy logic controllers for complex production systems. *Comput Ind Eng* 57(4):1247–1257
38. Wang J F, Xue J, Duque E T, Li S Q, Chang Q (2017) Fuzzy decision of machine switch on-off for energy efficient operation of manufacturing system. *Proceeding of the 13th IEEE International Conference on Automation Science and Engineering*, August 20–23, Xian, China, pp 1158–1162
39. Li J, Meerkov SM, Zhang L (2010) Production systems engineering: problems, solutions, and applications. *Annu Rev Control* 34(1):73–88
40. Hájek P (1998) *Metamathematics of fuzzy logic*, 4 edn. Springer Science & Business Media
41. Eker I, Torun Y (2006) Fuzzy logic control to be conventional method. *Energy Convers Manag* 47(4):377–394
42. Hermann C, Thiede S, Kara S, Hesselbach J (2011) Energy oriented simulation of manufacturing systems – concept and application. *CIRP Ann-Manuf Technol* 60(1):45–48
43. Sproedt A, Plehn J, Schönsleben P, Herrmann C (2015) A simulation-based decision support for eco-efficiency improvements in production systems. *J Clean Prod* 105(3):389–405
44. Gutowski T, Dahmus J, Thiriez A (2006) Electrical energy requirements for manufacturing processes. In: *Proceedings of the 13th CIRP International conference on Life Cycle Engineering*, May 31st–June 2nd, Leuven, Belgium, pp 1–5
45. Li W (2015) *Implementation towards improving energy and eco-efficiency of manufacturing processes*. Springer International Publishing, Switzerland, pp 113–142