IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 20, 2019, accepted November 18, 2019, date of publication November 26, 2019, date of current version December 11, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2955979

Energy Economics in Multistage Manufacturing Systems With Quality Control: A Modeling and Improvement Approach

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This work was supported in part by the National Natural Science Foundation of China under Grant 51605335, Grant 51675442, and Grant 71931007, in part by the Fundamental Research Funds for the Central Universities under Grant 31020190502004, and in part by the Open Fund of Henan Key Laboratory of Intelligent Manufacturing of Mechanical Equipment under Grant IM201902.

ABSTRACT It is imperative for manufacturing systems to improve production quality not only to maintain profitability, market share and competitiveness, but also to reduce energy waste resulted from defective items. Although quality and energy saving have attracted extensive attention in the past few decades, there is little research effort devoted to a systematic understanding of their intersection. Therefore, this paper analyzes the energy usage of a multistage production system with quality control. The Geometric reliability and Bernoulli quality models are assumed. A Markov process model is established to predict the dynamics of the production system. The energy economics of the production system are analyzed to include both production and energy cost. The optimal PWQ (Production with Quality Inspection) machine allocation method and the cost-effectiveness analysis method are formulated to increase the profit. According to the computational experiments, the proposed optimal PWQ machine allocation method can effectively reduce energy consumption. In addition, pay-back period (PBP) is an effective indicator which helps production managers make cost effective decisions for machine replacement. The research results in an in-depth understanding of the energy economics of systems with quality control, which is necessary for manufacturers to gain competitiveness with better product quality and higher energy efficiency.

INDEX TERMS Production quality, energy economics, performance improvement, Markov chain model.

I. INTRODUCTION

Sustainable manufacturing has become more prevalent for manufacturing companies in response to dramatic climate change, unsecured energy supply, and fluctuating energy prices. In industrial sector, worldwide energy consumption is expected to increase by more than 1.2% every year [1]. The number is even higher in developing economies, such as China and India. It is important to improve production-energy efficiency in order to reduce industrial energy usage, and contribute to competitive advantage [2]. According to a report of European Commission, an estimate of 25% energy usage could be reduced just through boosting energy efficiency of the industrial sector [3].

Production quality plays a significant role to the success of manufacturing systems not only to ensure high performance of its products, but also to reduce energy waste resulted from defective items. Newly developed production systems usually suffer from high scrap rates. For instance, the observed scrap rates can vary from 30 percent to as high as 60 percent in large volume battery manufacturing systems [4]. There is a clear opportunity to boost production energy efficiency with better quality management practices.

Although extensive efforts have been devoted to the modeling of quality flow and energy usage in production systems, they are treated separately without an integrated understanding of the complex intersection [5], [6]. The energy waste resulted from a defective product is not a simple summation of the energy consumption at each manufacturing stage [7]. It should also take into consideration of its impact on the production of the entire system [8]. It is not uncommon

The associate editor coordinating the review of this manuscript and approving it for publication was Yanzheng Zhu.

that machines waste a significant amount of production time on unidentified defective products. Without been properly coordinated, the impact could propagate to the entire system through starvation and blockage [9]. A significant energy waste would be incurred when machines are forced to become idle (i.e. starved or blocked) because the machines still consume energy, but cannot produce parts [10]. It is essential to have a systematic understanding of the energy consumption in multistage production systems with quality control, and establish a method to reduce the energy waste.

Therefore, this work strives to tackle two important problems. The first problem is to establish an integrated model to analyze the production and energy consumption in a multistage production system with quality control. In response to the problem, a Markov chain model is established to analyze the production dynamics of systems consisting of machines characterized by Geometric reliability model and Bernoulli quality model. The energy economics are analyzed taking full consideration of the energy consumption of the production system. The second problem is to boost energy efficiency through improving quality decision-makings. In response to the problem, decision-making models are constructed based on the energy economics analysis to optimize the quality inspection strategies, as well as machine replacement plans.

This research helps people to understand the complex interconnections among production, quality flow and energy consumption in a multistage production system. It presents the first step toward our objective to improve energy efficiency through better quality management. The rest of the paper is demonstrated as follows: literature review is investigated in Section II; Section III describes the assumptions and background; a Markov chain model is presented in Section IV; Section V proposes two joint quality and energy decision-making algorithms; computational experiments are performed in Section VI; Section VII summarizes the conclusions and future work.

II. LITERATURE REVIEW

Over the past few decades, extensive research efforts have been devoted to the modeling of production systems, which can be divided into simulation methods and analytical methods [11]. Simulation methods, such as Petri net and discrete event simulation, are flexible to precisely model complex production systems [12]. However, it is difficult to apply the simulation methods to investigate the fundamental properties of the production systems. In analytical methods, Markov chain models has been established for multistage production systems [13]. Markov chain models have been applied to investigate many theoretical and engineering problems. Zhu et al. studied a filtering problem of discrete-time Markov jump linear parameter varying systems subjected to packet dropouts and channel noises [14]. A hidden Markov model is established for the partial accessibility of system modes with filters. Désir et al. established a Markov chain model for constrained assortment optimization [15]. The model tackles item substitutions as transitions of Markov chain models, and can be applied to effectively approximate random utility models. In production system modeling, Li and Meerkov proposed an aggregation Markov chain model for serial Bernoulli production lines [16]. Li et al. extended the aggregation method to parallel Bernoulli lines and rework Bernoulli lines with overlapping methods [17], [18]. Decomposition Markov chain model is developed by Gershwin and Burman for performance analysis in production systems with exponential machines [19]. Colledani et al. utilized decomposition method to analyze production systems consisting of machines modelled with general Markovian fluid models [20]. Gershwin and Wermer applied the decomposition method in closed loop production systems [21].

Production quality models can be categorized into persistent-type and Bernoulli-type, depending on the characteristics of quality failures [22]. Persistent-type quality model is commonly seen in highly automated production systems. It depicts the quality failures that only happen after a change occurring in the machine. Therefore, in persistent-type failure systems, once a defective product is identified, all the following products are likely to be defective [23]. Bernoulli-type quality model, on the other hand, is proposed for systems, where the quality of each product is independent of the others [24], [25]. The model is appropriate for the production system that is sensitive to external disturbances (e.g. human mistakes and material flaw), and is subject to inefficient management. Both quality models are extensively considered in literature. For example, Kim and Gershwin developed an integrated quality and quantity model to study the quality rate and productivity in production systems with persistent-type quality failures [26]. Meerkov and Zhang proposed an aggregation method for performance analysis and improvement in production systems consisting of machines that obey Bernoulli reliability and quality models [27]. This paper adopts Bernoulli-type quality model. The analysis is helpful to improve the quality and energy efficiency of newly designed systems consisting of automatic and manual machines.

Most of the current research on quality management is performed to improve product quality and productivity [28]. Ju, et al. introduced an analytical model to improve the product quality in battery assembly lines [29]. The quality flow model investigates the properties of the assembly line and is integrated into a continuous improvement method. Shetwan, et al. surveyed the existing quality control stations allocation policies [30]. The review shows that heuristic methods can reach a qualified solution much faster than complete enumeration methods. Van Volsem, et al. proposed an optimal inspection method for a multistage production system [31]. The method utilizes a discrete event simulation to model the system and an evolutionary algorithm (EA) to optimize the inspection strategies. It is argued that the inspection method results in the lowest inspection cost while maintaining desirable production quality. Although the aforementioned analysis is very useful in improving productivity and quality, they do not provide enough insight into the integrated modeling

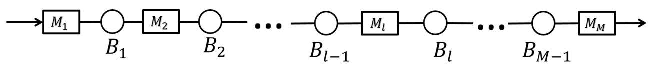


FIGURE 1. A multistage serial production line.

of quality and energy consumption. It is difficult to utilize the methods to achieve energy efficiency in multistage production systems.

Although many research efforts are spent on the energy management of production systems, they mainly focus on achieving energy saving goals with production control strategies without explicitly considering quality factors [32], [33]. For example, Dai, et al. investigated the energy efficiency in flexible production system scheduling [34]. The energy-oriented scheduling is constructed and solved as a multi-objective optimization problem. Rager, et al. discussed to minimize the final energy sources demand in parallel production systems through optimizing resource leveling [35]. Tian et al. proposed to improve a flexible job shop with energy efficient scheduling and real-time control [36]. The control system architecture is formulated in IoT environment to meliorate the resilience of the flexible job shop to disruption events. Chen et al. analyzed to reduce the energy consumption of a production system through controlling of machines' startup and shutdown [37]. A Markov chain model is utilized to accurately estimate the productivity of the production systems.

Therefore, the current literature fails to provide adequate references in an integrated modeling and improvement of production quality and energy efficiency in multistage production systems. The existing improvement methods consider the modeling and improvement separately. They describe the production systems with simplified indicators or static equations, and fail to take into consideration of the complex dynamics. As a consequence, the methods cannot sufficiently explore the improvement opportunities. The ever-growing energy prices and customer expectations put an enormous strain on production systems. A systematic understanding of the energy economics of systems with quality control is imperative for manufacturers to gain competitiveness with better product quality and higher energy efficiency. This paper is devoted to this end.

III. SYSTEM ASSUMPTIONS AND BACKGROUND

This paper considers a serial production system as shown in Figure 1. Each machine is represented as a rectangle and each buffer is represented with a circle. The system has M machines and $M-1$ buffers. The production system adopts the following assumptions and definitions.

1) Buffer $B_l, l = 1, \ldots, M-1$, has a finite capacity. For ease of expression, the capacity is still denoted as B_l. The instantaneous buffer level of B_l at time t is represented as $b_l(t)$.
2) There are two types of machines, which are machines with and without quality inspection. The machines without quality inspection are denoted as PO (Production Only) machines, and the machines with quality inspection are denoted as PWQ (Production with Quality Inspection) machines. Defective parts are identified and scrapped by PWQ machines. It is assumed that the inspection machines can neither miss defective parts, nor identify perfect parts as defective [16].
3) To ensure the quality of the finished products, the last machine in a production system is a PWQ machine.
4) Each machine M_l, $1 \leq l \leq M$, has an identical cycle time τ, that equals to a time step. The machine has one up state, i.e. $\alpha_l = 1$, and one down state, i.e. $\alpha_l = 0$.
5) Each machine M_l, $1 \leq l \leq M$, follows the Geometric reliability model. If the machine is up, it can be down because of a non-quality related event with probability p_l, which is denoted as the failure probability of M_l. If the machine is down, it can be brought back to up state with probability r_l, which is denoted as the repair probability of M_l. The transition is depicted in Figure 2. If the mean time to failure (MTTF) and mean time to repair (MTTR) of machin M_l are $MTTF_l$ and $MTTR_l$, then its failure probability and repair probability have $p_l = 1/MTTF_l$ and $r_l = 1/MTTR_l$, respectively.
6) Each machine M_l, $1 \leq l \leq M$, follows Bernoulli quality model. It means that the machine produces a good part with probability g_l, and produces a defective part with probability $1 - g_l$.
7) For each part inspected by a PWQ machine M_l, $1 \leq l \leq M$, it is good with a probability of q_l and defective with a probability of $1 - q_l$. The identified defective parts are removed from the production system by PWQ machines. The probability $q_l = \prod_{i=l-k}^{l} g_i$ is determined by the quality rates of machines $M_{l-k}, \ldots, M_l$, where M_{l-k-1} and M_l are two adjacent PWQ machines. q_l is defined as the quality buy rate of M_l.
8) Machine $M_l, l = 2, \ldots, M$, is starved at time t if $\alpha_l = 1$, and $b_{l-1}(t) = 0$.
9) Machine $M_l, l = 1, \ldots, M-1$, is blocked if $\alpha_l = 1$, $b_l(t) = B_l$, and Machine M_{l+1} does not take a part from buffer B_l.
10) The first machine will never be starved and the end-of-line machine will never be blocked.

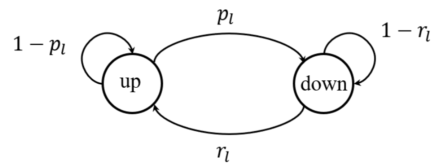


FIGURE 2. State transition diagram of geometric machine.

Remark 1. It is noted that PO machines can neither identify nor remove defective products from the system. All the PO machines have quality buy rates that equal to one.

Remark 2. The geometric reliability model can be applied to machines, whose average downtimes are significantly greater than machine cycle time. This can be found in machining production lines and heat treatment production lines, where the failures are primarily because of the breakdown of a key component, power outage, etc. [38]

IV. MARKOV CHAIN MODEL

The production system defined in Section III is characterized by an ergodic Markov chain with states defined with machine states and buffer levels, i.e. $\varphi = (\alpha_1, \ldots, \alpha_M, b_1, \ldots, b_{M-1})$. In a 2-machine 1-buffer production system, system state is $(\alpha_1, \alpha_2, b_1)$. $Prob(\alpha_1, \alpha_2, b_1)$ denotes the probability that system state is $(\alpha_1, \alpha_2, b_1)$. When $1 < b_1 < B_1 - 1$, the balance equation for $Prob(1, 0, b_1)$ can be expressed as:

$$\begin{aligned}
Prob\,(1, 0, b_1) &= q_1 r_1 (1 - r_2)\, Prob\,(0, 0, b_1 - 1) \\
&+ q_1 r_1 p_2 Prob\,(0, 1, b_1 - 1) + q_1 (1 - p_1) \\
&(1 - r_2)\, Prob\,(1, 0, b_1 - 1) \\
&+ q_1 (1 - p_1)\, p_2 Prob\,(1, 1, b_1 - 1) \\
&+ (1 - q_1)\, r_1 (1 - r_2)\, Prob\,(0, 0, b_1) \\
&+ (1 - q_1)\, r_1 p_2 Prob\,(0, 1, b_1) \\
&+ (1 - q_1)(1 - p_1)(1 - r_2)\, Prob\,(1, 0, b_1) \\
&+ (1 - q_1)(1 - p_1)\, p_2 Prob(1, 1, b_1).
\end{aligned}$$

The first term on the right-hand side of the equation measures the probability of transition from $(0, 0, b_1 - 1)$ to $(1, 0, b_1)$. The system can make the transition if machine M_1 is repaired and successfully produces a part with good quality to its downstream buffer B_1, and machine M_2 is not repaired. Therefore, the probability of the transition is $q_1 r_1 (1 - r_2)$. Similarly, the other seven terms measure the probabilities of transitions from $(0, 1, b_1 - 1)$, $(1, 0, b_1 - 1)$, $(1, 1, b_1 - 1)$, $(0, 0, b_1)$, $(0, 1, b_1)$, $(1, 0, b_1)$, $(1, 1, b_1)$ to $(1, 0, b_1)$. There are no other possible transitions.

In the similar way, the balance equations can be derived for all other probabilities, i.e. $Prob(1, 1, b_1)$, $Prob(0, 0, b_1)$, $Prob(0, 1, b_1)$, $Prob(1, 0, b_1)$, $0 \le b_1 \le B_1$. The steady-state probability distribution of the 2-machine 1-buffer system can be obtained by solving the equations. The solution technique is similar to that is discussed in literature [39] and is not included in the paper.

The analytical Markov chain model merely exists for 2-machine 1-buffer systems because the size of system state space grows exponentially in the numbers of machines and buffers. Approximation methods are essential to estimate the dynamics of long production systems. Therefore, the decomposition method is extended to study multistage production systems characterized by Geometric reliability model and Bernoulli quality model.

The decomposition method models a M-machine $M - 1$-buffer system into a sequence of $M - 1$ subsystems, which is shown in Figure 3. Each subsystem S_l, $1 \le l \le M - 1$, consists of buffer B_l, and two pseudo machines M_l^u and M_l^d, which locate in the upstream and downstream of buffer B_l, respectively. M_l^u approximates the upstream system of B_l. It is characterized by two geometrically distributed variables with parameters: failure probability p_l^u and repair probability r_l^u, as well as a Bernoulli distributed variable with parameter:

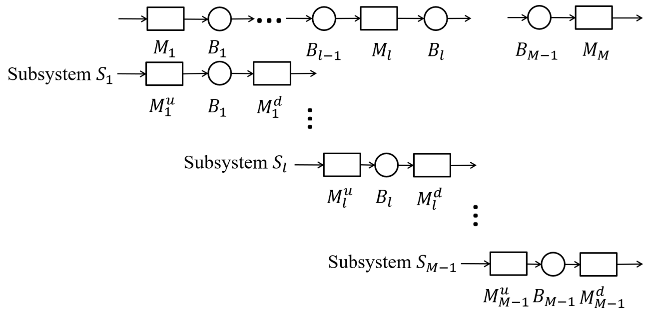


FIGURE 3. Decomposition of the production system.

quality buy rate q_l. Similarly, M_l^d approximates the downstream system of B_l. It is characterized by two geometrically distributed variables with parameters: failure probability p_l^d and repair probability r_l^d, as well as a Bernoulli distributed variable with parameter: quality buy rate q_{l+1}. The principle of the decomposition method is to closely match the material flow of buffer B_l in subsystem S_l and the original production system. An accurate estimation of parameters p_l^u, p_l^d, r_l^u and r_l^d is the key.

The parameters of pseudo machines can be estimated with decomposition equations. Decomposition equations are proved in literature [19] assuming all the machines have equal input and output rates. However, in this paper, the input and output rates of a PWQ machine are different because they need to reject defective items out from the production system. It is necessary to modify the decomposition equations in production systems with PWQ machines.

First, let's analyze the material flow equation in each subsystem. The input rate s_l^{in} and output rate s_l^{out} of machine M_l, $1 \le l \le M$, are related with quality buy rate as $s_l^{out} = q_l s_l^{in}$. Each buffer has the same input and output rates in steady state. Let $E(l)$ denote the input or output rate of buffer B_l, $1 \le l \le M - 1$, i.e. $E(l) = s_l^{out} = s_{l+1}^{in}$. Then for any two adjacent subsystems S_l and S_{l+1}, the following equation is satisfied:

$$E\,(l + 1) = q_{l+1} E(l). \tag{1}$$

$E\,(l)$ is estimated as

$$E\,(l) = q_l e_l^u (1 - Prob(b_l = B_l)) \tag{2}$$

$$E\,(l) = e_l^d (1 - Prob(b_l = 0)) \tag{3}$$

where $e_l^u = \frac{r_l^u}{r_l^u + p_l^u}$ and $e_l^d = \frac{r_l^d}{r_l^d + p_l^d}$ are the standalone efficiencies of M_l^u and M_l^d, respectively. $Prob\,(b_l = B_l)$ denotes the probability that buffer B_l is full. $Prob\,(b_l = 0)$ is the probability that buffer B_l is empty. $E(l)$ can also be estimated as

$$E\,(l) = q_l e_l (1 - Prob\,(b_{l-1} = 0) - Prob(b_l = B_l)) \tag{4}$$

where $e_l = \frac{r_l}{r_l + p_l}$ is the standalone efficiency of machine M_l. With some math manipulations, the following equation can be obtained as

$$\frac{p^d_{l-1}}{r^d_{l-1}} + \frac{p^u_{l-1}}{r^u_{l-1}} = \frac{1}{E\,(l-1)} + \frac{1}{e_l} - 2. \tag{5}$$

Secondly, the repair probability equation of each pseudo machine can be derived. The breakdown of pseudo machine $M^u_l, 1 \leq l \leq M-1$, is resulted from the breakdown of machine M_l or the empty of buffer B_{l-1}. To repair M^u_l, it is to either repair machine M_l or make buffer level b_{l-1}become non-empty, i.e. $b_l > 0$. Therefore, the repair probability of pseudo machine M^u_l can be expressed with

$$r^u_l = \phi_{l-1} Z_l + \psi_l Z'_l \tag{6}$$

where $\phi_{l-1} = q_{l-1} e^u_{l-1}$ refers to the probability that buffer B_{l-1} transfers from empty to non-empty. $Z_l = q_l \frac{r^u_l Prob(b_{l-1}=0)}{p^u_l E(l)}$ is the condition probability of buffer B_{l-1} being empty if pseudo machine M^u_l is down. $\psi_l = r_l$ is the repair probability of machine M_l. $Z'_l = 1 - Z_l$ is the condition probability that machine M_l is down if pseudo machine M^u_l is down. Similarly, the repair probability of pseudo machine M^d_l can be expressed with

$$r^d_l = \eta_{l+1} H_{l+1} + \omega_{l+1} H'_{l+1} \tag{7}$$

where $\eta_{l+1} = r^d_{l+1}$ is the repair probability of pseudo machine M^d_{l+1}. $H_{l+1} = \frac{r^d_l Prob(b_{l+1}=B_{l+1})}{p^d_l E(l)}$ is the condition probability of buffer B_{l+1} being full if pseudo machine M^d_l is down. $\omega_{l+1} = r_{l+1}$ is the repair probability of machine M_{l+1}. $H'_{l+1} = 1 - H_{l+1}$ is the condition probability that machine M_{l+1} is down if pseudo machine M^d_l is down.

With the two modifications, the failure and repair probabilities of M^u_l and M^d_l, $1 \leq l \leq M-1$, can be estimated by iteratively solving equations 5 to 7 in each subsystem S_l, $1 \leq l \leq M-1$. The solution procedure is based on the decomposition algorithm in literature [19], and is summarized as follows:

Algorithm 1 Decomposition Iterative Solution Algorithm

Initialize $p^u_l = p_l$, $r^u_l = r_l$,
$p^d_l = p_{l+1}$, and $r^d_{l+1} = r_{l+1}$, $1 \leq l \leq M-1$.
Then the algorithm iterates between Steps 1 and 2 until convergence.

1. For $l = 2, \ldots, M-1$, calculate $\frac{p^u_l}{r^u_l}$ with equation 5, r^u_l with equation 6. Approximate $E(l)$ according to $E\,(l) = q_l E(l-1)$
2. For $l = M-2, \ldots, 1$, calculate $\frac{p^d_l}{r^d_l}$ with equation 5, r^d_l with equation 7. Approximate $E(m)$ according to $E\,(l) = \frac{E(l+1)}{q_{l+1}}$.

V. DECISION MODELS FOR QUALITY INSPECTION

A. OPTIMAL PWQ MACHINE ALLOCATION ANALYSIS

In a production system, more and tighter inspection helps to reduce the energy waste resulted from unidentified defective products that are processed unnecessarily during production. However, intensive inspection efforts also require higher cost of equipment investment and production. Therefore, this section establishes an optimization method to determine the number and locations of PWQ machines to balance the energy cost saving and the expense.

1) CONTROL DECISIONS

The PWQ machine allocation problem can be formulated to determine for each machine M_l, whether it is a PWQ machine or a PO machine. Let's use $\pi_l = 1$ to denote machine M_l being a PWQ machine, and $\pi_l = 0$ to denote machine M_l being a PO machine. It is noted that when $\pi_l = 1$, machine M_l has greater average cost of investment $\bar{CI}_l$ and the unit production cost $c_{f,l}$. The decision variable can be expressed as $(\pi_1, \ldots, \pi_M)$. The objective of the analysis is to find the optimal $(\pi^*_1, \ldots, \pi^*_M)$ such that the average system profit SP is maximized:

$$\max_{(x_1,\cdot,\pi_m)} SP. \tag{8}$$

2) OPTIMAL CONTROL FORMULATION

The objective of the analysis is to improve the overall energy efficiencies as well as profit of the multistage production system [6]. The expected system profit during each time unit can be estimated as the difference between system income and expense:

$$\begin{aligned} SP = income - expense = c_p \min\left(TH_{sys}, CR\right) \\ - \vec{c}_f \cdot \vec{S}_{in} - c_E F_{sys} - c_o \max\left(TH_{sys}\right. \\ \left. - CR, 0\right) - c_u \max\left(CR - TH_{sys}, 0\right) - \bar{CI} \end{aligned} \tag{9}$$

where c_p represents the income for selling each product. $\vec{c}_f = (c_{f,1}, \ldots, c_{f,M})$ is the production cost per part of each machine, which includes material cost, labor cost, quality inspection cost, etc. c_E denotes the cost of an unit energy consumption. c_o refers to the unit overage cost and c_u represents the unit underage cost. $\bar{CI}$ is the average cost of investment (CI), which equals to the summation of the CI in each machine, i.e. $\bar{CI} = \sum_{l=1}^{M} \bar{CI}_l$. TH_{sys} is the average system production rate, which is estimated with [40]:

$$TH_{sys} = q_M \sum_{b_{M=1}}^{B_M} \sum_{\alpha^u_{M-1}=0}^{1} Prob(\alpha^u_{M-1}, 1, b_M). \tag{10}$$

CR is the customer demand rate, which is determined based on real customer orders. $\vec{S}_{in} = (s^{in}_1, \ldots, s^{in}_M)$ records the number of parts processed by each machine. F_{sys} is the average energy consumption rate of the production system. It can be determined by analyzing the dynamics of each machine.

At each time step, machine M_l, $1 \leq l \leq M$, can be in production state, idle state or breakdown state. Let $P_{p,l}$ and $P_{i,l}$ denote the probabilities that machine M_l are in production state and idle state. The probabilities are estimated as

$$P_{p,l} = e_l(1 - Prob\,(b_{l-1} = 0) - Prob(b_l = B_l)) \tag{11}$$

$$P_{i,l} = Prob\,(b_{l-1} = 0) + Prob(b_l = B_l). \tag{12}$$

It is assumed that the power consumption rates of machine M_l in production state and idle state are $d_{p,l}$ and $d_{i,l}$. Machines do not consume energy when they are breakdown. The average energy consumption rate of machine M_l is estimated as

$$F_l = d_{i,l}P_{i,l} + d_{p,l}P_{p,l}. \tag{13}$$

The average energy consumption rate of the whole system is the summation of that of all the machines:

$$F_{sys} = \sum_{l=1}^{M} F_l. \tag{14}$$

3) SOLUTION METHODOLOGY

It is observed that the formulated problem is a complex nonlinear optimization problem, which usually cannot be solved using analytical algorithms in a useful time frame. Therefore, the genetic algorithm is presented to solve the problem. The genetic algorithm (GA) has been considered as a very useful method, which is widely accepted to solve nonlinear optimization problems [41], [42]. The algorithm is an iterative process. A population of candidate solutions are continuously improved and updated in each iteration until the ending criteria is satisfied. The optimal solution is the best candidate in the final population [6]. The main steps of the GA algorithm are briefly depicted in the following Optimal PWQ Machine Allocation Algorithm.

B. COST-EFFECTIVE ANALYSIS

It is sometimes necessary to replace old equipment that has low energy efficiency [43], [44]. The key is to find the replacement investment option that is the most cost-effective. Currently, there is a lack of quantitative indicator to assist the decision making. Based on the energy economics analysis, the pay-back periods (PBPs) of different machine replacement investment options can be estimated to compare their efficiencies. The investment option that has the shortest PBP is the one selected.

PBP is defined as the period for which discounted benefit income will cover the total cost of the investment. The indicator is widely utilized in financial analysis to measure the time it takes for the investment to lead to a profit [45] . The mathematical expression of PBP is:

$$PBP = \inf\{n \geq 0 : OCR = \sum_{\tau=1}^{n} \frac{BI(\tau)}{(1+i)^{\tau-1}}\}, \tag{15}$$

where OCR is the overall cost of replacement (OCR). It includes the investment cost of replacing the machine, installation cost, testing cost, etc. $BI\,(t)$ is the benefit income (BI) at time unit t. i is the discount rate. The benefit income from the investment is measured as the energy cost saving. Suppose that the power consumption rate of machine M_l is reduced by $\delta d_{p,l}$ and $\delta d_{i,l}$ in its production state and idle state, respectively. The expected energy savings δF_{sys} in a time unit is estimated as

$$\delta F_{sys} = \delta d_{i,l}P_i, l + \delta d_{p,l}P_{p,l}. \tag{16}$$

Algorithm 2 Optimal PWQ Machine Allocation Algorithm

1. **Specify input parameters:** population size n, rate of elitism r, rate of mutation μ, and number of iterations ζ
2. **Set initialize population:** randomly generate n solutions (i.e. decision variable $(\pi_1, \ldots, \pi_M)$)
3. **Calculate the fitness:** calculate the fitness (i.e. system profit SP) of each solution
4. **For** $i = 1$ **to** ζ
5. Select the best $k = n * r$ individuals in the solution population for reproduction and save them into the candidate population
6. //Improvement procedures with genetic operators
7. **Forj = 1to(n − k)/2** //Crossover operator
8. Select two individuals S_1 and S_2 from the solution population with the Roulette Wheel method
9. Generate two new solutions S_1' and S_2' with single point crossover method
10. Save S_1' and S_2' to the candidate population
11. **Endfor**
12. **For** $j = 1$ **to n //Mutation operator**
13. Randomly select an individual solution S from the candidate population
14. Mutate S with rate μ and generate a new solution S'
15. Update S with S' in the candidate population
16. **Endfor**
17. Replace the current population with the candidate population and calculate the fitness
18. Set candidate population to empty
19. **Endfor**
20. Return the best solution in the current population

The expected $BI(t)$ at each time t can be calculated as

$$BI(t) = c_E \delta F_{sys}. \tag{17}$$

It is noted that in each time unit, the expected $BI(k)$ remains the same. With some math manipulation, the expected PBP of replacing machine M_m, i.e. PBP_m, can be estimated as

$$PBP_m = \left\lceil \frac{\ln\left[\frac{(1+i)c_E\delta F_{sys}}{(1+i)c_E\delta F_{sys} - iCOR_m}\right]}{\ln(1+i)} \right\rceil. \tag{18}$$

Therefore, the investment option of replacing machine M_l, $1 \leq l \leq M$, is the most cost-effective if:

$$PBP_l < PBP_k, \quad \forall l \neq k. \tag{19}$$

VI. COMPUTATIONAL EXPERIMENTS

The study considers a multistage manufacturing system with 10 machines and 9 buffers. The system is a line segment from an automotive production line, which is shown in Figure 4.

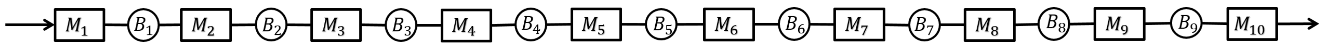


FIGURE 4. Production system consisting of 10 machines and 9 buffers.

TABLE 1. Parameters of the production system.

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
$p_l, 1 \leq l \leq 10$	0.02	0.03	0.08	0.02	0.09	0.08	0.08	0.02	0.05	0.02
$r_l, 1 \leq l \leq 10$	0.21	0.13	0.18	0.14	0.19	0.21	0.18	0.22	0.15	0.22
$g_l, 1 \leq l \leq 10$	0.89	0.98	0.81	0.97	0.95	0.92	0.86	0.95	0.85	0.97
$d_{p,l}$ (KW)	64	66	58	56	62	60	56	70	60	58
$d_{i,l}$ (KW)	32	36	34	36	30	24	24	30	36	26
$c_{f,l}$ ($/part)	1.4	1.3	1.5	1.3	1.3	1.5	1.8	1.5	1.6	1.3
	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	
$B_l, 1 \leq l \leq 9$	10	12	8	10	8	6	10	10	16	
$b_l(t_0), 1 \leq l \leq 9$	5	6	4	5	4	3	5	5	8	

TABLE 2. Cost rate of upgrading each machine.

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
$CI_l, 1 \leq l \leq 10$ ($/day)	162	194.4	216	140.4	129.6	162	216	205.2	194.4	162

TABLE 3. OCR of each machine.

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
$OCR_l, 1 \leq l \leq 10$ ($)	3000	3800	4000	3600	3300	2900	3200	3000	3100	6300

TABLE 4. Energy consumption rate of each machine after replacement.

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
$d_{p,l}$ (KW)	38.4	39.6	34.8	33.6	37.2	36	33.6	42	36	11.6
$d_{i,l}$ (KW)	19.2	21.6	20.4	21.6	18	14.4	14.4	18	21.6	5.2

The cycle time of each machine is 1 minute. Table 1 records the production parameters. The table also shows the production cost $c_{f,l}$ of each machine M_l, $1 \leq l \leq 10$, when it is a PO machine. The production cost of each machine is assumed to increase by 30% when it is upgraded to a PWQ machine. The investment cost CI_l for upgrading each machine from PO machine to PWQ machine is shown in Table 2. The OCR of each machine is presented in Table 3. The energy consumption rates of each machine when it is replaced are demonstrated in Table 4. The unit income c_p is \$50 per product and the unit energy cost c_E is \$0.15/kWh. The unit overage cost c_h is \$10 per product and the unit underage cost c_u is \$15 per product. The average market requirement rate is 442 parts per day. The computational experiments are performed on a laptop with Intel(R) Core(TM) i5-8250U CPU (1.60GHz 1.80GHz) and 8.0 GB memory.

A. VALIDATION OF OPTIMAL PWQ MACHINE ALLOCATION METHOD

First of all, the optimal PWQ machine allocation algorithm is run in the system for 50 times. The control parameters of the optimal PWQ machine allocation method are demonstrated as follows: number of iterations ζ is 90; rate of mutation μ is 0.05; and size of population n is 40. The discount rate is assumed as $i = 1\%$. Each run takes approximately 28 seconds. All the 50 runs make the same decision, that machines M_3,M_7, M_9 and M_{10} are upgraded to PWQ machines. One run is randomly selected to show the learning curve in Figure 5. The optimal algorithm finds the best allocation policy in the 18$^{\text{th}}$ iteration.

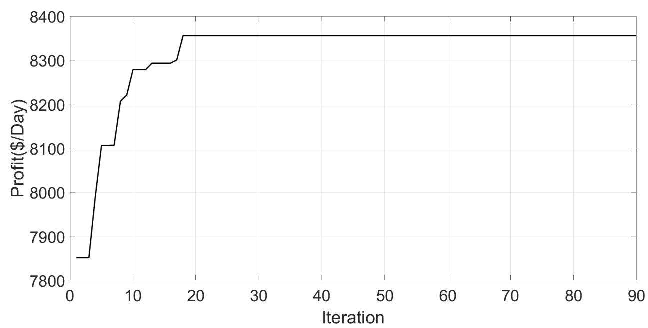


FIGURE 5. Learning curve of optimal PWQ machine allocation method.

The optimal PWQ machine allocation method is then compared with other two quality inspection methods to demonstrate its effectiveness. Method 1 is denoted as the least inspection effort (LIE) method, where only the end-of-line machine M_{10} is PWQ machine. Method 2 is denoted as the most inspection effort (MIE) method, where all the machines

TABLE 5. Four PWQ machine allocation methods.

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
Optimal method	PO	PO	PWQ	PO	PO	PO	PWQ	PO
LIE	PO	PO	PO	PO	PO	PO	PO	PO
MIE	PWQ	PWQ	PWQ	PWQ	PWQ	PWQ	PWQ	PWQ

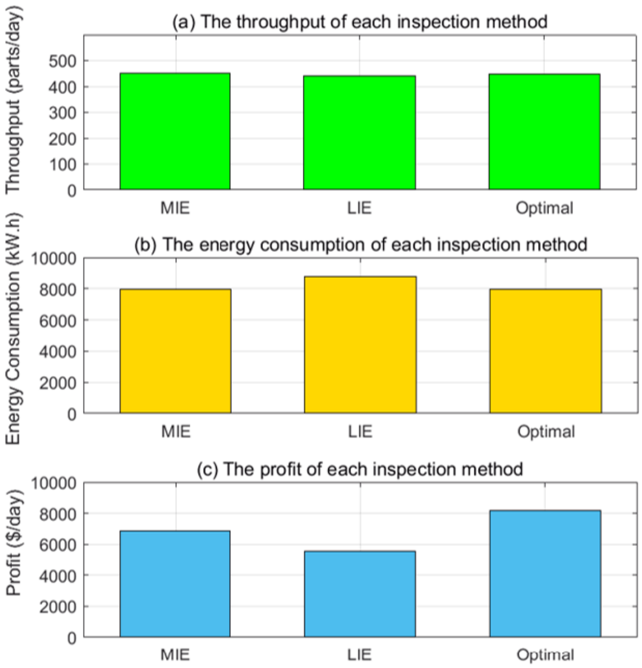


FIGURE 6. Throughput, energy consumption and control benefit of each quality inspection method.

are PWQ machines. Table 5 summarizes the three PWQ machine allocation methods. The production line is simulated for 16 hours every day for 1000 days with the three PWQ machine allocation methods.

The comparison of the methods is demonstrated in Figure 6. It can be observed that:

1) According to Figure 6(a), MIE method leads to the greatest throughput and LIE method results in the smallest throughput. It indicates that system throughput slightly decreases as the number of PWQ machines decreases. This is because more intensive inspection efforts help machines to focus on good quality parts, which naturally increases system throughput.
2) In Figure 6(b), MIE method consumes the least energy while LIE method results in the greatest energy consumption. It is because MIE can most timely identify and remove defective parts. However, in LIE method, all the defective parts are not identified until they reach the last machine M_{10}. A significant amount of energy is wasted on the unidentified defective parts. In addition, the optimal PWQ allocation method has a very close energy consumption as MIE method. This indicates that system should only maintain appropriate number of PWQ machines since excessive PWQ machines do not further reduce energy consumption. they merely cause unnecessary production cost (e.g., inventory cost, inspection cost, etc.).
3) Figure 6(c) shows the average system profit obtained using the three allocation methods. The optimal PWQ machine allocation method outperforms the other methods in the simulation case. The result presents a good validation of the optimal PWQ machine allocation method.

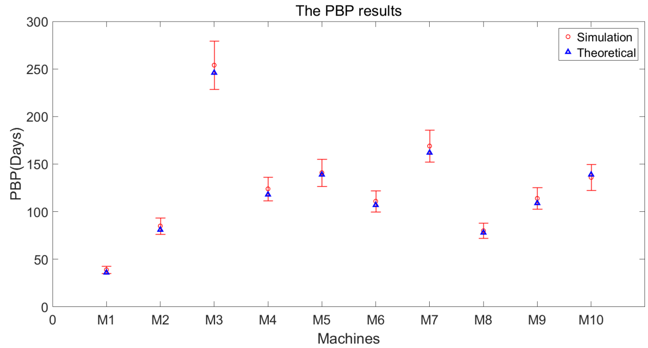


FIGURE 7. Estimation results of PBP.

B. VALIDATION OF PBP ESTIMATION METHOD

Then the PBP estimation method is validated in conjunction with the optimal PWQ machine allocation method as demonstrated in the previous part. Equation 19 is utilized to compute the expected PBP of each machine and then compare it with the simulation PBP. The result is depicted in Figure 7. The triangles represent the expected PBPs computed with equation 19, which is denoted as theoretical PBPs. The error bars show the PBPs computed from the simulation with 10% errors. The circles are the average PBPs computed from the simulation.

It can be observed that the theoretical PBPs are within the 10% errors for all the machines. The most efficient option is to replace Machine M_1, that has an expected PBP of 36 days from theoretical computation and 39 days from simulation.

VII. CONCLUSION AND FUTURE WORK

This research studies the energy economics of multistage production systems with quality control. A Markov process method is established to study production dynamics. The energy usage is analyzed and integrated into the economics analysis. Based on the analysis, the optimal PWQ machine allocation method and the cost-effectiveness analysis method are established. The simulation results demonstrate that the methods can effectively improve the energy performance.

The research depicts the complex interconnection among production, quality flow and energy consumption in multistage production systems. It presents the first step toward the objective to improve energy efficiency with quality management. In the future, the energy economics analysis will be extended to more complex production systems, such as flexible production systems, production systems with quality rework, etc. In addition, the current energy economics analysis methods are developed based on steady state production system assumptions. However, it is not uncommon that modern production systems need to respond to frequent changes resulted from technology insertions, engineering modifications, etc. The systems usually stay in transient states rather than steady states. The future work will be performed to investigate the energy economics of transient production systems, and explore the improvement opportunities. In particular, switched system theory can be very useful to model and control the transient production systems. The production and energy consumption can be modelled with nonlinear approximation models, such as piecewise affine models and polynomial models. State-feedback control algorithms, that are investigated by Zhu and Zhang [46], can be applied to improve productivity, reduce energy waste, and boost production quality rate through controlling the operation of machines.

REFERENCES

[1] *International Energy Outlook 2016*, U.S. Energy Inf. Admin., Washington, DC, USA, May 2016.

[2] M.-L. Tseng, S. F. Chiu, R. R. Tan, and A. B. Siriban-Manalang, "Sustainable consumption and production for Asia: Sustainability through green design and practice," *J. Cleaner Prod.*, vol. 40, pp. 1–5, Feb. 2013.

[3] *ICT for Innovation and a Sustainable Economy*, Election Commission, Winnipeg, MB, Canada, 2012.

[4] A. Dinger, "Batteries for electric cars: Challenges, opportunities, and the outlook to 2020," Boston Consulting Group, Boston, MA, USA, Tech. Rep., 2010. [Online]. Available: https://www.ourenergypolicy.org/wp-content/uploads/2016/03/file36615.pdf

[5] S. Hu, F. Liu, Y. He, and T. Hu, "An on-line approach for energy efficiency monitoring of machine tools," *J. Cleaner Prod.*, vol. 27, pp. 133–140, May 2012.

[6] F. Shrouf, J. Ordieres-Meré, and A. García-Sánchez, "Optimizing the production scheduling of a single machine to minimize total energy consumption costs," *J. Cleaner Prod.*, vol. 67, pp. 197–207, Mar. 2014.

[7] C. Qing, G. Xiao, S. Biller, and L. Li, "Energy saving opportunity analysis of automotive serial production systems," *IEEE Trans. Autom. Sci. Eng.*, vol. 10, no. 2, pp. 334–342, Apr. 2013.

[8] C. Gahm, F. Denz, M. Dirr, and A. Tuma, "Energy-efficient scheduling in manufacturing companies: A review and research framework," *Eur. J. Oper. Res.*, vol. 248, no. 3, pp. 744–757, 2016.

[9] N. Weinert and C. Mose, "Investigation of advanced energy saving stand by strategies for production systems," *Procedia CIRP*, vol. 15, pp. 90–95, Jun. 2014.

[10] J. Zou, Q. Chang, J. Arinez, and G. Xiao, "Data-driven modeling and real-time distributed control for energy efficient manufacturing systems," *Energy*, vol. 127, pp. 247–257, May 2017.

[11] X. Ou, Q. Chang, J. Arinez, and J. Zou, "Gantry work cell scheduling through reinforcement learning with knowledge-guided reward setting," *IEEE Access*, vol. 6, pp. 14699–14709, 2018.

[12] J. Zou, Q. Chang, J. Arinez, and G. Xiao, "Analysis and evaluation of control action end-state impact on manufacturing system future production," *IEEE Access*, vol. 6, pp. 60187–60197, 2018.

[13] Z. Yu, L. Zhou, Z. Ma, and M. A. El-Meligy, "Trustworthiness modeling and analysis of cyber-physical manufacturing systems," *IEEE Access*, vol. 5, pp. 26076–26085, 2017.

[14] Y. Zhu, Z. Zhong, W. X. Zheng, and D. Zhou, "HMM-based H_∞ filtering for discrete-time Markov jump LPV systems over unreliable communication channels," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 12, pp. 2035–2046, Dec. 2018.

[15] A. Désir, V. Goyal, D. Segev, and C. Ye, "Constrained assortment optimization under the Markov chain-based choice model," *Manage. Sci.*, 2019, doi: 10.1287/mnsc.2018.3230.

[16] J. Li and S. M. Meerkov, *Production Systems Engineering*. Livemore, CA, USA: WingSpan Press, 2007.

[17] J. Li, "Performance analysis of production systems with rework loops," *IIE Trans.*, vol. 36, no. 8, pp. 755–765, 2004.

[18] J. Li, "Modeling and analysis of manufacturing systems with parallel lines," *IEEE Trans. Autom. Control*, vol. 49, no. 10, pp. 1824–1832, Oct. 2004.

[19] S. B. Gershwin and M. H. Burman, "A decomposition method for analyzing inhomogeneous assembly/disassembly systems," *Ann. Oper. Res.*, vol. 93, pp. 91–115, Jan. 2000.

[20] M. Colledani and S. B. Gershwin, "A decomposition method for approximate evaluation of continuous flow multi-stage lines with general Markovian machines," *Ann. Oper. Res.*, vol. 209, no. 1, pp. 5–40, 2013.

[21] S. B. Gershwin and L. M. Werner, "An approximate analytical method for evaluating the performance of closed-loop flow systems with unreliable machines and finite buffers," *Int. J. Prod. Res.*, vol. 45, no. 14, pp. 3085–3111, 2007.

[22] D. C. Montgomery, *Introduction to Statistical Quality Control*, 4th ed. New York, NY, USA: Wiley, 2001.

[23] W. H. Woodall and D. C. Montgomery, "Research issues and ideas in statistical process control," *J. Qual. Technol.*, vol. 31, no. 4, pp. 376–386, 1999.

[24] M. Colledani, T. Tolio, A. Fischer, B. Iung, G. Lanza, R. Schmitt, and J. Váncza, "Design and management of manufacturing systems for production quality," *CIRP Ann.*, vol. 63, no. 2, pp. 773–796, 2014.

[25] L. Zhang and X. Yue, "Operations sequencing in flexible production lines with Bernoulli machines," *IEEE Trans. Autom. Sci. Eng.*, vol. 8, no. 3, pp. 645–653, Jul. 2011.

[26] J. Kim and S. B. Gershwin, "Integrated quality and quantity modeling of a production line," *OR Spectr.*, vol. 27, nos. 2–3, pp. 287–314, 2005.

[27] S. M. Meerkov and L. Zhang, "Product quality inspection in Bernoulli lines: Analysis, bottlenecks, and design," *Int. J. Prod. Res.*, vol. 48, no. 16, pp. 4745–4766, 2010.

[28] S. Du, R. Xu, and L. Li, "Modeling and analysis of multiproduct multistage manufacturing system for quality improvement," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 5, pp. 801–820, May 2018.

[29] F. Ju, J. Li, G. Xiao, N. Huang, and S. Biller, "A quality flow model in battery manufacturing systems for electric vehicles," *IEEE Trans. Autom. Sci. Eng.*, vol. 11, no. 1, pp. 230–244, Jan. 2014.

[30] A. G. Shetwan, V. I. Vitanov, and B. Tjahjono, "Allocation of quality control stations in multistage manufacturing systems," *Comput. Ind. Eng.*, vol. 60, no. 4, pp. 473–484, 2011.

[31] S. Van Volsem, W. Dullaert, and H. Van Landeghem, "An evolutionary algorithm and discrete event simulation for optimizing inspection strategies for multi-stage processes," *Eur. J. Oper. Res.*, vol. 179, no. 3, pp. 621–633, Jun. 2007.

[32] Y. Li, Q. Chang, J. Ni, and M. P. Brundage, "Event-based supervisory control for energy efficient manufacturing systems," *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 1, pp. 92–103, Jan. 2018.

[33] N. Frigerio and A. Matta, "Analysis of an energy oriented switching control of production lines," *Procedia CIRP*, vol. 29, pp. 34–39, May 2015.

[34] M. Dai, D. B. Tang, A. Giret, M. A. Salido, and W. D. Li, "Energy-efficient scheduling for a flexible flow shop using an improved genetic-simulated annealing algorithm," *Robot. Comput.-Integr. Manuf.*, vol. 29, no. 5, pp. 418–429, 2013.

[35] M. Rager, C. Gahm, and F. Denz, "Energy-oriented scheduling based on evolutionary algorithms," *Comput. Oper. Res.*, vol. 54, pp. 218–231, Feb. 2015.

[36] S. Tian, T. Wang, L. Zhang, and X. Wu, "An energy-efficient scheduling approach for flexible job shop problem in an Internet of manufacturing things environment," *IEEE Access*, vol. 7, pp. 62695–62704, 2019.

[37] G. Chen, L. Zhang, J. Arinez, and S. Biller, "Energy-efficient production systems through schedule-based operations," *IEEE Trans. Autom. Sci. Eng.*, vol. 10, no. 1, pp. 27–37, Jan. 2013.

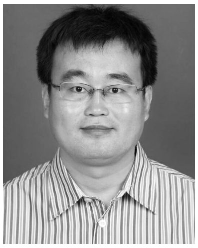
[38] G. Chen, C. Wang, L. Zhang, J. Arinez, and G. Xiao, "Transient performance analysis of serial production lines with geometric machines," *IEEE Trans. Autom. Control*, vol. 61, no. 4, pp. 877–891, Apr. 2016.

[39] S. B. Gershwin, *Manufacturing Systems Engineering*. Engelwood Cliffs, NJ, USA: Prentice-Hall, 1994.

[40] Y. Li, Q. Chang, M. P. Brundage, S. Biller, J. Arinez, and G. Xiao, "Market demand oriented data-driven modeling for dynamic manufacturing system control," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 45, no. 1, pp. 109–121, Jan. 2015.

[41] W. H. Ip, Y. Li, K. F. Man, and K. S. Tang, "Multi-product planning and scheduling using genetic algorithm approach," *Comput. Ind. Eng.*, vol. 38, no. 2, pp. 283–296, 2000.

[42] M. Jin, R. Tang, Y. Ji, F. Liu, L. Gao, and D. Huisingh, "Impact of advanced manufacturing on sustainability: An overview of the special volume on advanced manufacturing for sustainability and low fossil carbon emissions," *J. Cleaner Prod.*, vol. 161, pp. 69–74, Sep. 2017.
[43] M. P. Brundage, Q. Chang, J. Zou, Y. Li, J. Arinez, and G. Xiao, "Energy economics in the manufacturing industry: A return on investment strategy," *Energy*, vol. 93, pp. 1426–1435, Dec. 2015.
[44] J. Madan, M. Mani, J. H. Lee, and K. W. Lyons, "Energy performance evaluation and improvement of unit-manufacturing processes: Injection molding case study," *J. Cleaner Prod.*, vol. 105, pp. 157–170, Oct. 2015.
[45] P. Jovanović, "Application of sensitivity analysis in investment project evaluation under uncertainty and risk," *Int. J. Project Manage.*, vol. 17, no. 4, pp. 217–222, 1999.
[46] Y. Zhu and W. X. Zheng, "Multiple Lyapunov functions analysis approach for discrete-time switched piecewise-affine systems under dwell-time constraints," *IEEE Trans. Autom. Control*, to be published.



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