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An Indirect Estimation of Machine Parameters for Serial Production Lines with Bernoulli Reliability Model

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***Abstract*— Automated measurement of the machine reliability parameters for a production system enables a continuous update of the mathematical model of the system, which can be used for various analysis and productivity improvement. However, the continuous update may be impeded by some machines of which automated parameter measurements are out of order. Such a situation has been observed, for instance, when some of the machines in the line cannot save log files, or IoT devices that measure these machines stop functioning. In this context, this paper addresses the problem of estimating the efficiencies of those machines while avoiding a direct manual measurement (by human) of up- and down times for them. It turns out that those efficiencies can be computed using starvation/blockage data of the neighboring machines along with the system information. With this, a continuous update of the model is possible even though some machines do not report status in automated manner. The method is indirect as opposed to a direct manual measurement by human. The results are derived for serial production lines with Bernoulli reliability characteristics. Simulation studies are carried out to verify the accuracy of proposed estimation method in both two-machine line case and multi-machine line case.**

I. INTRODUCTION

Advances of Internet of Things (IoT) and Cyber-Physical Systems (CPS) technologies have accelerated the development of smart factories, where real-time data from the factory floor are collected and utilized to manage the whole operation for improved efficiency, low level of inventories, on-demand manufacturing and energy management, etc [1] – [4].

As one of the constituents of technologies for smart factories, *smart production systems* have been a topic of active research [5] – [7]. While smart factories address a wide range of potential improvement in various aspects of manufacturing as a whole, smart production systems focus on a specific goal of productivity improvement. A production system is called ‘smart’ if it is capable of self-diagnosing and autonomously designing optimal continuous improvement projects [7]. The underlying theory for smart production system is the work of production systems engineering (PSE) [8], which provides a mathematical foundation to solutions of many important problems of production systems (bottleneck identification, lean buffering, and customer demand satisfaction, etc. See [8] for more details). Theory of PSE utilizes a mathematical model of the production line at hand and uses it for various analyses. In order to apply the rigorously developed set of tools in PSE, a mathematical model needs to be constructed, and the parameters of the model such as efficiency (from up- and down times) of each machine and buffer capacity shall be obtained. This process has been done manually for many production lines [9] – [12] in order to derive an optimal productivity improvement strategy. However, for a production system to become smart, an automated measurement system is a key component. This is because the characteristics of production lines change over time due to aging or improving tasks [13], [14]. Without the automated measurement, such changes may not be continuously (periodically) reflected in the model.

In reality, there exist situations where some of the machines in the production line fail to execute automated measurement necessary for the mentioned continuous model update. Indeed, authors of this manuscript encountered manufacturing lines in the area of Daegu, Korea, that implemented data logging system under the government initiative of smart factory, but some of the logging functions are not operational and repair of which is costly in time, resource and effort.

The problem addressed in this paper is to indirectly estimate the reliability parameters for some of the machines so that the mathematical model of the production line can be continuously updated when some of the machine status are not properly recorded. To begin with a simple case, we consider serial production lines that consist of the machines following the Bernoulli reliability model. In this model, all machines have identical cycle time, and each machine produces a part with a certain probability if the machines are not starved or blocked in every cycle time. The actual examples that can be analyzed using Bernoulli reliability model are cited in [8].

It must be pointed out that a manual *direct* measurement of the selected machines in the line is always possible, although not desirable: it requires human effort and time, and has to be repeated whenever some changes are noticed. We refer the method developed in this work as ‘indirect estimation’ in the sense that the efficiency parameter of a machine is obtained not by a direct manual measurement by human, but by an estimation from the data of the other machines in the line.

The main contribution of this work is to present a method of indirect parameter estimation for machines that fail to report up and down times in an automated manner. This method is expected to serve as a feature that enhances resiliency of smart production systems because it provides a means to deal with failures of some sensors or circuits around them.

The outline of this paper is as follows. Section II formu-

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lates the problem. Section III reviews the method of calculating the performance measures. Section IV develops the indirect parameter estimation method. Section V examines the accuracy of the proposed method. Conclusions are given in Section VI.

II. PROBLEM FORMULATION

Consider a production system with automated measurement and analysis capabilities, for example, as shown in Fig. 1. The cyber part performs data collection, parameter estimation if necessary, and maintains the mathematical model of the physical system up to date. It is also capable of performing productivity analysis on the model so that continuous improvement strategies are derived.

For the physical part of the system in Fig. 1, serial production lines shown in Fig. 2 are considered that consist of M machines $(m_1, ..., m_N)$ and $M-1$ buffers $(b_1, ..., b_{M-1})$. All machines have constant and identical cycle times denoted by τ. Each machine follows the Bernoulli reliability model with the probability that a machine stays up for each duration of τ denoted by p_i. The capacity of each buffer is denoted by a positive integer N_i.

The mathematical analysis of the production line requires the parameter τ, p_i and N_i. Thus, we should identify these parameters in the modeling process. Cycle time τ and buffer capacity N_i are easily acquired through direct measurement of the machines and buffers. The Bernoulli parameter p_i, however, should be estimated from the operation data of each machine such as uptime and downtime. Typically, the efficiency of a machine is used for p_i.

In this paper, we consider automated measurement devices that measure the state and performance of each machine, i.e., p_i, ST_i, BL_i for $i = 1, ..., M$ and also PR of the line, where ST_i is the starvation probability, BL_i is the blockage probability of machine m_i, respectively, and PR is the production rate of the line. Detailed explanations are given in the following section.

Now consider the scenario where the measurement devices for one or multiple machines are not available. For convenience, we refer to such a machine by *unknown machine*. Specifically, the problem addressed in the paper is as follows:

Problem Consider a serial line with M machines. Bernoulli parameters of some machines are unknown. Find a method of estimating p_i for unknown machines, and identify the conditions under which the estimation is feasible.

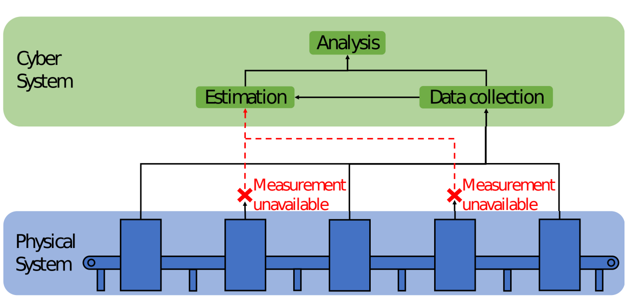


Fig. 1: Automated measurement and estimation process for production system analysis.

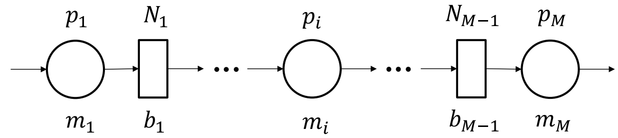


Fig. 2: Standard form of serial production line

III. ANALYSIS OF PERFORMANCE MEASURES

Performance measures in a production line include production rate, starvation, and blockage. The measures and how they relate to all other parameters in the system are briefly reviewed in this section based on the work of [8]. This will be used later to construct the method of efficiency estimation of the unknown machines. Definitions of the three performance measures are given as follows:

- Production rate (PR): the probability that the last machine of the production line produces the parts.
- Starvation of machines i (ST_i): the probability that m_i is starved during the time slot.
- Blockage of machine i (BL_i): the probability that m_i is blocked during the time slot.

Note that the throughput, i.e., the number of produced parts per unit time, is commonly used as a measure of productivity. For Bernoulli lines, the throughput is given by PR/τ.

Exact solutions for performance measures of a production line exist only for the two-machine serial line, i.e., $M = 2$. In order to analytically calculate the performance measures, the production line is modeled as a Markov chain, of which states are the occupancy of the buffer. For real numbers $0 < x, y < 1$ and a natural number N, define the function

$$Q(x,y,N) = \begin{cases} \dfrac{(1-x)(1-\alpha)}{1-\frac{x}{y}\alpha^N}, & \text{if } x \neq y, \\ \dfrac{1-x}{N+1-x}, & \text{if } x = y, \end{cases}$$

with

$$\alpha = \frac{x(1-y)}{y(1-x)}.$$

Then, the performance measures of a two-machine line is given by:

$$\begin{aligned} PR &= p_1(1-Q(p_2,p_1,N)) && (1)\\ &= p_2(1-Q(p_1,p_2,N)), \\ BL_1 &= p_1 Q(p_2,p_1,N), && (2)\\ ST_2 &= p_2 Q(p_1,p_2,N). && (3) \end{aligned}$$

For the production lines with $M > 2$, the Markov chain approach is not practical because the number of states is the multiple of all possible states of each buffer, i.e., $\Pi_{i=1}^{M-1} N_i$, which increases exponentially as the number of buffers increases. Alternatively, the following aggregation method is used. Forward and backward probabilities of each machine are defined recursively with an iteration index $s = 0, 1, 2, \ldots$, as follows:

$$\begin{aligned} p_i^b(s+1) =& p_i(1 - Q(p_{i+1}^b(s+1), p_i^f(s), N_i)), \\ & i = 1, \ldots, M-1, \\ p_i^f(s+1) =& p_i(1 - Q(p_{i-1}^f(s+1), p_i^b(s+1), N_{i-1})), \\ & i = 2, \ldots, M \end{aligned} \tag{4}$$

with $p_i^f(0) = p_i, \quad i = 1, \ldots, M$ and $p_1^f(s) = p_1,\ p_M^b(s) = p_M$, for all s. The forward and backward probabilities of each machine converge in the procedure of (4) and yields

$$p_i^b := \lim_{s\to\infty} p_i^b(s),\ p_i^f := \lim_{s\to\infty} p_i^f(s). \tag{5}$$

Using the aggregation method, the performance measures of the serial lines with $M > 2$ are given by

$$\begin{aligned} \widehat{PR} &= p_1^b = p_M^f & (6)\\ &= p_{i+1}^b(1 - Q(p_i^f, p_{i+1}^b, N_i)) \\ &= p_i^f(1 - Q(p_{i+1}^b, p_i^f, N_i)), \\ & \quad i = 1, \ldots, M-1, \\ \widehat{BL}_i &= p_i Q(p_{i+1}^b, p_i^f, N_i), & (7)\\ \widehat{ST}_i &= p_i Q(p_{i-1}^f, p_i^b, N_{i-1}) & (8)\\ & \quad i = 1, \ldots, M, \end{aligned}$$

Where the hats indicate that they are not exact value but approximated by the aggregation. Notice that, under this method, the entire line with M machines is approximated by a two virtual machine line with the buffer b_{i-1}. This is depicted in Fig. 3, where the parameters are defined in (5).

IV. Indirect Estimation of Machine Parameter

A. Two-Machine Line

When m_1 is an unknown machine, p_1 can be calculated using (3). This is carried out in the following theorem.

Theorem 1: Consider the production line shown in Fig. 2 with $M = 2$. The Bernoulli parameter p_1 is given by solving

$$Q(x, p_2, N_1) = \frac{ST_2}{p_2} \tag{9}$$

for x. The solution is unique. If

$$ST_2 = \frac{p_2(1-p_2)}{N_1 + 1 - p_2}, \tag{10}$$

then $p_1 = p_2$.

Proof: We first show that (9) has a unique solution. The function $Q(x, y, N)$ is continuous and strictly decreasing in x and takes values on $(0, 1)$ for any $0 < y < 1$ and positive integer N [8]. Also, it is straightforward to show that $Q(x, y, N)$ satisfies

$$\lim_{x\to 0} Q(x, y, N) = 1, \text{ and } \lim_{x\to 1} Q(x, y, N) = 0,$$

for any $0 < y < 1$ and positive integer N. Now $p_2 \in (0, 1)$ because it is a probability. The right side of (9), i.e., $\frac{ST_2}{p_2}$ also belongs to $(0, 1)$. This is because $0 < ST_2 < p_2$ due to the definition of ST_2. Consequently, (9) has a unique solution. The solution of (9) can be found by a bisection algorithm.

When (10) is satisfied, $p_1 = p_2$ solves (9) due to (3), (10) and the definition of $Q(x, y, N)$. Since the solution is unique, we obtain $p_1 = p_2$. ■

Similarly, when m_2 is unknown, p_2 can be solved from other parameters using (2). This is summarized in the following theorem:

Theorem 2: Consider the production lines shown in Fig. 2 with $M = 2$. The Bernoulli parameter p_2 is given by solving

$$Q(x, p_1, N_1) = \frac{BL_1}{p_1} \tag{11}$$

for x. The solution is unique. If

$$BL_1 = \frac{p_1(1-p_1)}{N_1 + 1 - p_1}, \tag{12}$$

then $p_2 = p_1$.

Proof: The proof is omitted because it is almost identical to that of Theorem 1. ■

The implication of the results are as follows. If m_1 is unknown machine, p_1 cannot be computed from the operation data of m_1. However, p_1 can be obtained by Theorem 1. The same applies for the case when m_2 is an unknown machine.

B. Production lines with $M > 2$

When $M > 2$, the results of aggregation method, i.e., (7) – (8), are used for the indirect estimation of the Bernoulli parameter of an unknown machine. Let m_i, $i \neq 1, M$ be the unknown machine. We first find the relationship of p_i^f and p_i^b with other parameters. Combining (4) and (5) gives

$$\begin{aligned} p_i^b &= p_i(1 - Q(p_{i+1}^b, p_i^f, N_i)), & (13)\\ & \quad i = 1, \ldots, M-1, \\ p_i^f &= p_i(1 - Q(p_{i-1}^f, p_i^b, N_{i-1})), & (14)\\ & \quad i = 2, \ldots, M. \end{aligned}$$

Then, p_i can be obtained from (13) as follows:

$$p_i = \frac{p_i^b}{1 - Q(p_{i+1}^b, p_i^f, N_i)}. \tag{15}$$

In order to use this relationship, p_i^b, p_{i+1}^b and p_i^f must be evaluated. However, since p_i is not known, the aggregation procedure in (4) cannot be used to obtain p_i^b, p_{i+1}^b, and p_i^f. An alternative is necessary.

First we approach to obtain p_i^b. Consider the aggregated virtual two machine line shown in Fig. 3. Then, p_i^b is the Bernoulli parameter of the second virtual machine m_i^b. If the Bernoulli parameter of the first virtual machine, i.e., p_{i-1}^f and

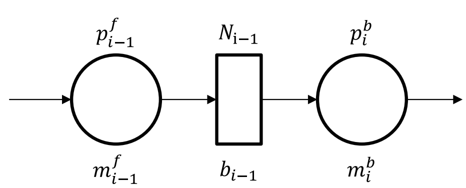


Fig. 3: Equivalent two machine serial line by the aggregation method, $i = 2, 3, \ldots, M$.

the blockage of m^f_{i-1} are known, then the result of Theorem 2 leads a way to obtain p^b_i. It turns out that combining (8) and (14) gives

$$p^f_j = p_j - \widehat{ST}_j, \quad j = 2, \ldots, M. \tag{16}$$

Since $\widehat{ST}_j$ is approximated starvation probability of machine j from the aggregation method, p^f_{i-1} is obtained from p_{i-1} and measured ST_{i-1} using (16). Using (2) and (7), the blockage of m^f_{i-1} is evaluated as

$$BL^f_{i-1} = p^f_{i-1}\frac{BL_{i-1}}{p_{i-1}}. \tag{17}$$

Thus, with p^f_{i-1} and BL^f_{i-1} obtained as such, applying Theorem 2 yields p^b_i. Evaluating the value of p^f_i is carried out in a similar manner as above but using the two line virtual machines consisting of m^f_i and m^b_{i+1}. In this case, p^f_i is the unknown parameter of the first virtual machine m^f_i. The value of p^b_{i+1}, parameter of m^b_{i+1}, is obtained from

$$p^b_j = p_j - \widehat{BL}_i, \quad j = 1, \ldots, M-1, \tag{18}$$

which are derived by combining (7) and (13). The starvation of m^b_{i+1} is obtained by

$$ST^b_{i+1} = p^b_{i+1}\frac{ST_{i+1}}{p_{i+1}}. \tag{19}$$

Now, applying Theorem 1 gives the value of p^f_i. Finally, p_i is obtained from (15) using the values of p^b_{i+1}, p^b_i and p^f_i. We will use the notation $\hat{p}_i$ to indicate that this value is an estimation.

Notice that $\hat{p}_i$ may be obtained starting from (14) instead of (13) in a similar manner. The values of $\hat{p}_i$ obtained by the two methods are always identical from our experience, although it has not been proved.

If the unknown machine is m_1, $p^f_1 = p_1$ satisfies from the boundary condition of (4). Thus we can obtain $\hat{p}_1$ with Theorem 1 and (18). Similarly, $\hat{p_M}$ can be obtained with Theorem 2 and (16) in the case when m_M is the unknown machine.

It must be pointed out that the proposed estimation process requires the information of the machine and buffer located before and after the unknown machine. In other words, the estimation method is applicable when more than a single machine are unknown, as long as the unknown machines are not consecutive.

In summary, we state the following as a solution to the problem formulated in Section II. If some machines are unknown, the efficiencies are estimated by using Theorem 1, Theorem 2, and the method presented in Section IV as long as no two unknown machines are consecutively located.

V. Accuracy of Estimation

A. Effect of measurement errors

We investigate how measurement errors affect the estimation. For simplicity, only two machine cases are considered. The proposed method calculates p_2 (or p_1) from the measured values of p_1 and BL_1 (or p_2 and ST_2). Since p_1 and BL_1 are measured values by the automated measurement device, the accuracy depends on the number of measurement and the way they are computed. The errors in p_1 and BL_1 propagate to p_2 through (11). Since p_2 is the solution of (11) and the coefficients of (11) involve p_1 and BL_1, analytical study of the error propagation is not straightforward. Instead, we carry out numerical simulations to investigate the effect of errors in p_1 and BL_1 on the error of p_2.

For the numerical investigation, we generated 10,000 two-machine lines by randomly selecting parameters: p_i are selected in the range of $[0.7, 0.9]$ and N is selected in the range of $[1, 10]$. For each generated production line, we vary the errors in p_1 and BL_1 in the range of $\pm 10\%$, and evaluate the errors in p_2. The errors are denoted by ε_1 and ε_{BL_1} which are, respectively, the error of p_1 and BL_1 in fractions. The errors in the estimated p_2 is denoted by ε_2 that is defined as

$$\varepsilon_2 = \frac{|\hat{p}_2 - p_2|}{p_2}$$

where $\hat{p}_2$ is the estimated value by Theorem 2 and p_2 is the value used in the simulation. Fig. 4 shows the average ε_2 over 10,000 lines for given values of ε_1 and ε_{BL_1}. In the figure, ε_2 increases almost linearly with the ε_1 or ε_{BL}. It seems that ε_{BL} affects less than ε_1 does. In all cases, the average ε_2 is well less than 7%.

B. Model validation with estimated parameters

A model of the production system undergoes a validation step by comparing the analytically obtained (through the process of aggregation if $M > 2$) *PR* with the measured value. In particular, since the aggregation process is an approximation, the validation is necessary for the model to be used for various analyses such as bottleneck identification and evaluating quantitatively productivity improvement scenarios.

The estimated Bernoulli parameter of the unknown machine may bear some errors even if all the measurements are perfectly accurate. This is because (6) – (8) used to obtain the probability (for $M > 2$) come from the aggregation procedure, which is an approximation. Here, we investigate

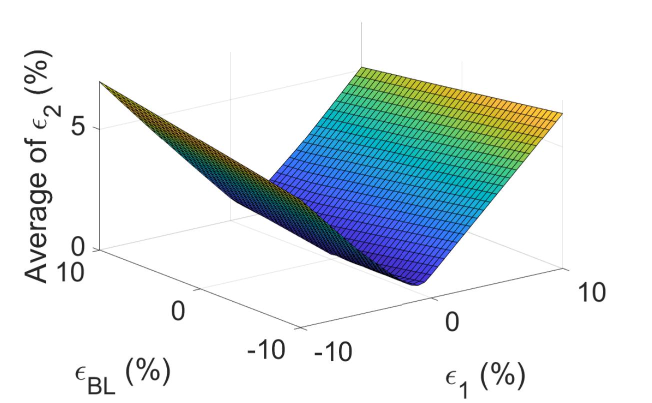


Fig. 4: Estimation errors of p_2 from errors of BL_1 and p_1.

how closely the model predicts PR with the estimated parameter for the unknown machine.

For this purpose, we introduce two metrics:

$$\varepsilon_{est} = \frac{|p_i - \hat{p}_i|}{p_i}, \tag{20}$$

$$\varepsilon_{PR} = \frac{|PR_s - PR(p_1,...,\hat{p}_i,...,p_M,N_1,...,N_{M-1})|}{PR_s} \tag{21}$$

where the former shows the accuracy of the estimated parameter, and the latter shows how well the model is validated. Here, PR_s denotes the value of PR obtained through discrete event simulations and $PR(p_1,...,\hat{p}_i,...,p_M,N_1,...,N_{M-1})$ is the PR obtained by the aggregation method.

For the investigation, we consider production lines with M=5, 10, 15, and 20. For each case, the parameters are randomly selected in the following ranges:

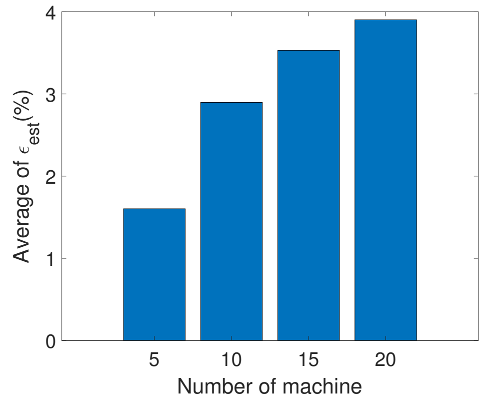
$$\begin{aligned} p_i &\in [0.7,1], \quad i = 1,...,M, \\ N_i &\in [1,10], \quad i = 1,...,M-1. \end{aligned} \tag{22}$$

For each production line, we discrete-event simulate the behavior of the production line to obtain the performance measures. Detailed procedure of the simulation is described as follows.

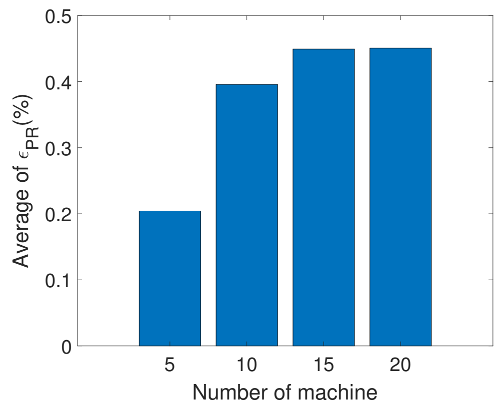
1) Initial states of all machines are selected as up.
2) The state of each machine in the time slot is determined at the beginning of each time slot.
3) In each simulation, the data from the first 10,000 time slots are discarded as it is considered as a transient period. The data from the subsequent 200,000 time slots are used to evaluate PR, ST_i and BL_i.
4) For each system, simulations are carried out 20 times, with different seeds, and the performance measures of this production system are determined by averaging the results of 20 simulations.

For each production system, in the order of $i = 1,2,...,M$, machine m_i is treated as an unknown machine, and $\hat{p}_i$ is obtained by the proposed method. In other words, we indirectly estimate the parameter of the first machine with the p_2, ST_2 and BL_2, then estimate the parameter of the second machine with the p_1, ST_1, BL_1, p_3, ST_3 and BL_3 and estimate the parameter of following machine similarly. Next, using the model with the estimated parameter, values of ε_{est}, ε_{PR} are calculated. As a result, for each M=5, 10, 15, 20, the total of 10,000M values of ε_{est}s and ε_{PR} are obtained, respectively.

Fig. 5 shows that the average value of ε_{est} for each M in Fig. 5(a) and the average value of ε_{PR} in Fig. 5(b). It shows that the average of ε_{est} in all cases is well less than 4%. The average value of ε_{PR} for all cases is well less than 0.5% indicating higher accuracy compared to ε_{est}. The results show that the model of the production line obtained as a result of the proposed method in this work is well validated.



(a)



(b)

Fig. 5: Average value of ε_{est} (a) and ε_{PR} (b)

C. Accuracy in Bottleneck Identification

The most common use of the mathematical model of a production line is to identify the bottleneck machine denoted by BNm. The bottleneck machine is defined as the machine which has the largest $\partial PR/\partial p_i$ among all machines in the line. The question investigated in this subsection is as follows. Suppose that we identify a BNm in a situation when a machine is unknown. Is this BNm the same as the one we would have found if all machine parameters are known? We investigate this question for the case of $M = 5$. Two methods are available to identify the bottleneck: sensitivity analysis that evaluates the partial derivatives using the aggregated model; and the arrow method that utilizes ST_i and BL_i instead of directly evaluating the partial derivatives. The arrow method is simple and widely used in practice [8].

Let us denote the bottleneck machine resulted from the first method by BNm_{Agg}, and that from the latter by BNm_{Arr}. Both methods are not exact, however, in most cases, they give the same result. Since both are not exact, we also identify the bottleneck machine based on discrete-event simulations: numerically evaluating $\partial PR/\partial p_i$ by perturbing p_i and carry out simulations. We denote this bottleneck by BNm_{DES} and regard BNm_{DES} as the true bottleneck.

The investigation is done for 5,000 randomly generated serial production lines. Again, the parameters of each machine of a line are selected in the range given in (22). For each line, we first find BNm_{DES}, BNm_{Agg}, and BNm_{Arr}. Then, for each line, we treat m_i as an unknown machine in the order of $i = 1,2,3,4,5$, apply the proposed method to estimate

TABLE I: Accuracy of each bottleneck identification method

Identified BNm	Accuracy(%)
$\widehat{BNm}_{Agg}$	96.85
$\widehat{BNm}_{Arr}$	89.6
BNm_{Agg}	96.1
BNm_{Arr}	91.68

p_i, and find $\widehat{BNm}_{Agg}$ and $\widehat{BNm}_{Arr}$ using the model with the estimated parameter. The hat notation indicates that these bottleneck machines are found from the mathematical model that contains an unknown machine. As a result, for each production line, we have one value of BNm_{DES}, one value of BNm_{Agg}, one value of BNm_{Arr}, five values of $\widehat{BNm}_{Agg}$ and five values of $\widehat{BNm}_{Arr}$.

The results are expressed in the form of accuracy that $\widehat{BNm}_{Agg}$ is equal to the true bottleneck (BNm_{DES}), and also $\widehat{BNm}_{Arr}$ equal to BNm_{DES}. The results are summarized in Table I. Although one machine is unknown, and its parameter had to be estimated by the method given in section IV.B, both methods yield high accuracy for identifying the true bottleneck machine. In addition, we also show in Table I the accuracy of BN identification, if all machines are known. Compared to the case when all machines are known, the indirect estimation of parameters proposed in this work maintains the effectiveness of bottleneck identification. The accuracy is slightly higher for the sensitivity analysis method and the accuracy is lowered only by 2% for the arrow method. Therefore, the indirect method is effective to be used in practice.

VI. CONCLUSION

In the context of smart production system that is capable of continuously improving productivity of serial production lines with Bernoulli reliability characteristics, we have developed a method that indirectly estimates the unknown machine's efficiency from the data of neighboring machines. The effectiveness of the proposed method is validated by discrete event simulations. For the method to be applicable, the efficiencies, starvation and bottleneck probabilities of the machines before and after the unknown machine must be available.

As future work, a method of detecting unknown machines and engaging the proposed estimation scheme to update the mathematical model needs to be developed in order to realize smart production systems. We believe that the results of this work are useful to increase resiliency of the smart production systems for the situation when automated logging devices of some machines fail.

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