Detecting Low-Yield Machines in Batch Production Systems Based on Observed Defective Pieces

Philip F. E. Adipraja, Chin-Chun Chang, *Member, IEEE*, Hua-Sheng Yang, Wei-Jen Wang, *Member, IEEE*, and Deron Liang

***Abstract*—In batch production systems, detecting low-yield machines is essential for minimizing the production of defective pieces, which is a complex problem that currently requires multiple experts, considerable capital, or a combination of both to overcome. To solve this problem, we proposed a cost-efficient and straightforward method that involves using maximum likelihood estimation and bootstrap confidence intervals to estimate per-machine yield; this method enables identification of low-yield machines and generation of a list of these machines. Manufacturing engineers can use the list to perform necessary verification and maintenance processes. Before implementing this method, a manufacturer with 50–500 machines should build a dataset containing approximately 6–20 times as many batches as there are production machines. When this condition is met, the proposed method can be used effectively to detect up to five low-yield machines.**

***Index Terms*—Batch production, expectation–maximization (EM) algorithm, machine maintenance suggestion, per-machine yield estimation.**

I. Introduction

IN THE manufacturing industry, the demand for highly customized products is increasing [1]. To meet this demand, a manufacturer can use a batch production system, which involves numerous production machines, various production flows, and the production of numerous batches of products [2]. Because a production process is often complex, numerous types of defects may occur because of various causes [3]. In this context, a low-yield machine is a key indication that a high number of defective products may be generated for various reasons, including poor machine conditions and misconfiguration [4]. This is a challenge for manufacturers that are striving to achieve zero-defect manufacturing (ZDM) [5], especially those that are using batch production systems. Although the practical implementation of ZDM is challenging, manufacturers tend to be willing to take any reasonable measures to achieve or work toward ZDM [6]. Accordingly, detecting and maintaining low-yield machines are crucial to achieving ZDM. Numerous studies have proposed product-oriented or process-oriented diagnosis methods for doing so (Table I) [6]. In product-oriented diagnosis, defective products are investigated to detect service machines that generate product defects. In process-oriented diagnosis, a machine health monitoring system is implemented for every machine to detect problematic machines and facilitate maintenance scheduling.

In practice, process-oriented and product-oriented diagnoses can be combined to complement each other. A manufacturer may implement product-oriented diagnosis methods such as root cause analysis (RCA) [7], [8], [9], [10], [11], [12]. The flow of RCA-based methods can be conceptually divided into three major steps. First, a manufacturer must perform product defect detection and collect analytical data on defects. Second, expert engineers must analyze the defect data to identify the root cause. Third, these engineers service or adjust the manufacturer's production machines on the basis of the analysis results. Generally, RCA-based methods consider numerous parameters [8], [11]. Machine learning can be applied to build automated models for conducting RCA, but this type of analysis is currently still labor intensive for experts, as shown in Table I. Moreover, in a batch production system, the dependency on expert knowledge is high, and the training data provided for machine learning may be insufficient [8].

Alternatively, a manufacturer may apply process-oriented methods, which involve the use of machine-condition-monitoring sensors and a prognostics and health management (PHM) system [13], [14], [15], [16], [17], [18], [19], [20]. Conceptually, the flow of PHM-based methods can be divided into three major steps. First, data collection is performed; to achieve this, a manufacturer usually deploys numerous monitoring sensors and controllers for each production machine. Second, because numerous parameters are used in sensor data, a machine learning or deep learning model is usually used to extract data features. Third, engineers must be notified when a fault is identified through a PHM-based method. These engineers then verify the health conditions of the identified machines and plan a suitable maintenance schedule. PHM-based methods are widely used in the manufacturing industry, but several challenges must be addressed, including false alarms and machine misconfigurations [4], [13], [17]. In addition, this method incurs a high initial cost and is only affordable for large manufacturers (Table I) [14].

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TABLE I
COMPARISON OF METHODS FOR DETECTING LOW-YIELD MACHINES

Methods	Benefits	Limitations
Existing process-oriented diagnosis (e.g., PHM-based)	• Real time monitoring system. • Detailed machine health data.	• Expensive. • May have unnoticeable misconfiguration issue.
Existing product-oriented diagnosis (e.g., RCA-based)	• High accuracy as verified by experts. • Can be automated using machine learning.	• Expensive due to expert involvement. • Requires many parameters. • Low transferability (between experts).
Proposed method	• Requires dataset with few parameters. • Affordable. • Numerical per-machine yield for historical data.	• Only detect low-yield machines without any failure information. • Manufacturer may require time to accumulate and analyze production data.

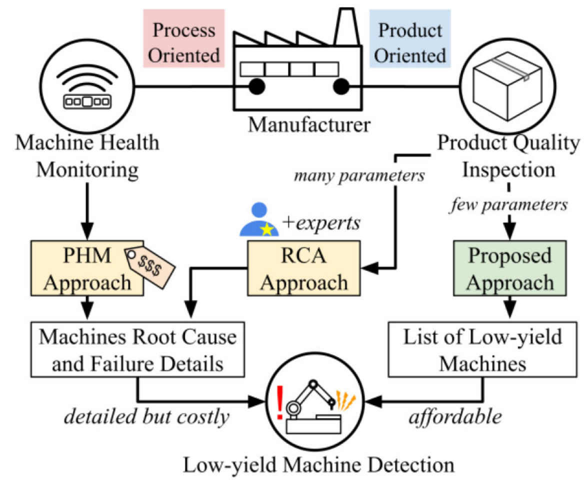

Fig. 1. Illustration of the proposed method relative to recent studies.

Although existing machine diagnosis methods (e.g., RCA and PHM) can be used to detect machines with low yields and identify their failures, these methods are generally either labor intensive (because of the involvement of human experts) or costly to implement (Table I). Consequently, small- and medium-sized manufacturers are likely to encounter challenges in implementing these methods. To address these limitations, we proposed an alternative method for detecting low-yield machines. The proposed method uses historical per-batch production data and maximum likelihood estimation (MLE) to estimate per-machine yield. MLE can be performed by applying the expectation–maximization (EM) algorithm. Subsequently, the results of the per-machine yield estimation can be used to identify low-yield machines. Fig. 1 illustrates how the proposed method can be used to quickly identify and quantify the number of low-yield machines on the basis of production data; this process can be performed without the involvement of human experts. In addition to using the results of the proposed method, engineers can leverage multimodal data sources (e.g., PHM and RCA) and machine learning to develop a decision support system that can obtain detailed information regarding failures or problems related to the identified low-yield machines [21], [22].

This proposed method can be categorized as a product-oriented method, and it is based on a study that performed per-machine yield estimations to predict per-batch yield for the next 1–4 weeks [2]. Although the method used in that study allows for machine yield to be estimated, the obtained estimation results are insufficiently reliable because of two limitations. First, it does not consider the frequency with which a machine is used. Second, it tends to identify the machines used in earlier batch production steps as having a greater probability of being low-yield machines relative to those used in later production steps.

To overcome these limitations, we proposed a method that employs an improved EM-based algorithm [2]; this algorithm incorporates per-machine miss rate as a variable to estimate the tolerance of each inspection equipment. We also included an additional step, that is, obtaining the confidence intervals of per-machine yield estimations and then performing hypothesis testing to narrow down the number of low-yield machine candidates. By considering the dynamic accuracy of inspection devices and large production batches, we further analyzed the number of observed defective pieces, enabling the identification of low-yield machines that may require immediate maintenance.

Furthermore, we performed simulation experiments to validate the function of the proposed method. Because actual per-machine yield data are unavailable, we conducted simulations to generate per-machine yield and batch production data. In addition, we designed our simulation to explore the minimum dataset size required for the proposed method to successfully detect low-yield machines. Subsequently, under the proposed method, production data is used as an input to estimate per-machine yield. On the basis of our simulation experiment results, the proposed method was applied to effectively detect low-yield machines when a given condition was met. To effectively detect up to five low-yield machines, manufacturers with 50–500 machines must collect approximately 6–20 times as many batches of production data as there are production machines. However, using fewer batches of production data may lead to less reliable results (see Section IV for a detailed explanation). In practice, a large manufacturer should be able to obtain this amount of data within a day and to apply the proposed method for analyses on a daily basis. For small manufacturers, the feasible time frame for completing these tasks is approximately one week.

The contributions of this study are as follows.

1) The proposed method is straightforward (only uses the common production data with a few parameters) and cost efficient (does not require experts or investment to obtain additional sensors or hardware) compared with other RCA and PHM methods.
2) The proposed method employs MLE and bootstrap confidence intervals to estimate per-machine yield, which can then be used to detect low-yield machines for the purpose of facilitating maintenance scheduling. The method was validated using simulation datasets in our experiments.

The proposed method can be used to improve production management. First, it can be used to enhance maintenance planning because it can quickly identify low-yield machines, thereby reducing the time required to identify the root causes of manufacturing problems. In addition, it can help manufacturers minimize the occurrence of defects and work toward achieving zero defects in future production. Second, because the proposed method requires only a few parameters derived from production data and does not involve human experts, it is more cost-effective than other recently developed RCA methods are. Thus, a manufacturer with limited resources can easily adopt this method. Furthermore, if a larger budget becomes available, they can combine the proposed method with RCA and PHM to obtain more detailed results.

The remainder of this article is organized as follows. Sections II and III describe the proposed method for generating a list of low-yield machines that may require immediate maintenance. Section IV discusses the simulation design and results and the practical considerations for the proposed methods. The final section concludes the study.

II. Proposed Method

The two major functions of the proposed method are described in Figs. 2 and 4, respectively. In the first function, per-machine yield estimation is performed in accordance with steps (1)–(6) of Fig. 2, and the mathematical formulation of step (4) is explained in Section III. Because each production machine is most likely used differently during a batch production process, estimated per-machine yield obtained from small samples is less reliable than that obtained from large samples. To address this challenge, for the first function, we combined resampling with the bootstrapping method [23] to calculate each per-machine yield with a confidence interval, and we excluded the machines with a high yield or high standard deviation to obtain a final sorted list of low-yield machines in the second function, which operates in accordance with steps (1)–(9) of Fig. 4.

A. Overview of Per-Machine Yield Estimation

To perform per-machine yield estimation (Fig. 2), the batch production dataset must be preprocessed and reformatted (Table II). Data preprocessing comprises three major tasks (step 1 in Fig. 2). First, the data related to manual or human labor are excluded because the objective is to detect low-yield machines. Second, when no data pertaining to the observed defective pieces in a machine are collected because of the absence of inspection equipment, the parameters for these pieces are set to zero for the machine. Third, the multiple consecutive batch steps that are applied to the machine are merged into one batch step (including the number of observed defective pieces).

According to a study [2], machine yield estimations are highly influenced by the number of observed defective pieces and the number of batches for which a machine is used. When the EM algorithm is used to analyze a dataset, a single set of per-machine yield data may be produced; among these per-machine yield data, some may be more reliable than others

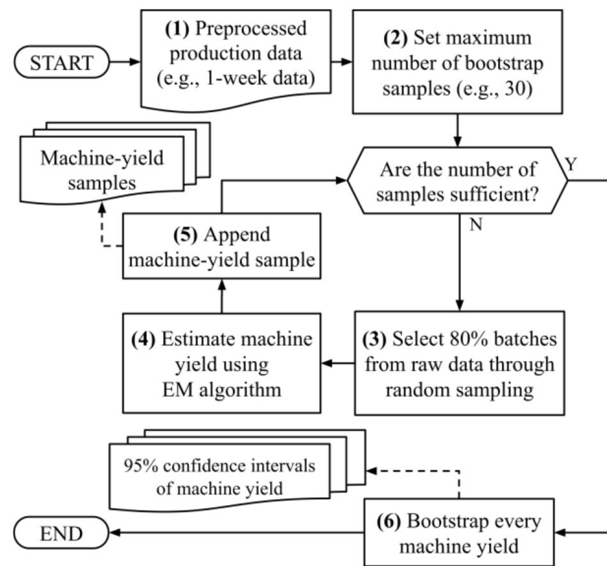

Fig. 2. Proposed method for estimating per-machine-yield.

TABLE II
Example of Required Production Data

Batch Number	Production Sequence	Machine Name	# of Processed Pieces	# of Detected Defective Pieces
Batch-13	1	MCH12	100	0
	2	MCH54	100	2
	3	MCH11	98	0
	4	MCH68	98	3
	5	MCH54	95	1
Batch-62	1	MCH54	500	0
	2	MCH37	500	5
	3	MCH94	495	0
…	…	…	…	…

because the EM algorithm provides a more accurate estimation for the machines processing a larger number of batches than for those processing a smaller number of batches. To examine the reliability of per-machine yield estimations, more samples must be used to obtain the confidence interval for each estimated per-machine yield. To this end, we resampled a batch production dataset to randomly select 80% of the records in the dataset (i.e., step 3 in Fig. 2). With this technique, the required number of subdatasets can be generated. We set the number of subdatasets to 30 (i.e., step 2 in Fig. 2). Subsequently, we applied the EM algorithm to the resampled subdatasets and obtained 30 datasets of per-machine yield (i.e., steps 4 and 5 in Fig. 2). Finally, we applied the bootstrapping method [23] to estimate the approximate confidence intervals of the per-machine yield (i.e., step 6 in Fig. 2). The bootstrapping method is a promising method for constructing confidence intervals. This is supported by a study [23] that demonstrated its usefulness in estimating confidence intervals for quantifying uncertainty regarding the locations of multiple change points.

Two major parameters are used in the first function, the size of a resampled dataset and the number of resampled datasets. Several studies have demonstrated that for the bootstrapping method, a sample size of $\geq$30 is usually sufficient [24], [25],

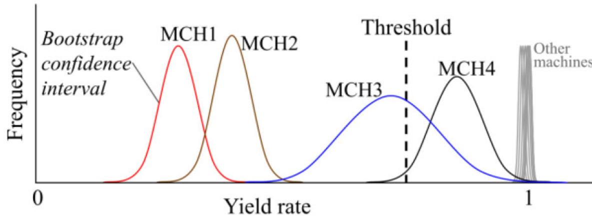

Fig. 3. Threshold and bootstrap confidence intervals of per-machine yield estimation as obtained through one-sided hypothesis testing.

[26]. Therefore, we collected a minimum of 30 samples for each estimated per-machine yield because each run of the EM algorithm requires considerable processing time. For the resampling of the original dataset, we performed random sampling to select 80% of the records in the dataset. Two factors must be considered for this parameter. First, an objective is to create as many variations as possible for each resampled dataset; thus, resampled datasets must be differentiated from each other to the greatest extent. Second, the EM algorithm requires a large dataset to estimate per-machine yield [2]; thus, the size of a resampled dataset should be maximized. On the basis of our experience, we used 80% of a dataset to ensure the quality of EM estimations while maintaining a favorable variation for the 30 resampled datasets. Notably, the 80% value is configurable and may be reduced when a larger dataset is used as the basis for obtaining resampled datasets. This topic is further discussed in Section IV-C.

B. Obtaining Low-Yield Machine List

The second function of the proposed method is to generate a low-yield machine candidate list by performing one-sided hypothesis testing. The one-sided hypothesis test (or one-tailed test) is a test of statistical significance that is performed to determine whether a given sample is significantly greater or less than a given threshold value. For each machine, the bootstrap method in the first function should provide the bootstrap confidence interval of its yield estimation. However, we limited the number of low-yield machine candidates because a manufacturer may have hundreds of machines; we averaged all per-machine yield estimates and used the resulting global average as a threshold value. This predefined threshold was then used to distinguish between low- and high-yield machines through a one-sided hypothesis test.

Therefore, for a per-machine yield estimation obtained through bootstrapping, a low-yield machine is identified when the two following conditions are met.

1) The machine yield estimate is less than the predefined yield threshold.
2) The threshold position is within the critical area of the machine yield estimation ($p < 0.05$).

On the basis of these two conditions, we determined whether a particular machine yield was significantly less than the average.

A yield threshold can be defined using the global average of all per-machine yields (Fig. 3). Subsequently, to obtain a low-yield machine candidate list, the machines with estimated yield

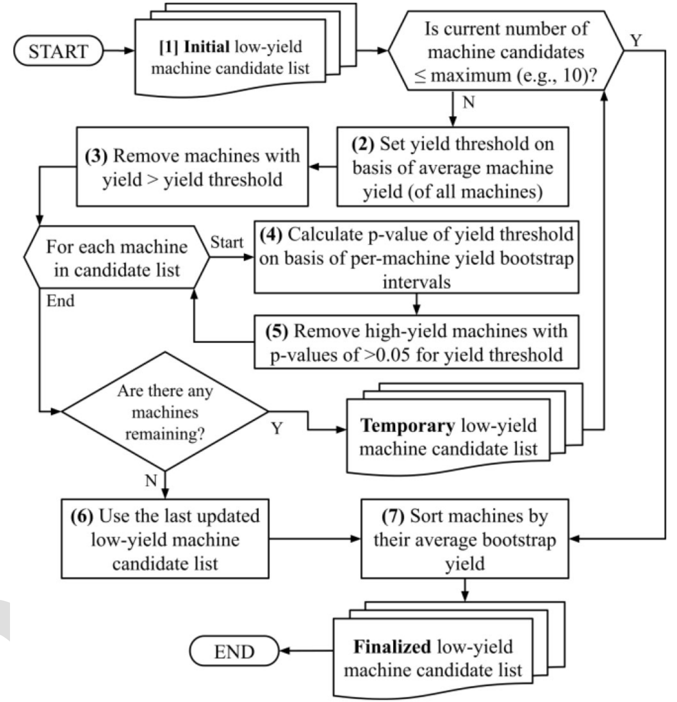

Fig. 4. Proposed method for obtaining a low-yield machine candidate list.

that are significantly less than the threshold must be identified. That is, in the one-sided hypothesis test, the *p*-value of the threshold must be calculated using the per-machine bootstrap confidence interval. In Fig. 3, the *p*-value of the threshold is <0.05 for *MCH1* and *MCH2* but >0.05 for *MCH3*. Therefore, *MCH3* is excluded from the low-yield machine candidate list; *MCH4* is also excluded because its yield is greater than the threshold.

Before performing the second function, a manufacturer must predefine the maximum number of low-yield machine candidates (e.g., 10). Fig. 4 illustrates the steps for performing a one-sided hypothesis test until a low-yield machine candidate list is obtained. The *p*-value of the yield threshold relative to the yield bootstrap interval of the corresponding machine is also estimated (i.e., step 4 in Fig. 4). At this point, the yield threshold has an independent p-value for each machine. It is then used to determine whether a given machine is retained or removed as a low-yield machine candidate (i.e., step 5 in Fig. 4). Finally, after the final low-yield machine candidate list is obtained, it is provided to maintenance engineers.

III. Estimation of Per-Machine Yield

This section explains how the proposed method estimates per-machine yield (i.e., step 4 in Fig. 2). First, the reasonable assumptions applied for the proposed method are introduced. Second, the concept of inspection equipment miss rate is explained. Finally, mathematical notations are used to describe the proposed method for estimating per-machine yield.

A. Assumptions Applied for Proposed Method

The objective of the proposed method is to obtain a low-yield machine list that can be used as maintenance reference.

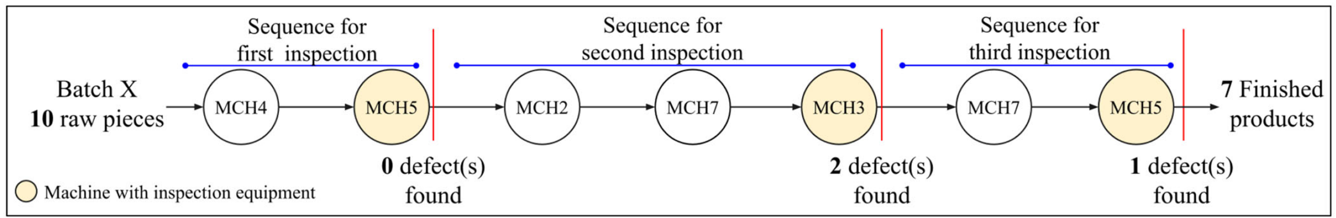

Fig. 5. Implementation of inspections and detection of defective pieces during batch production.

Because numerous factors can affect production yield and defect observability, several reasonable assumptions must be made to develop a specific model for batch production systems. The assumptions are as follows.

1) *Dominant Factor for Production Yield:* We assumed that defective pieces are caused by production machines. In practice, a defective product may be affected by numerous factors, including human operators, types of machines used, quality of raw materials, complexity of product designs, and manufacturing methods and environments [3], [27].
2) *Defect Observability:* We assumed that when a machine with inspection equipment detects defective pieces, the defects could have been caused by any of the machines used before this inspection step is performed. This is because inspections can only be conducted during specific manufacturing steps.
3) *Removal of Defective Pieces:* On the basis of the first-pass yield [28], the yield of a batch is determined to be equal to the product of the machine yield of all involved machines (assuming that defective pieces are not reworked or corrected). We assumed that when defects are detected by inspection equipment, the defective pieces are promptly removed. Only nondefective pieces (including unobserved defective pieces) are processed in the next step. Usually, a manufacturer may commit additional human resources to determine whether defective pieces can be reworked [29]. However, we did not consider this step in our proposed method because of the first assumption, that is, that only machine-related factors are considered.

B. Inspection Equipment Miss Rate

In a batch production system, a batch of products may be inspected several times during a manufacturing process (Fig. 5). The observed results of an inspection process reveal the number of defective pieces produced during a specific inspection step, and this information is crucial for estimating per-machine yield. In practice, inspections are only performed during specific steps. Therefore, identifying the specific machine responsible for each defect of each produced piece is infeasible. This problem was addressed in a study [2]; specifically, when a defective piece was detected by an inspection machine during a given manufacturing step, all the machines involved in the preceding manufacturing steps and the current one become suspects. The method applied in that study [2] allows for per-machine yield to be estimated; however, a problem with this method is that the machines involved in earlier batch steps tend to have lower estimated per-machine yield relative to the machines involved in later batch steps.

To address this problem, we improved the method by considering the accuracy of inspection equipment. Several studies have demonstrated that the accuracy of inspection equipment has a tolerance of approximately 10%–30% [30], [31]. This finding indicates that some defective pieces may be undetected during an inspection step and transferred to subsequent batch steps. Manufacturing steps can be divided into multiple sequences of steps on the basis of inspection steps. For example, in Fig. 5, if defective pieces are detected during an inspection step that occurs within a given sequence, all the machines involved in that sequence are more likely to be the cause of the defects relative to the machines involved in preceding sequences.

In Fig. 5, seven manufacturing steps involving five machines are presented, all inspection steps are assumed to have a 10% tolerance, and defective pieces are assumed to have been detected in the final machine (rightmost machine, M5). In this scenario, all the machines involved in the sequence in which the defects were detected (i.e., the sixth [M7] and seventh [M5] machines) have an overall 90% probability of being the cause of the defects. Conversely, the machines involved in the first to fifth steps only have an overall 10% probability of being the cause of the defects; specifically, those involved in the first and second steps (M4 and M5) only have an overall 1% probability of being the cause of the defects (10% of 10% probability).

C. Complete Equations of EM Algorithm

The notations used in this study are defined in Tables III and IV. Specifically, Table III contains all the notations representing known values that can be extracted from real-world data, and Table IV contains all the notations representing the variables that are initially unknown and must be subsequently estimated.

In this study, per-machine yield was estimated on the basis of the principle of likelihood. That is, if several batches contain newly produced defective pieces after a specific machine is used, the estimated yield of that machine should be low. Therefore, we developed a likelihood function for each manufacturing step to estimate per-machine yield, which can be expressed as (1) and (2). For the per-machine yield θ, several z_{ink} values may affect y_{in}. If y_{in} is detected as a defective piece ($y_{\text{in}} = 1$), one of the corresponding z_{ink} values should be 1.

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TABLE III
LIST OF NOTATIONS WITH PREVIOUSLY KNOWN VALUES

Notation	Description
I	Total number of batches in manufacturing process
N_i	Initial number of pieces in *i*th batch
J_i	Number of manufacturing steps performed for *i*th batch
C_{in}	Number of manufacturing steps performed before *n*th piece is removed as a defective piece or with full completion of manufacturing process for *i*th batch
y_{in}	Condition of *n*th piece (of *i*th batch in manufacturing process) detected as a defective piece (value of 1) or nondefective piece (value of 0)
l_i	Actual yield of *i*th batch
F_M	Initial number of unobserved defective pieces processed by machine *M*
B_M	Total number of defective pieces detected by machine *M*
b_{ij}	Number of defective pieces detected during *j*th manufacturing step for *i*th batch
$S_{\mathrm{Prod}(M)}$	Set of production machine indexes in *(i,j)* indexes (used as tuple elements) of all batches (that use machine *M*); that is, production machine is used in *j*th manufacturing step for *i*th batch.
$S_{\mathrm{Sus}(M)}$	Set of suspicious machine indexes in *(i,j,k)* indexes (used as tuple elements) of all batches (that use machine *M*); that is, suspicious machine is used in *k*th manufacturing step of *i*th batch when defective pieces are detected during *j*th manufacturing step.
M	*M*th production machine in manufacturing process
m_{ik}	Machine used in *k*th manufacturing step for *i*th batch
f_{iM}	Number of nondefective pieces at end of manufacturing process for *i*th batch that uses machine *M*
r_{iM}	Number of times machine *M* is used in manufacturing process for *i*th batch

In contrast, all corresponding z_{ink} values should be 0, if y_{in} is detected as a nondefective piece ($y_{\mathrm{in}} = 0$). Let Y be the set of y_{in} and Z be the set of z_{ink} for each manufacturing step. When all batches are considered, the likelihood function of Y and Z given per-machine yield θ can be defined as $P(Y, Z|\theta)$. $P(Y, Z|\theta)$ can be calculated by considering the condition of each piece in each batch that undergoes a manufacturing process, and the equation applied is as follows:

$$P(Y, Z|\theta) = \prod_{i=1}^{I}\prod_{n=1}^{N_i}\left((FD_{\mathrm{in}})^{y_{\mathrm{in}}} \times \left(\prod_{k=1}^{C_{\mathrm{in}}} P_{ik}\right)^{1-y_{\mathrm{in}}}\right) \quad (1)$$

where

$$FD_{\mathrm{in}} = \prod_{k=1}^{C_{\mathrm{in}}}\left(\left((1-P_{ik})\prod_{s=1}^{k-1}P_{\mathrm{is}}\right)\left((1-a_{i;C_{\mathrm{in}}})\prod_{v=k}^{C_{i;n-1}}a_{iv}\right)\right)^{z_{\mathrm{ink}}}. \quad (2)$$

If no defective pieces are present (all $y_{\mathrm{in}} = 0$), the likelihood of all per-machine yield θ would be 1. Otherwise, when $y_{\mathrm{in}} = 1$, the corresponding z_{ink} can be calculated by using FD_{in} by applying (2), which can be used to calculate the likelihood of a defect occurring on the basis of the yield of the corresponding production machines (i.e., production steps).

TABLE IV
LIST OF NOTATIONS WITH UNKNOWN INITIAL VALUES

Notation	Description
$P(Y,Z\|\theta)$	Complete likelihood functions for Y (set of y_{in}) and Z (set of z_{ink}) as conditioned using machine yield θ
z_{ink}	Indicator variable ($\in \{0,1\}$) of *n*th piece of *i*th batch detected to contain a defect due to a machine used in *k*th manufacturing step. For example, if $z_{ink} = 1$, *n*th piece of *i*th batch is defective because of *k*th machine.
FD_{in}	Likelihood function of defect rate if *n*th piece of *i*th batch is observed to be defective
P_{ik}	Yield of machine involved in *k*th manufacturing step for *i*th batch
a_{iv}	Miss rate of machine involved in *v*th manufacturing step for *i*th batch (probability of machine failing to detect defective pieces passing through it)
q_{ik}	Natural logarithm of P_{ik}
θ	Set $\{q_{ik}\|(1 \le i \le I) \wedge (1 \le k \le J_i)\}$
A_M	Miss rate of machine *M*
A'_M	Miss rate of machine *M* for next iteration
$\Pr(M)$	Yield of machine *M*
$\Pr'(M)$	Yield of machine *M* for next iteration
d_M	Total expected number of defective pieces generated by machine *M* in every manufacturing step for all batches
g_M	Total number of expected nondefective pieces generated by machine *M* in every manufacturing step for all batches
$P(z_{ink} = 1\|y_{in}, \theta)$	Likelihood that *k*th manufacturing step for *i*th batch causes *n*th piece to be defective (value of 1) with given θ
FZ_{ink}	Likelihood that *k*th manufacturing step causes defects if *n*th piece of *i*th batch is detected to be defective
$E[z_{ink}]$	Expectation that *k*th manufacturing step causes *n*th piece of *i*th batch to be defective
e_{ijk}	Expected number of defective pieces generated in *k*th manufacturing step when defective pieces from *i*th batch are observed in *j*th manufacturing step
h_{ijk}	The number of nondefective pieces produced until *k*th manufacturing step; however, a subsequent manufacturing step causes defects to these pieces, and they are detected to be defective at *j*th manufacturing step (inspection step) for *i*th batch.
x_M	Summation of all instances of h_{ijk}, where the *k*th manufacturing step of the *i*th batch uses machine *M*.
F'_M	Estimated number of undetected defective pieces processed by machine *M*

Furthermore, as explained in Section III-B and illustrated in Fig. 5, when a defective piece is detected during a given inspection step, the production steps occurring between that inspection step and the previous inspection step exhibit a considerably greater likelihood of causing the defect relative to the other production steps. Therefore, we must determine the likelihood value of each corresponding production machine by considering the miss rate of each machine (represented by a_{iv}).

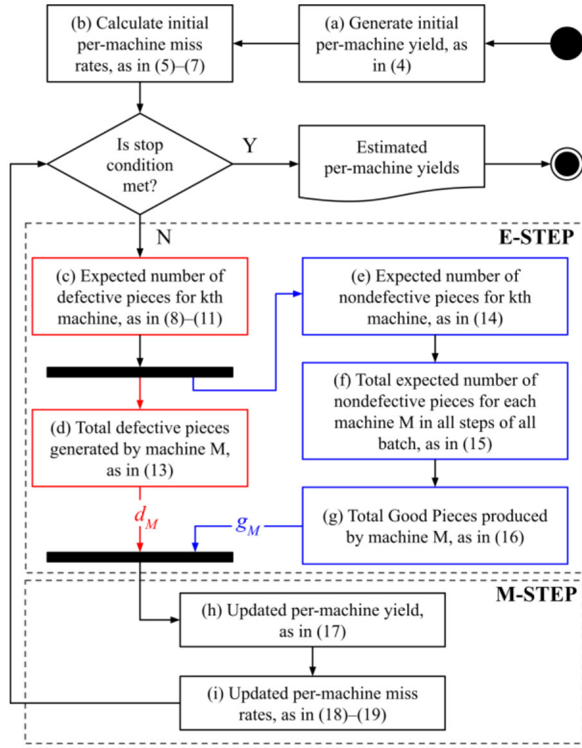

Fig. 6. Activity diagram demonstrating application of an EM-based algorithm of the proposed method to estimate per-machine yield.

To estimate per-machine yield per step (4) (Fig. 2), we developed a novel EM algorithm that comprises three main stages (Fig. 6). First, the algorithm calculates the initial values of various parameters, including per-machine yield $\Pr(M)$ and per-machine miss rates A_M, which are calculated per steps (a) and (b), respectively, in Fig. 6. Second, it performs an estimation (E-step) and updates parameter values (M-Step) per steps (c)–(i) in Fig. 6. Third, it iteratively improves the estimation until the stop condition is met and finally outputs the optimal estimation for per-machine yield.

During the initialization stage, the proposed algorithm maps each batch step to a production machine. That is, the jth manufacturing step of the ith batch should be mapped to a given machine M. Therefore, the manufacturing steps for a batch that uses machine M can be defined using the following function:

$$S_{\text{Prod}(M)} = \{(i, j) | \forall m_{ij} = M\}. \quad (3)$$

For example, per Table II, $S_{\text{Prod}(54)} = \{(13, 2), (13, 5), (62, 1)\}$, indicating that *MCH54* was used in the second and fifth manufacturing steps of the 13th batch and the first manufacturing step of the 62nd batch.

Subsequently, the initial per-machine yield and initial per-machine miss rates should be calculated per steps (a) and (b) (Fig. 6). Instead of applying the random guess method, the algorithm calculates initial per-machine yield using the following formula:

$$\underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{I} \left(\sum_{k=1}^{J_i} q_{ik} - \ln l_i \right)^2 \quad (4)$$

where $q_{ik} \leq 0$. Therefore, the yield of machine M, $\Pr(M)$, can be obtained by calculating the natural exponent of each element in θ.

The algorithm must also calculate the initial per-machine miss rates (represented as A_M) by considering all batches. A_M is initially set as the ratio of the number of unobserved defective pieces processed by machine M (represented as F_M) to the number of defective pieces detected by machine M (represented as B_M), and it is expressed as (5) to (7).

The number of unobserved defective pieces F_M is the sum of all defective pieces produced by subsequent manufacturing steps after a given machine during a manufacturing step, regardless of the machine that is used. For example, according to Table II, *MCH54* detects two and one defective pieces during the second and fifth manufacturing steps, respectively, of the production of the 13th batch; therefore, total $B_{54} = 2 + 1 = 3$. However, *MCH54* is assumed to have missed $3 + 1$ defective pieces when it is used during the second manufacturing step of the production of the 13th batch. Furthermore, it misses five defective pieces when it is used in the first manufacturing step of production of the 62nd batch. Therefore, *MCH54* has a total $F_M = (3 + 1) + (5) = 9$. Consequently, the miss rate of *MCH54* is $A_{54} = 9/(9 + 3) = 0.75$

$$A_M = \frac{F_M}{F_M + B_M} \quad (5)$$

where

$$F_M = \sum_{i=1}^{I} \sum_{j=1}^{J_i - 1} \begin{cases} \sum_{k=j+1}^{J_i} b_{ik}, & \text{if } (i, j) \in S_{\text{Prod}(M)} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

and

$$B_M = \sum_{i=1}^{I} \sum_{j=1}^{J_i - 1} \begin{cases} b_{ij}, & \text{if } (i, j) \in S_{\text{Prod}(M)} \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

At the start of the E-Step of the second stage, the algorithm calculates the expected number of defective pieces produced by each suspect machine when inspection equipment from any batch step detects defective pieces, per step (c) in Fig. 6. For instance, according to Table II, when the fourth manufacturing step (*MCH68*) detects three defective pieces, the first four machines would each have their own probability of contributing to the defects, with their probability being influenced their per-machine yields and miss rates. In addition, we calculated the relative probability of each machine being the cause of the defects (Fig. 5). To achieve this, the probability of the kth manufacturing step causing the nth piece of the ith batch to be defective is expressed as follows:

$$P(z_{\text{ink}} = 1 | y_{\text{in}}, \theta) = \begin{cases} 0, & \text{if } y_{\text{in}} = 0 \\ FZ_{\text{ink}}, & \text{if } y_{\text{in}} = 1 \end{cases} \quad (8)$$

where

$$FZ_{\text{ink}} = \frac{\left((1 - P_{ik}) \prod_{s=1}^{k-1} P_{\text{is}}\right)\left((1 - a_{i;C_{\text{in}}}) \prod_{v=k}^{C_{i;n-1}} a_{iv}\right)}{\sum_{t=1}^{C_{\text{in}}} \left(\left((1 - P_{it})\left(\prod_{u=1}^{t-1} P_{iu}\right)\right)\left((1 - a_{i;C_{\text{in}}}) \prod_{w=k}^{C_{i;n-1}} a_{iw}\right)\right)}. \quad (9)$$

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Subsequently, the corresponding expected probability of the kth manufacturing step causing the nth piece of the ith batch to be defective is expressed as follows:

$$\begin{aligned} E[z_{\text{ink}}] &= 0 \times P(z_{\text{ink}} = 0 | y_{\text{in}}, \theta) \\ &\quad + 1 \times P(z_{\text{ink}} = 1 | y_{\text{in}}, \theta) \\ &= P(z_{\text{ink}} = 1 | y_{\text{in}}, \theta). \end{aligned} \tag{10}$$

To estimate the number of defective pieces caused by each machine, the result of the likelihood estimation performed using (10) must be multiplied by the number of defective pieces detected in that manufacturing step as follows:

$$e_{ijk} = E[z_{\text{ink}}] \times b_{ij}. \tag{11}$$

At this point, when defective pieces are detected during the jth manufacturing step for the ith batch, the number of defective pieces caused by the suspect kth manufacturing step should be mapped to machine M. Hence, the algorithm must define the set of (i, j, k) indexes of machine M as follows:

$$S_{\text{Sus}(M)} = \{(i, j, k) | \forall m_{ik} = M\}. \tag{12}$$

Each EM iteration improves the per-machine yield estimation, which is the percentage of good pieces relative to the total number of processed pieces, as calculated by applying (17). Thus, the total expected number of good pieces g_M and defective pieces d_M produced by each machine M should be estimated in advance, given an estimate of e_{ijk}.

Per step (d) in Fig. 6 and on the basis of (12), the total expected number of defective pieces d_M can be calculated as follows:

$$d_M = \sum_{(i,j,k) \in S_{\text{Sus}(M)}} e_{ijk}. \tag{13}$$

Subsequently, the algorithm calculates the number of expected nondefective pieces produced during the kth manufacturing step h_{ijk}, which is followed by a subsequent manufacturing step that causes defects. These pieces are detected as defective pieces during the jth manufacturing step of the production of the ith batch, per step (e) in Fig. 6. Accordingly, h_{ijk} can be expressed as follows:

$$h_{ijk} = \begin{cases} 0, & \text{if } j = k \\ h_{ij;k+1} + e_{ijk}, & \text{if } j > k \end{cases} \tag{14}$$

Per step (f) in Fig. 6, the h_{ijk} of machine M can then be summed to obtain x_M as follows:

$$x_M = \sum_{(i,j,k) \in S_{\text{Sus}(M)}} h_{ijk}. \tag{15}$$

Subsequently, per step (g) in Fig. 6, the algorithm calculates g_M by summing x_M and the total number of detected nondefective pieces processed by machine M as follows:

$$g_M = x_M + \left(\sum_{i=1}^{I} f_{iM} \cdot r_{iM} \right). \tag{16}$$

In the M-step of the second stage, the algorithm, per steps (h) and (i) in Fig. 6, applies (17) to calculate the new estimated yield for machine M, that is, the percentage of good pieces relative to the total number of processed pieces produced by machine M. In addition, the algorithm calculates the new estimated per-machine miss rate by applying (18) and (19)

$$\Pr'(M) = \frac{g_M}{g_M + d_M} \tag{17}$$

$$A'_M = \frac{F'_M}{F'_M + B_M} \tag{18}$$

where

$$F'_M = \sum_{i=1}^{I} \sum_{j=1}^{J_i - 1} \begin{cases} \sum_{k=1}^{j} e_{ijk}, & \text{if } (i,j) \in S_{\text{Prod}(M)} \\ 0, & \text{otherwise.} \end{cases} \tag{19}$$

In the third stage of the algorithm, it continues the calculation steps from (8) to (19) until one of the following stop conditions is met:

1) *Convergence Threshold:* This condition is met if the difference between the per-machine yield in the current iteration and those in the previous iteration is less than the threshold. This difference is calculated by obtaining the relevant mean square error (MSE) [32] through the proposed algorithm.
2) *Maximum Number of Iterations:* This condition is met if the number of iterations reaches the predefined maximum number of iterations.

The findings of a study [2] suggest that a threshold difference of 0.001 and a maximum number of iterations of approximately 60–100 are sufficient for the stop conditions. Furthermore, additional iterations do not significantly improve estimations.

IV. Simulation Results and Discussions

Data on actual per-machine yield are difficult to obtain from manufacturing sites because of feasibility-related limitations [2]. Therefore, whether the estimated yield of a machine is accurate cannot be determined. To verify the performance of the proposed method, we conducted simulations on the basis of a predefined per-machine yield to generate production data pertaining to the simulated manufacturing process (see Section IV-A). The proposed method was applied to estimate per-machine yield and detect low-yield machines. Finally, we used the simulated production data and the predefined per-machine yield to evaluate the performance and limitations of the proposed method in detecting low-yield machines in a batch production system (see Sections IV-A and IV-C). Furthermore, we described how the proposed method can be applied at a manufacturing site and discussed the results obtained by applying the proposed method to the data of a real company (T-company) for a 1-week period in July 2018.

A. Simulation Process

To evaluate the performance and limitations of the proposed method, we simulated several possible scenarios by applying various configurations to build datasets for each simulation. The following variables were used for each configuration.

a) Number of production machines (50, 250, or 500 machines).

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TABLE V
DISTRIBUTION PARAMETERS APPLIED IN EACH SIMULATION SCENARIO

#	Description	Min	Max	Average	Standard Deviation
A	Number of raw pieces	1	20000	2000	1500
B	Number of batch steps	5	50	20	7
C	Number of inspection machines in each batch	2 machines	Batch length	10% of batch length	2 machines
D	Detection accuracy of inspection equipment	85%	100%	90%	2%

b) Number of machines with inspection equipment (30% of production machines).
c) Number of batches (10, 100, 200, 300, 400, 500, 1000, or 1500 batches for small datasets; 2000, 2500, 3000, or 3500 batches for medium datasets; and 4000, 4500, or 5000 batches for large datasets).
d) Number of low-yield machines (1, 2, 3, 4, 5, 6, or 7 machines).
e) Yield of low-yield machines (0.4, 0.6, 0.8, 0.9, or 0.95).

Notably, in our simulations, the variable number of machines with inspection equipment was fixed at 30% of production machines. This value was obtained from a real-world manufacturing site of T-company.

The major steps for performing the simulations in this study are as follows.

1) A value is selected for each simulation variable.
2) Per-machine properties, including per-machine yield and whether an inspection equipment is installed, are predefined and act as ground truth data.
3) Per-batch properties, including the number of batch steps, the number of raw pieces, the number of inspection steps, and the names of the machines used in each batch step, are predefined.
4) The data of defective pieces are generated to simulate real-world manufacturing conditions.
5) The proposed method is applied to estimate per-machine yield on the basis that variables a), b), and c) are known and that variables d) and e) are the targets for estimation. Subsequently, the estimation and ground truth are compared to evaluate the performance of the proposed method.
6) The simulation process is complete when all possible scenarios are simulated. Notably, each simulation scenario is simulated 20 times to obtain the average performance values for 20 simulations.

In each simulation, randomized values were applied for steps 3 and 4 on the basis of the distribution parameters listed in Table V. In Table V, parameters A, B, and C were derived from the real-world datasets of T-company, whereas parameter D was configured in accordance with the suggestions of other studies [30], [31].

B. Simulation Results

The main objective of the proposed method is to detect low-yield machines to facilitate maintenance planning; this is

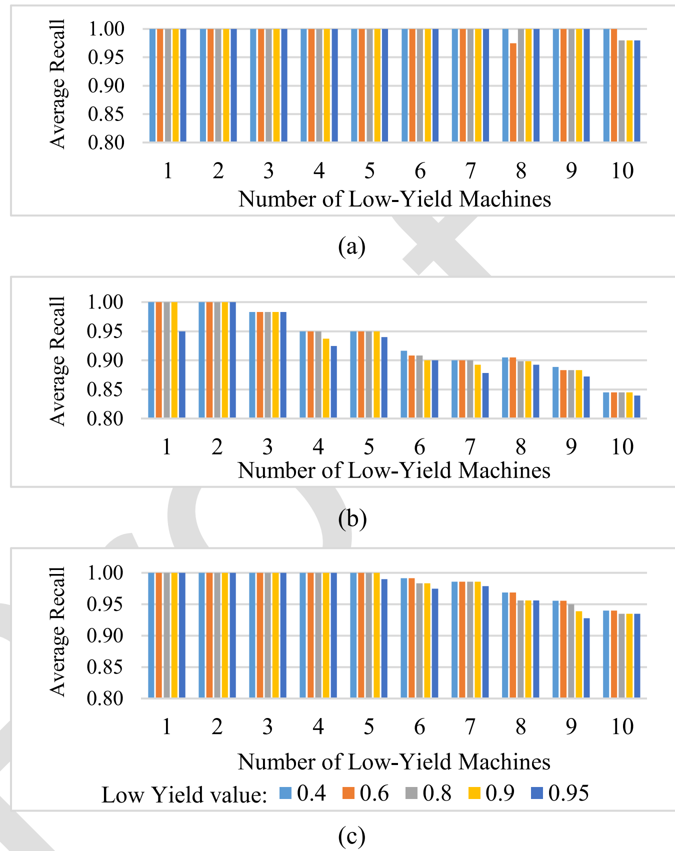

Fig. 7. Recall of the proposed method for manufacturer with (a) 50 production machines and 1000 production batches, (b) manufacturer with 250 production machines and 2000 production batches, and (c) manufacturer with 500 production machines and 3000 production batches.

achieved through per-machine yield estimation. Although the average accuracy of per-machine yield estimation is high, the use of accuracy as a performance indicator for the proposed method provides no benefits. Only the machines with low yield that require immediate maintenance must be identified. Therefore, the evaluation of the proposed method was conducted on the basis of the number of low-yield machines that were correctly detected (true positive) and the number of low-yield machines that were determined to be reliable machines (false negative), which pertains to recall rate. Table VI and Fig. 7 present the evaluation results of the simulation, with the results stratified by variable configuration. In addition, each value in Table VI and Fig. 7 represents the average of 20 simulations performed with the same setup.

The proposed method could detect low-yield machines effectively when batch production data met specific criteria (Table VI). For a manufacturer with 50 production machines and at least 400 production batches, the proposed method could detect a low-yield machine with a 100% recall. However, it required at least 1000 production batches to detect up to five low-yield machines with 100% recall.

For a moderately large manufacturer with 250 production machines and at least 2000 production batches, the proposed method could detect one to five low-yield machines with a high recall of at least 95% (Table VI). For a large manufacturer

TABLE VI
RECALL OF THE PROPOSED METHOD IN DETECTING ONE, THREE, AND FIVE LOW-YIELD MACHINES (WITH LOW-YIELD VALUE OF 0.4)

# of Batches	Number of Production Machines: 50			250			500		
	Number of Actual Low-yield Machines: 1	3	5	1	3	5	1	3	5
10	0	0	0	0	0	0	0	0	0
100	0	0.02	0.02	0	0	0	0	0	0
200	0.85	0.55	0.57	0	0	0	0	0	0
300	0.90	0.87	0.84	0	0	0	0	0	0
400	**1.00**	0.77	0.75	0.05	0.02	0.01	0	0	0
500	1.00	0.75	0.72	0.10	0.13	0.14	0	0	0
1000	1.00	**1.00**	**1.00**	0.85	0.85	0.74	0.25	0.17	0.20
2000	1.00	1.00	1.00	**1.00**	**0.98**	**0.95**	0.65	0.85	0.77
3000	1.00	1.00	1.00	1.00	0.98	0.97	**1.00**	**1.00**	**1.00**
5000	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.00

TABLE VII
RESULTS OF A SIMULATION IN WHICH ALL LOW-YIELD MACHINES WERE CORRECTLY IDENTIFIED

Machine Name	Simulated Data: # of Batches [a]	# of Processed Pieces [b]	Estimated Data: Bootstrap Confidence Interval [c] Low	High	Average	Width	# of Estimated Defective Pieces [d]
MCH248	75	3,083,496	0.4470	0.4590	**0.4530**	0.0120	1,779,082
MCH249	96	3,919,625	0.4483	0.4595	**0.4539**	0.0112	2,180,411
MCH250	82	3,277,659	0.4474	0.4618	**0.4546**	0.0144	1,821,557
MCH27	30	1,076,217	0.9995	0.9996	0.9995	0.0001	569
MCH67	74	2,803,200	0.9996	0.9996	0.9996	0.0001	1,196
…	…	…	…	…	…	…	…

[a] Number of batches processed by a given machine
[b] Sum of number of pieces processed in all batch steps by a given machine
[c] Bootstrap confidence interval of machine yield estimation
[d] Value as calculated using 100% of dataset

with 500 production machines and at least 3000 production batches, the proposed method could detect up to five low-yield machines with a 100% recall (Table VI).

Fig. 7(a)–(c) plots the simulation results of ten scenarios in which a manufacturer has between 1 and 10 low-yield machines. The recall of each scenario is an average of 20 simulations. The results reveal that the presence of more low-yield machines indicate lower recall values. For example, for a manufacturer with 250 production machines and 2000 production batches, the recall of the proposed method was only approximately 87% when nine low-yield machines were present. That is, only one low-yield machine was not identified. Furthermore, the results indicate that relative to detecting machines of yield 0.95, detecting machines of yield 0.4 leads to a slightly higher recall. (i.e., approximately 3% difference; Fig. 7).

Table VII lists a set of simulation results obtained from one of the 20 simulations performed for a specific scenario, that is, the scenario in which a manufacturer had 250 production machines, 1000 production batches, and three low-yield production machines (i.e., *MCH248*, *MCH249*, and *MCH250*), each of which had a yield of 0.4. In a manufacturing simulation, each machine could be used several times to process multiple batches and multiple pieces. Subsequently, each machine generated defective pieces that could only be detected by inspection equipment. On the basis of these values, the proposed method estimated the yield of each machine at a 95% confidence level. Thereafter, three low-yield machines were correctly identified; that is, the recall of this simulation was 100%.

C. Discussions

On the basis of the simulation results reported in Section IV-B, we identified the following two factors that affected the performance of the proposed method in detecting low-yield machines.

1) *Number of Low-Yield Machines:* The performance of the proposed method was reduced when the number of low-yield machines increased (Fig. 7).
2) *Number of Production Batches:* For a given number of production machines, the proposed method required a specific number of production batches to effectively detect low-yield machines.

According to the results in Table VI, to effectively detect up to five low-yield machines, manufacturers with 50–500 machines may require a dataset containing approximately 6–20 times as many batches of data as there are production machines. Although applying the minimum dataset requirements (e.g., 400 batches for a manufacturer with 50 machines) can enable the proposed method to successfully identify 3 to 4 out of 5 low-yield machines, low-yield machines are usually associated with considerably lower yield estimations (lower and wider confidence intervals) relative to other production machines in practice (see Tables VII and VIII). Engineers can use larger datasets if they expect more low-yield machines.

We also discovered that the performance of the proposed method in detecting low-yield machines is stable, regardless of its yield. For example, the results indicate that relative to detecting machines of yield 0.95, detecting machines with yield 0.4 leads to a slightly higher recall. In the end, it did not substantially affect the performance of the proposed method.

Before the proposed method can be applied at a manufacturing site, its limitations must be clarified. As highlighted in the first assumption statement, numerous factors can affect final production yield. Because the proposed method considers production machines as the only cause of production defects, failure to consider other manufacturing factors (e.g., human operators, raw materials, product designs, methods, and environment) may reduce its effectiveness. Nevertheless, the proposed method should be adequately effective when it is applied at a well-controlled manufacturing site.

The workflow for implementing the proposed method to detect low-yield machines can be divided into three main steps. First, a manufacturer must control manufacturing factors, such as human operators, raw materials, product design, methods, and environment. Second, the manufacturer must collect approximately 6–20 times as many batches of production data as they have production machines. If this amount of data is difficult to collect on a daily basis, it can be collected on a weekly basis. This factor should be considered by a

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TABLE VIII
ANALYTICAL RESULTS OF 1-WEEK (THIRD WEEK OF JULY 2018) MANUFACTURING DATASET COLLECTED FROM A PRODUCTION LINE OF T-COMPANY

Machine Name	Simulated Data		Estimated Data				
	# of Batches a)	# of Processed Pieces b)	Bootstrap Confidence Interval c)				# of Estimated Defective Pieces d)
			Low	High	Average	Width	
MCH007	51	266,000	0.8550	0.8982	**0.8766**	0.0432	41,325
MCH004	10	36,719	0.9563	0.9800	0.9681	0.0237	2,551
MCH005	1	70,983	0.9669	0.9759	0.9714	0.0090	1,956
MCH438	13	293,220	0.9713	0.9772	0.9742	0.0059	8,454
…	…	…	…	…	…	…	…

a) Number of batches processed by a given machine
b) Sum of number of pieces processed in all batch steps by a given machine
c) Bootstrap confidence interval of machine yield estimation
d) Value as calculated using 100% of dataset

manufacturer when determining the effective frequency with which the proposed method is applied. Third, the manufacturer can apply the proposed method to estimate per-machine yield at a 95% confidence level and use a threshold to detect low-yield machines.

In the third step of the proposed method, two configurable parameters are used, namely, the size of a resampled dataset and the number of resampled datasets. First, 30 resamples can be easily generated using a moderately powerful computer. Second, because the size of a resampled dataset should be maximized and should exhibit adequate variance, we can usually use 80% of the records in the original dataset. However, a resampled dataset should ideally contain approximately 6–20 times as many batches of data as there are production machines.

Table VIII lists the analytical results of the proposed method; these results were obtained using the 1-week manufacturing datasets (specifically the third week of July 2018) of Taiwan-based Company T, which had 250 production machines and at least 1000 production batches. The results reveal that for that week, only *M*CH*007* (an automatic dry film laminator) met the criteria for identification as a low-yield machine. According to the simulation results, the closer a low yield was to the yield of reliable machines, the more difficult distinguishing between them was. That is, whether the other machines were low-yield machines was difficult to determine. Subsequently, engineers can assess those machines for problems by applying a reasonable method, such as visual inspection, RCA, or PHM (if available).

The major benefit of the proposed method is that it helps a manufacturer to detect problematic machines quickly. By taking propriate measures (e.g., immediate maintenance and quick finetuning), a manufacturer can reduce the number of defective pieces produced during their manufacturing process. Therefore, the proposed method can increase the time-efficiency and cost-efficiency of a production line.

V. CONCLUSION

We presented a new method for detecting low-yield machines in a batch production system. The proposed method uses resampling to generate numerous sets of batch production data, performs per-machine yield estimation for each dataset by applying a novel EM algorithm, and calculates the confidence interval for each estimated per-machine yield by applying the bootstrapping method. Under the proposed method, one-sided hypothesis testing is then conducted to generate a low-yield machine list on the basis of the confidence intervals of the estimated per-machine yield. Subsequently, we conducted simulations to understand the minimum requirements for the proposed method to successfully detect low-yield machines. The simulation results indicate that the proposed method can effectively detect at least one low-yield machine after a specific amount of batch production data is collected. Given that less production data may lead to less reliable results, and as indicated in Table VI, manufacturers with 50–500 machines can effectively detect up to five low-yield machines if they can collect a dataset that contains approximately 6–20 times as many batches as they have production machines. Notably, engineers can check per-machine yield estimations and decide whether a machine requires verification (e.g., through visual inspection, RCA, or PHM if available) and maintenance.

In some circumstances, a low-yield machine is not necessarily a problem. Because of the nature of machines (e.g., an automatic dry film laminator), achieving a 100% yield is an impractical objective. Thus, if estimations based on historical data indicate that the per-machine yield of a machine has declined, engineers can use any feasible method (e.g., RCA and PHM) to perform maintenance. Therefore, this study lays the foundation for further investigations of per-machine yield, such as those involving the use of multimodal data sources and machine learning [21], [22]. These studies can help to improve the performance of the proposed method in detecting low-yield machines to obtain maintenance recommendations.

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