

Data-driven system prognostics and diagnostics for SMT component placement machines

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ABSTRACT

Prognostic-based maintenance analyses past events and predicts the future state of a machine based on the understanding of the degradation function of the machine's components. Diagnostics-based maintenance tests equipment according to a fixed routine for a machine's proper functioning and reliability. Current Surface-mount Technology (SMT) machines are not equipped with self-prognostic and diagnostic functions. In this paper, a system prognostic and diagnostic method is proposed, implemented in software, for estimating a machine's health condition and faulty components of a SMT component placement machine outfitted with machine logs that consist of take-up count, miss count and time information. At each execution period the method processes features extracted from the machine logs to obtain a set of parity parameters, which are further used to analyse the machine. The prognostic algorithm computes the health status indicator of the component placement machine. The computed final status indicator is compared to a threshold value to check the system's health condition. The diagnostic algorithm predicts and identifies the faulty pick-up nozzles and faulty input trays. The proposed algorithms minimise the effects of faulty components on production lines and assist to produce optimal maintenance decisions and reliability functions for equipment.

KEYWORDS SMT machine; prognostic algorithm; diagnostic algorithm; health status indicator; component placement machine

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1. Introduction

Surface-mount Technology (SMT) is a method that mounts electric components directly onto printed circuit boards (PCB). SMT was developed in the 1960s and was originally known as planar mounting. SMT has become a mature technology and implemented in the mass production of surface-mount electronic device (SMD). According to the Surface Mount Council (SMC), SMT not only can increase circuit density, it also improves electrical performance. Compared to the older type of PCB manufacturing process, i.e., Through-hole technology (THT), SMT achieves 50 to 90 percent space savings. Besides, SMT also reduces the process cost and handling cost, and has higher reliability. Thus, SMT has become the industry norm for electronic assemblies and has rapidly replaced Through-hole technology (THT) (Williams and Intel, 1999).

In the past, engineers needed to conduct fault prognostics manually on machines and make judgements on a machine's health status according to their experience. Current SMT component placement machines are not equipped with built-in fault prognostic functions. Periodic maintenance normally takes place without knowing the actual health condition of the component placement machine. This is not efficient since the machine downtime is not clear and unnecessary parts replacement may occur. According to Lee et al. (2014), a lot of research has been carried out in prognostics and health management (PHM) since machinery maintenance technology was developed. The Centre for Maintenance Optimization and Reliability

Engineering (C-MORE) at The University of Toronto developed a PHM methodology that uses equipment age data, condition monitoring data, and data concerning the effects of failure and preventative replacement to make optimal maintenance decisions and reliability functions for equipment. The basic model is composed of a continuous-time nonhomogeneous discrete Markov process (Montgomery et al., 2012). Camci et al. (2007) established a PHM system for the U.S. Air Force in 2007 that integrates with real-time maintenance PHM information and maintenance data. The developed PHM algorithms acquire some parameters that rely on the feedback from the human maintainer in reaction to questions. The PHM algorithm recommends maintenance actions using historical and real-time data. Next, the PHM is also applied for product life cycle management of critical systems, such as aircraft engines. According to Janasak and Beshears (2007), GE Aircraft Engines (GEAE) technicians have fully defined their engine efficiency and have a thorough knowledge of the physics behind the main failure modes. GEAE can monitor aircraft engines for faults and exceedances through over 300 operating parameters and provide trend alerts to clients. Holland et al. (2010) stated that over 6 million drivers are served by the General Motor (GM) with the PHM system for their vehicles. The GM vehicle is equipped with sensors for data-driven prognostics and diagnostics in regard to battery life, oil life and tyre pressure.

Prognostics is the analysis of past events including maintenance history. It is used to predict the future state of a machine based on the understanding of the degradation

in function of machine components. According to Camci (2005), maintenance cost is cut down by approximately 25% if prognostic-based maintenance is implemented. However, currently the prognostic technology is still immature and there is a lack of the support from the standard calculation methods for validation and verification of uncertainty (Vogl et al., 2019). Prognostics can be categorised into three classes: model-based, data-driven and probability-based prognostics (Lee et al., 2014). Model-based prognostic systems include those using a dynamic model of the expected system, such as physics-based model, autoregressive moving average techniques (ARMA), Kalman particle filtering, and empirical methods. The accuracy of model-based prediction relies on the understanding of the progression of the component failure mode which requires the establishment of a complex dynamic system using mathematical models. Zhou et al. (2014) proposed a prognostic method that combines the data-driven and probability-based techniques to predict the RUL of the equipment. Xiang et al. (2018) proposed a data-driven diagnostic model for vending machines. The reported results show that the proposed system achieved above 80% accuracy in terms of precision, recall, and F-measure. Automated optical inspection (AOI) is commonly used for the inspection of component solder joints to detect solder defects. Enhancements of the inspection algorithms have been carried out recently to improve the reliability and time efficiency especially for those high-density and large-scale integration SMT assembly processes. Chang et al. (2019) proposed an approach based on machine learning to reduce the AOI false detection rate. Gao et al. (2017) proposed a line-based clustering method to detect the accurate position and orientation of ball grid arrays. A convolutional recurrent reconstructive network has been proposed by Yoo et al. (2022) to decompose the anomaly patterns generated by solder paste printer defects. Another convolution neural network method that combines pre-processing, detection network, and visualisation is proposed to localise electronic components and recognise defects in the AOI detection algorithms by Wu et al. (2022). Xu et al. (2021) proposed a precise positioning algorithm for circular mark points and transistor components using polar coordinate transform and smoothness selection.

The issue that is often faced in an SMT production line is the malfunction of the component placement machine. Take-up miss often occurs due to mechanical failure of the nozzle and suction tube. Four possible root causes that may increase the take-up miss of the component placement machine are: (1) The condition of each feeder: after the machine has operated for a long period, a feeder's location may lose its precision thus causing the fed-in components to not be in the exact position; (2) The condition of each nozzle: dust or impurities trapped inside the nozzle, loss of vacuum, short or worn nozzles, nozzle tip wear and sticking nozzles; (3) The condition of parts: the uneven surface of the parts may cause air leakage; and (4) Operator error. This paper proposes Data-driven System Prognostic

and Diagnostic Algorithms for SMT component placement machine by analysing machine logs. The proposed algorithms include three major processes: (1) machine log feature extraction process; (2) system prognostic process; and (3) system diagnostic process. The proposed algorithms have been tested on a Panasonic Chip Mounter (CM602) with 12 nozzles and 100 component addresses. The results show that the proposed algorithms are able to determine a system's health condition and further identify the faulty components correctly when the prognostic results show that a machine's status is unhealthy.

2. Overall system design

The proposed system comprises a prognostic and diagnostic method for SMT component placement machines by analysing machine logs. Figure 1 shows a schematic diagram which illustrates the embodiment of the SMT component placement machine connected to a computational device through a server using an intranet connection. The overall system design consists of a computational device for computing and monitoring purposes. The computational device first imports the raw machine log data from a SMT component placement machine through a server in an intranet network. The process of the proposed algorithm of raw machine log data collection can be performed using other storage devices or data transfer methods.

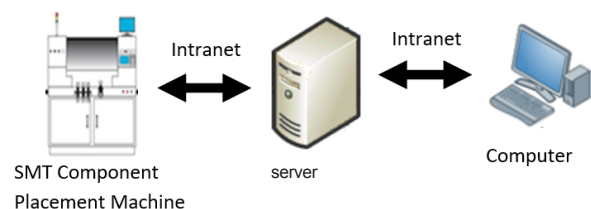


Figure 1. Schematic diagram of the networking system.

A Data-driven System Prognostic and Diagnostic model was designed using a real SMT machine's activities log file collected from the industry. The proposed system first imports the raw machine logs from the SMT component placement machine into a computational device. Then, important features such as take-up count and miss count of each nozzle and each input tray are extracted from the raw machine logs for further processing to compute the error rates of the SMT machine in taking up electronic components. The ratio of the miss count to the total take-up count over certain periods is calculated at this stage. Since machine logs are generated at random time intervals, features extracted from each machine log are collected for a pre-defined duration. Then, the collected extracted features are fed into the prognostic algorithm. Figure 2 shows the flow chart of the proposed prognostic and diagnostic algorithms.

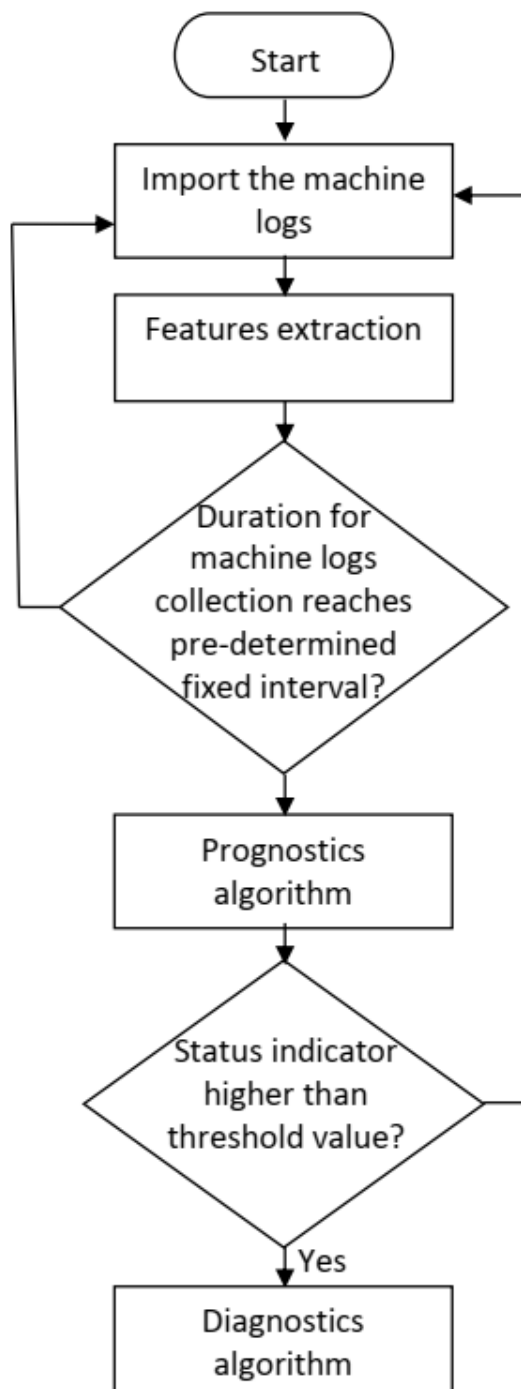


Figure 2. Flow chart of the overall proposed prognostic algorithm.

Based on the extracted features, the prognostic algorithm generates a parameter called ‘Status Indicator (SI)’ as an indication of the machine’s health condition. The proposed prognostic algorithm compares the SI value to a pre-defined threshold value. If the generated SI is lower than the threshold value, the system is considered healthy and the process goes back to machine log data collection.

If the generated SI exceeds the threshold value, the process returns to machine log data collection and concurrently the SMT component placement machine is considered unhealthy and the diagnostic algorithm comes into operation. The diagnostic algorithm examines the health condition of each nozzle and each input tray. A diagnostic chart is generated at the end of the diagnostic algorithm to ease the maintenance process.

3. Methodology

The feature extraction algorithm for the proposed prognostic system is shown in Figure 3. Variable i represents the number of machine logs collected within the pre-defined duration. The value of i starts with zero and increments by one after every machine log import process. Besides, time information is also extracted at this step. A SMT component placement machine is formed by single or multiple machine stages. The preferred embodiment feature extraction algorithm classifies the features according to different machine stages. The classified features will go through the same process independently to check the health condition of different machine stages. Then, the features extraction algorithm continues with board count extraction. Board count is automatically increased by one after the completion of a PCB board mounting process. Board count returns to one if there is a manual reset by the operator or a change in PCB model.

There are two types of take-up count recorded in machine logs: one is the total number of pick-ups by each nozzle and the other is the total number of pick-ups from each component input tray. There are also two types of miss count recorded in machine logs: one is the total number of unsuccessful pick-ups by each nozzle and the other is the total number of unsuccessful pick-ups from each component input tray. Recorded values of pick-up count and miss count are accumulated unless the board count returns to one. When the board count returns to one, the accumulated values of take-up count and miss count return to zero and both the counts re-start again. To identify whether the values recorded in pick-up count and miss count are accumulated or not, the proposed feature extraction algorithm checks the board count and the value of i . If board count is equal to one or the value of i is equal to zero, the pick-up count and miss count are re-started; otherwise, the pick-up count and miss count are accumulated.

For non-accumulated pick-up count and miss count, each take-up count of each nozzle, Tn_{ij} , each take-up count of each input tray, Tt_{ij} , each miss count from each nozzle, Mn_{ij} , and each miss count from each input tray, Mt_{ij} , are extracted and recorded for future processing purposes, where j represents the address of each nozzle and input tray. As for accumulated pick-up count and miss count, each accumulated take-up count of each nozzle, ATn_{ij} , each

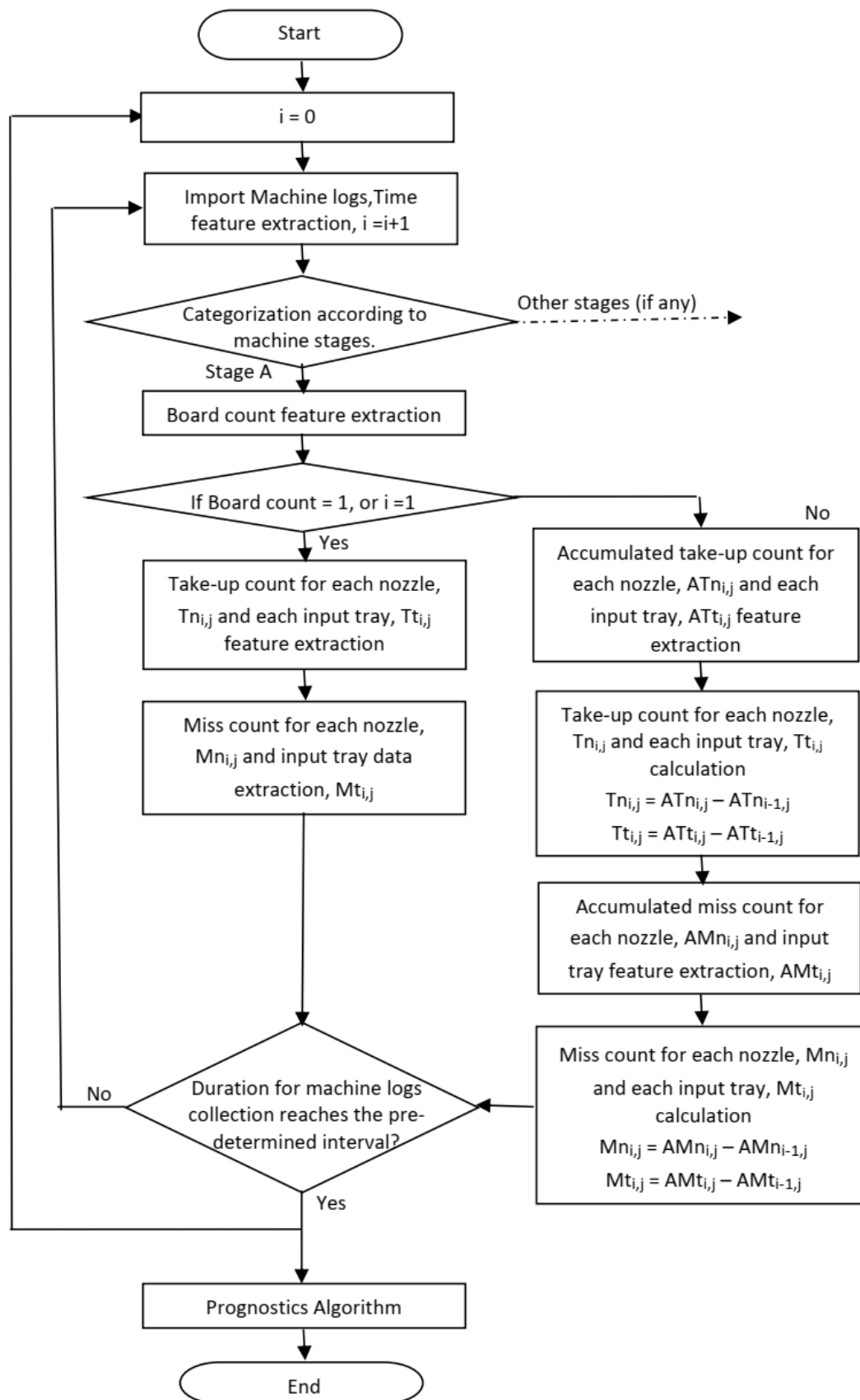


Figure 3. Flow chart of the feature extraction algorithm.

accumulated take-up count for each input tray, $AT_{i,j}$, each accumulated miss count from each nozzle, $AMn_{i,j}$, and each accumulated miss count from each input tray, $AMt_{i,j}$, are recorded. Non-accumulated pick-up count and miss count are obtained by deducting the previous accumulated values (at time $t-i$) from the current accumulated values (at time i).

The final step of the feature extraction algorithm checks the duration of the machine log data collection. If the duration is less than the pre-defined fixed interval, the proposed algorithms continues with the data collection. Otherwise, the system will proceed with the prognostic algorithm and concurrently re-start the machine log data collection for another round.

The proposed prognostic algorithm is a mathematical model to process the extracted information from the feature extraction algorithm. The proposed mathematical model first calculates the total pick-up counts and miss counts at each and every nozzle and input tray which occurred in the previous fixed duration. Parameter $SDSI$ (short duration status indicator) is calculated based on the function f using the inputs: (1) total pick-up count of each nozzle, STn_j ; (2) total pick-up count of each input tray, STt_j ; (3) total miss count of each nozzle, SMn_j ; and (4) total miss count of each input tray, SMt_j . The proposed prognostic algorithm uses the following mathematical model to generate parameter $SDSI$.

$$SDSI = f(STn_j, STt_j, SMn_j, SMt_j) = \log_{10} \left(\sum 2^{\frac{SMn_j}{STn_j} \times 500} - \text{number of nozzle} + 1 \right) + \log_{10} \left(\sum 2^{\frac{SMt_j}{STt_j} \times 500} - \text{number of input tray} + 1 \right). \quad (1)$$

In order to make the system more robust, part drop events of previous k states are incorporated into the SI calculation using a filter memory mathematical function (2).

$$SI = \sum_{i=0}^k 0.7^i \times SDSI_{\text{Current state}-i}. \quad (2)$$

The proposed prognostic algorithm uses an increasing function as the mathematical model. The higher the miss count at each nozzle or tray, the higher the calculated value of SI obtained. The threshold value of the parameter SI is obtained from statistical analysis of a series of previous collected SI data and the system's health condition which was manually decided and recorded by the on-site engineers before the threshold value was fixed. If the calculated SI value is higher than the threshold value, the system is classified as unhealthy and warning signals will be generated to notify operators. If the calculated SI value is lower than the threshold value, the system is classified as healthy and the prognostic algorithm ends. Figure 4 shows the flowchart for the proposed prognostic algorithm.

The proposed system proceeds to the diagnostic algorithm if the SI value is higher than the pre-defined threshold. The diagnostic algorithm is another mathematical

model that calculates the probabilities of each nozzle and each component input tray being faulty. The mathematical models of the diagnostic system are shown in Equations (3) and (4) where k is from 1 to the total number of nozzles or total number of input trays.

$$\text{Probability of faulty Nozzle } j = \frac{SMn_j / STn_j}{\sum SMn_k / STn_k}, \quad (3)$$

$$\text{Probability of faulty Input tray } j = \frac{SMt_j / STt_j}{\sum SMt_k / STt_k}. \quad (4)$$

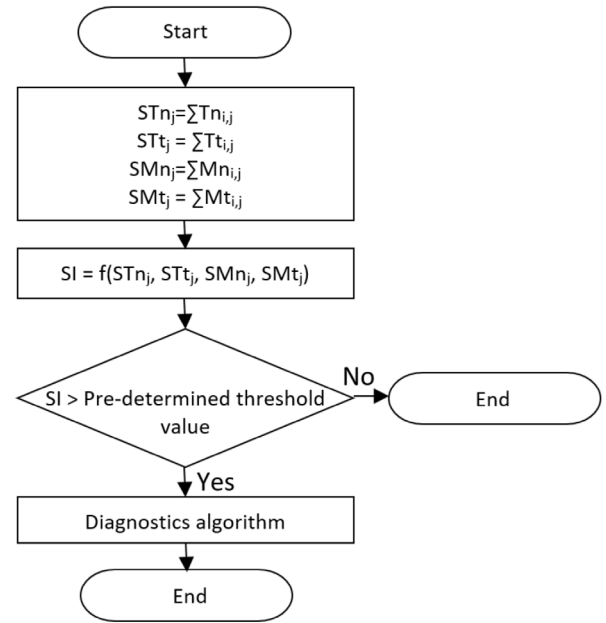


Figure 4. Flow chart of the proposed prognostic algorithm.

4. Results and discussion

The proposed algorithms have been tested on a Panasonic Chip Mounter (CM602) with 12 nozzles and 100 component addresses in a real industry environment. CM602 generates machine logs at random time intervals. In this section, the duration for the proposed algorithm to continue with the SI calculation after the machine log data are collected is fixed at equal or greater than 15 minutes. In other words, once the time stamp of the machine logs generated is exceeded by at least 15 minutes from the time stamp of the first machine logs, the integer values of the total pick-up count of each nozzle, total pick-up count of each input tray, total miss count of each nozzle, and total miss count of each input tray that occurred in that particular time interval are collected and the $SDSI$ value calculation proceeds using Equation (1). Then, the $SDSI$ values of the previous three states are included in calculating the SI score of the current state using Equation (2). The computed SI

plot is illustrated in Figure 5. In the proposed prognostic system, the system is considered unhealthy when the computed SI score is higher than the threshold value. The threshold value of the parameter SI is obtained from statistical analysis of a series of previously collected SI data and the system health condition which was manually decided and recorded by the on-site engineers before the threshold value was fixed. In this paper, the threshold for the SI score is fixed at 11. Table 1 shows the summaries of the prognostic decision of the proposed algorithms based on the SI plots in Figure 5.

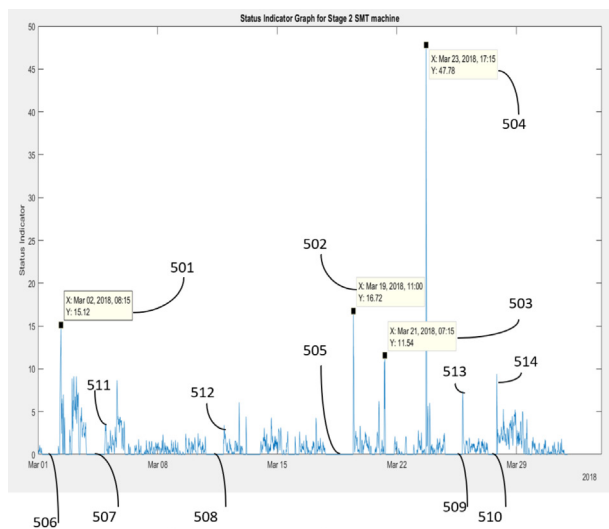


Figure 5. Computed SI plot for a SMT component placement machine operating in a real industry environment using the proposed prognostic algorithm.

Table 1. Summaries of the analysis of the prognostic results illustrated in Figure 5.

Observation	Date	SI Score	Remarks
501	2 March 2018, 8:15am	15	Unhealthy, no activity was recorded for nearly 1 day in observation 506 .
502	19 March 2018, 11:00am	16.72	Unhealthy, no activity was recorded for nearly 1.5 days in observation 505 .
503	21 March 2018 7:15am	11.54	Unhealthy
504	23 March 2018 5:15pm	47.78	Unhealthy
511	4 March 2018 4:25pm	3.67	Healthy, no activity was recorded for nearly 1 day in observation 507 .
512	11 March 2018 3:56am	3.46	Healthy, no activity was recorded for nearly 1 day in observation 508 .
513	24 March 2018 6:00am	7.69	Healthy, no activity was recorded for nearly 1 day in observation 509 .
514	26 March 2018 3:44am	10.02	Healthy, no activity was recorded for nearly 0.5 days in observation 510 .

The results show that the proposed prognostic algorithm is able to detect a system's health condition; however, a sudden increase in SI scores is observed in the plot when the machine starts operating after long hours of no operation, so a false system unhealthy signal may be generated in this situation.

The diagnostic algorithm generates diagnostic charts in the form of a bar chart as illustrated in Figure 6. The x-axis of the chart represents nozzle addresses NPB, NPD, NPE and NPK (**601**, **603**) and input tray addresses, 30006-1, 40009-2, 40010-2 (**602**, **604**), the y-axis represents the fault probability of the nozzles and input trays. NPA to NPL used on the x-axis are the symbols representing a nozzle's address used in the raw machine logs. The chart shows the potential faulty nozzles and faulty input trays only, as healthy nozzles and healthy input trays are all hidden in the diagnostic chart. The diagnostic results recorded at 2 March 2018, 7:00am (**609**, **610**) show that for nozzles NPB, NPE and NPK, regarding the take-up components from input tray 30006-1, 20% of take-up misses occur at NPB and NPE and 60% of take-up misses occur at NPK (**605**); however, 100% of take-up misses occur at input tray 30006-1 (**606**). From this diagnostic analysis, it can be interpreted that input tray 30006-1 is the faulty component, take-up misses occur for every nozzle that picks up a component from input tray 30006-1. As for the diagnostic results recorded at 23 March 2018, 5:15pm (**611**, **612**), the results show that nozzle NPD takes up a component from input trays with addresses 40009-2 and 40010-2. The diagnostic results show that 100% of take-up misses occur at nozzle NPD (**607**). For input trays, 18% of take-up misses occur at address 40009-2 and 82% of take-up misses occur at address 40010-2. These diagnostic results can be interpreted as nozzle NPD being the faulty component. Take-up miss occurs for components being taken up by nozzle NPD no matter which input tray it is from.

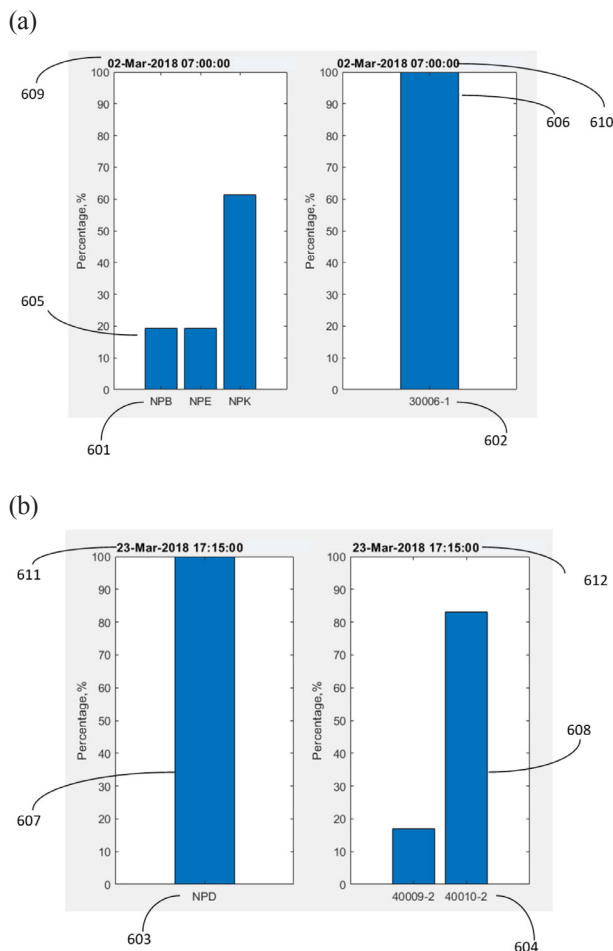


Figure 6. Diagnostic bar charts.

5. Conclusion

A prognostic method for SMT component placement machines has been proposed in this paper. By extracting the useful features carried in the raw machine logs such as total take-up count and the total miss count of each nozzle and each input tray, the proposed system is able to perform a prognostic function on the SMT component placement machine using the proposed prognostic mathematical model. The prognostic mathematical model has been proposed to calculate the Status Indicator Parameters of the component placement machine. Calculated Status Indicator results are compared to a threshold value. A low Status Indicator Parameter indicates that the miss count is low and the component placement machine is healthy. When the Status Indicator Parameter exceeds the pre-defined threshold value, it indicates that the system is classified as unhealthy and the process proceeds to the diagnostic algorithm. The diagnostic mathematical model has been proposed to calculate the probability of each nozzle and each input tray being faulty. Based on the generated diagnostic chart, faulty nozzles and faulty input trays can be easily detected and this eases the maintenance

process. The proposed system has been tested using a SMT component placement machine operating in a real industry environment. The results show that the proposed system is able to display a machine's health status accurately and give indications regarding which nozzles or input trays are faulty and thus minimise the effects of faulty components on the production lines and assist in making optimal maintenance decisions. The proposed algorithms can be further enhanced to measure the Overall Equipment Effectiveness (OEE) of SMT machines for manufacturing productivity measurement. Besides, by integrating the proposed algorithms with the AOI, additional parameters are able to be captured and analysed together to provide more reliable prognostic and diagnostic results. Additional sensors such as pressure measurement can be included as well to further enhance the prognostic and diagnostic system.

Notes on contributor



Dr Yeh Huann Goh received his B.Eng, M.Eng.Sc and Ph.D. in Electrical Engineering from The University of Malaya in 2004, 2007 and 2014 respectively. He joined the Faculty of Engineering and Technology at Tunku Abdul Rahman University College, Setapak as a senior lecturer in 2015.

His research areas include feature extraction for speech signal processing, derivation of new bidirectional Kalman filter and its application in speech signal processing. His contributions can be seen in the form of journal publications and conference proceedings. On professional qualifications, Dr Goh successfully registered as a Professional Engineer (P.Eng) in the Electrical Engineering discipline with the Board of Engineers (BEM) and Professional Technologist (P.Tech) in the Electrical discipline with the Malaysia Board of Technologists (MBOT). Dr Goh is also an active member in The Institution of Engineers, Malaysia (IEM, MAL).

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