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Extended Deming's model and data mining approach for diagnosis management

Supot Soommat[a,*], **Sanguan Patamatamkul**[b], **Thamrong Prempridi**[a], **Manop Sritulyachot**[a], **Pijarn Ineure**[c], **Surapan Yimman**[d], **Larry Klein**[e]

[a] Department of Engineering Management, Faculty of Engineering, Vongchavalitkul University, Nakhonratchasima 30000, Thailand
[b] Department of Civil Engineering, Faculty of Engineering, Naresuan University, Phitsanulok 65000, Thailand
[c] Department of Six-Sigma, Seagate Technology, Nakhonratchasima 30170, Thailand
[d] Department of Industrial Physics & Medical Instrument, Faculty of Applied Science, King Mongkut's University of Technology North Bangkok, Bangkok 10800, Thailand
[e] Department of Failure Analysis, Seagate Technology, Minnesota 55435, USA

*Corresponding author, e-mail: ssoommat@yahoo.com

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ABSTRACT: We develop a data mining approach and an extended Deming's management model to save diagnosis time in the slider process of the hard disk drive industry. The data mining approach consists of five mining algorithms, namely, the K-Mean clustering, the Kruskal-Wallis test, the multivariate chart, the association rules, and the continuity-based measurement. They provide an automatic diagnosis on manufacturing data to determine the defective process stages, machines, materials, and methods. The extended Deming's model provides a close-loop management of diagnosis. This analysis framework helps engineers to identify defective factors rapidly in order to deliver diagnosis results within an hour. Additionally, all results of extended Deming's management loop can be recorded and converted to be useful wisdom for effective manufacturing management.

KEYWORDS: slider process, hard disk drive industry, time reduction and wisdom conversion

INTRODUCTION

The defect diagnosis in the slider process of the hard disk drive industry (HDDI) is an important task to improve the yield and reduce the cost. Current diagnosis management is a time consuming process due to multiple process stages, machines, materials, and methods. The time-consuming nature of diagnosis increases the manufacturing cost. This article aims to develop a data mining approach as well as a management model of manufacturing data for saving diagnostic time.

Data mining approach is a well-known tool for knowledge discovery from a massive amount of data. Its analysis procedure can be a combination of a machine learning algorithm, statistical analysis, artificial intelligence, and data management[1,2]. There are five standard steps in a data mining procedure: (1) problem definition, (2) data preparation and transformation, (3) data mining, (4) interpretation of the results, and (5) presentation[1,2]. Many data mining algorithms have been applied to knowledge discovery in many fields; e.g., marketing and sales[3], biotechnology and chemical process industry[4], medical applications[4], energy production[4], quality control and minimizing an expensive testing in the HDDI[5], fault detection and quality control in electrical welding[6], and many other applications in current manufacturing[7].

Literature directly related to this study, and short reviews include the work of Chou et al[8], applied a priori association rules[9], and a continuity-based measurement (CBM) function[8] to capture defective machines in a semiconductor industry which continuously produced poor product quality. The same series of products worked through several machines, as well as process flows. The pattern of poor machines showed up if they continuously performed with a high reject rate in the same product names when compared to non-defective machines. Chen-Fu et al[10] applied K-Mean clustering[11], a Kruskal-Wallis (K-W) test[12], and decision trees[13,14] to capture defective process stages and defective machines in the semiconductor industry. The K-W test was used to screen out the defective process stages using a machine-oriented approach. The defective machines from defective process stages were screened out by using decision trees. Both researchers did not cover the materials and method types that can be subject to high risk of poor quality and impact manufacturing yield. Here our objective is to develop a new data mining approach to cover materials and method types as well as a management model for more effective management in manufacturing.

Description of problems

The slider processes of HDDI can be stated as follows. There is a set of m slider lots S_j $(j = 1, \dots, m)$, a set of w machines M_k $(k = 1, \dots, w)$, a set of p materials ψ_l $(l = 1, \dots, p)$ and a set of q method types Λ_r $(r = 1, \dots, q)$. Each slider lot consists of an ordered set of d process stages $P_{j1}, P_{j2}, \dots, P_{jd}$. The order of process stages cannot be changed, and process stage P_{jd} must be processed by exactly one given machine, material, and method during T_{jd} time units without preemption, i.e., when the operation has already been started. It cannot be interrupted until finished. Also, each machine can handle only one job at a given time, and a slider lot can be processed on only one machine in a given time period. The problem requires finding defective process stages, machines, materials, and methods on slider lots.

There are three main factors influencing the diagnosis time in the existing approach. First because of the diagnosis procedure of laboratory tools, high magnification tools are used to capture defective images from submitted units. Thus the delivered result is dependent upon machine capability and engineer skill. Second, a reasonable sample size for analysis is difficult to obtain. A high sample size directly increases diagnosis time. On the other hand, a small sample size creates insufficient information and repeats the diagnosis. Third, the results from laboratory tools require a process mapping, i.e., it requires further work to locate the defect in production line. Here our objective is to identify the defective factors by applying the data mining approach and the extended Deming's management model on a massive amount of manufacturing data.

DESCRIPTION OF PROPOSED APPROACH

There are five data mining algorithms: (1) the K-Mean clustering, (2) the three combinations of machine, material, method for Kruskal-Wallis (K-W) test [15], (3) the multivariate chart [16], (4) the a priori association rules [9], and (5) the continuity-based measurement (CBM) [8]. The management model proposes a GPDCARW flow (General, Plan, Do, Check, Act, Results, and Wisdom). It is an extension of the GPDCAR [17] and PDCA [18–20] models. Both data mining algorithms and management models are combined for the proposed approach and short reviews of each step are described below.

General (G): The general information of the problem for the management are the defective process stages, machines, materials and methods analysis that affect the final testing yield.

Plan (P): Data preparation and transformation, system inputs, goal setting, and technology selection require the establishment of a plan phase. The data preparation and transformation are undertaken by retrieving a specific piece of data from a massive database, and require the matching of the formula to each data mining algorithm [1,2]. The inputs require the name lists of process stages, machine numbers, material types, method types, yield level of each slider lot, and type I error (α) [10,15,21,22] for statistical test; α is the risk of rejecting a null hypothesis when it is actually true. The goal is to obtain zero defective lists.

Do (D): It operates the data mining script for diagnosis. The data mining for this purpose occurs in the following steps:

1. K-Mean clustering [11] classifies the final testing yield Y_j $(j = 1, \dots, m)$ of each slider lot S_j $(j = 1, \dots, m)$ into two groups ($K = 2$, i.e., low and high group) [10,15,21,22]. The yield is the ratio of outputs and inputs at final testing, i.e., 90% yield is 90 output sliders from 100 input sliders within a slider lot. The method for clustering the yield is presented in Algorithm 1.

   Algorithm 1: To cluster yield into two groups, i.e., low and high group.

   Step 1: Selected yield group $= 2$ (low and high group).

   Step 2: Randomly select mean of each yield group.

   Step 3: Calculate the distance between mean of each yield group and individual data point and regroup the data points in the same group using the closest distance between the data points and the mean of each yield group. Recalculate the new mean of each group.

   Step 4: Stop once each yield mean of iteration equals that of the previous iteration. Then report new mean of each yield group including yield cutting point (i.e., the separating point between low and high group). Otherwise, return to step 3.

2. Set $\alpha = 0.03$.

3. Perform the K-W test [12], i.e., the machine, material, and method approach [15]. This is required

to prevent an oversight of defective diagnosis for materials and methods if the single machine testing shows no significant difference. The method for this K-W test is presented in Algorithm 2.

Algorithm 2: To perform the K-W test.

Step 1: Select process stage P_{jd} and set $\alpha = 0.03$.

Step 2: Create a null hypothesis for machine-oriented approach. The null hypothesis is H_0: $\mu_1 = \mu_2 = \cdots = \mu_w$ and H_1 is at least one machine difference yield, where $\mu_1, \mu_2, \ldots, \mu_w$ are the average yield of machine $1, 2, \ldots, w$.

Step 3: Compute a set of mh yields; Y_{mh} ($m = 1, \ldots, w$ and $h = 00, \ldots, nn$), where w is the number of machines in P_{jd} process stage and h is a set of manufacturing hours that starts from 00 to nn, where nn is the maximum number of manufacturing hours a day, i.e., 20, 21, 22, 23, or 24.

Step 4: Compute K-W test by using [12]

$$H = \frac{12}{n(n+1)} \sum_{x=1}^{mh} R_x^2 - 3(n+1)$$

where H is a statistic test of K-W, R_x is a rank sum of sample x, where the rank of each measurement is computed according to its relative magnitude in the total of n data samples, where n is the number of machines multiplied by the number of manufacturing hours. If $w - 1$ is the number of degrees of freedom. H_0 will be rejected if $P(H > \lambda^2_{\alpha,w-1}) < \alpha$.

Step 5: Do the K-W test for material and method in the machine-oriented manner. Set the null hypothesis for materials and method. Calculate the set of mh yield for the material-oriented approach. Y_{mh} ($m = 1, \ldots, p$ and $h = 00, \ldots, nn$), where p is the number of materials. The H_0 will be rejected if $P(H > \lambda^2_{\alpha,p-1}) < \alpha$. In the same manner, calculate the set of mh yield for the method-oriented approach. Y_{mh} ($m = 1, \ldots, q$ and $h = 00, \ldots, nn$), where q is the number of materials. The H_0 will be rejected if $P(H > \lambda^2_{\alpha,q-1}) < \alpha$.

Step 6: Perform steps 1–5 for all P_{jd} process stages.

Step 7: Collate the p-value of each process stage using the machine-oriented approach to report defective process stages; the process stage is defective if the p-value is less than α. If not, verify the material and method oriented approach at the highest machine number process stages, reporting the defective materials or methods if $p < \alpha$. Otherwise, stop and report no potential root causes.

4. Perform the multivariate chart [16] to generate a set of wpq yield vectors, where w is the number of machines, p is the number of materials, and q is the number of methods. The method for yield vector generation is presented in Algorithm 3.

   Algorithm 3: To generate yield vectors.

   Step 1: Define set of w machines M_k ($k = 1, \ldots, w$), set of p materials ψ_l ($l = 1, \ldots, p$), set of q method types Λ_r ($r = 1, \ldots, q$), and set of slider lot S_j ($j = 1, \ldots, m$) in d process stages, $P_{j1}, P_{j2}, \ldots, P_{jd}$.

   Step 2: Select defective process stages or the highest machine number process stages.

   Step 2.1: If defective process stage occurs, generate the yield vector form in the order: machines, methods, materials. The yield vectors are called transactions: Y_{krl} ($k = 1, \ldots, w$; $r = 1, \ldots, q$; $l = 1, \ldots, p$).

   Step 2.2: If no defective process stage, the highest machine number process stage must be defined. Then, consider the p-value of the material and method from K-W testing. If a defective material occurs, generate the yield vector form in the order: materials, machines, methods. Yield vectors: Y_{lkr} ($l = 1, \ldots, p$; $k = 1, \ldots, w$; $r = 1, \ldots, q$). If a defective method occurs, generate yield vector form in the order: methods, machines, materials. Yield vectors: Y_{rkl} ($r = 1, \ldots, q$; $k = 1, \ldots, w$; $l = 1, \ldots, p$).

   Step 3: Compare yield level of each vector to the K-Mean clustering results, i.e., low group $\leqslant$ cutting point yield $>$ high group. Stop and report if all defective process stages, materials, and methods are defined. Otherwise, back to step 1.

5. Perform the a priori association rule [9] as an expression $Z \Rightarrow S$, where Z and S are sets of transactions from the multivariate chart. If given a database D of transactions, where each transaction $T \in D$ is a set of items $Z \Rightarrow S$. It means that whenever a transaction T contains Z then T also contains S. The strong rule requires the percentage support and percentage confidence to meet the minimum threshold that specify from the users. The percentage support

(Sup) and percentage confidence (Con) equations are shown in (1) and (2).

$$\text{Sup}(ZS) = \frac{\text{number of transactions contains}(ZS)}{\text{total number of transactions}} \quad (1)$$

$$\text{Con}(ZS) = \frac{\text{Support}(ZS)}{\text{Support}(Z)} \quad (2)$$

The method of the a priori association rules for creating a set of defective factors that are associated with a low yield portion is presented in Algorithm 4.

Algorithm 4: To perform the a priori association rules of defective sets.

Step 1: The analysis hour is first partitioned according to the item sets. The support count of each item set (1-item sets) is performed. The item sets that cannot satisfy the required minimum support count are pruned. Thus 1-item sets are created, The 1-item set is the set of machine, material and method.

Step 2: Item sets are joined together (2-item sets) to create the second-level candidates, the 2-item sets is a pair of machine-material, machine-method, and material-method. The support count of each candidate is accumulated. After pruning unsatisfactory item sets according to minimum percentage support, the frequent 2-item sets are created.

Step 3: Item sets are joined together to give 3-item sets to create the third-level candidates (a set of machine-material-method). The support count of each candidate is accumulated. After pruning unsatisfactory item sets according to minimum percentage support, the frequent 3-item sets are created.

Step 4: Terminate if no item sets. Select the item sets that meet a 20% support and 100% confidence minimum. Otherwise, repeat step 1.

Step 5: Calculate the φ for the selected item sets to obtain the discovered rule of $Z \Rightarrow S$[8]

$$\varphi = \frac{|Z \wedge S| - |Z||S|/N}{\sqrt{|Z||S|(1 - |Z|/N)(1 - |S|/N)}},$$

where N is the total number of tuples, $|Z|$ is the number of tuples that contain the antecedent Z, $|S|$ is the number of tuples that contain the antecedent S, and $|Z \wedge S|$ is the number of tuples that contain both Z and S.

Step 6: Transfer the selected item sets to verify CBM[8] in algorithm 5.

6. Perform the CBM[8] to verify a continual function on the selected item sets. The method is presented in Algorithm 5.

Algorithm 5: To verify a continual function of the selected item sets.

Step 1: Select ordered manufacturing hours ($h = 00, \ldots, nn$).

Step2: Calculate the CBM: $\varphi' = \varphi \times$ Continuity of the selected item sets. The continuity function is

$$\text{Continuity} = \begin{cases} \frac{1}{\sum_{i=1}^{|X|-1} d(\lambda(x_i), \lambda(x_{i+1}))/|X|-1} & \text{if } |X| > 1 \\ 0 & \text{if } |X| \leqslant 1 \end{cases}$$

where $X(x_1, x_2, \ldots, x_h)$ are the manufacturing hours, $\lambda(x_i)$ is the order of the manufacturing hours which cannot be changed. The $d(\lambda(x_i), \lambda(x_{i+1}))$ is the distance of the low yield hours between $\lambda(x_i)$ and $\lambda(x_{i+1})$ which can easily be calculated by $\lambda(x_{i+1}) - \lambda(x_i)$ and $i = 1, \ldots, nn + 1$.

Step 3: Identify defective factor if $\varphi' > 0.50$ or $> 50\%$. Otherwise, report that no defective factors were found.

Check (C): Check defective lists match the goal, i.e., check process stages, machine numbers, material types and method types. Zero defective lists are required.

Action (A): If the defective lists are not zero, the system will continue to re-operate the data mining script and re-report the defective lists to engineers. The corrective action is required until zero defective lists are obtained.

Results (R): The results are recorded into the R after the corrective actions are undertaken.

Wisdom (W): The results from R are converted to be useful wisdom using DTCN[23] (design to customer need). The benchmarking technique is used to compare the performance of defective factors in the same function, i.e., comparison yield of machines, materials or methods within the same process stages and manufacturing periods. The RPN (Risk Priority Number) ranking is a used as a method for benchmarking processes. It uses a $O \times S \times D$[24] formula to identify the risk level, where O is the occurrence rating (1: seldom,…,10: often), S is the severity rating (1: less,…,10: most) and D is the detectable rating for the current control system (1: detectable,…,10: non detectable). The highest RPN is the highest risk of

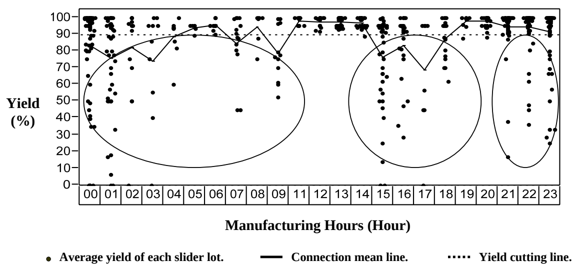

Fig. 1 Final yield as a function of manufacturing hour. Tracking time was between 00 h and 23 h (within one day).

manufacturing cost. The minimum RPN for this study is 200[25].

APPLICATIONS AND RESULTS

Following the research framework of the data mining approach and extended Deming's management model, a study was conducted for the slider process of HDDI in Thailand, with a critical requirement for root cause investigation of the low final testing yield problem. The yield trend showed a low yield in some hours (in circles) as shown in Fig. 1. There were three material types (A, B, and C) and two methods (1 and 2) that were manufactured in the process. There were eight process stages and 657 slider lots (S_j; $j = 1,\dots,657$) during manufacturing hours from 00 h to 23 h. Each process stage contained different machine numbers, i.e., five machines at process stage 1, 2, 3, 5, 6, and 7, ten machines at process stage 8, and fifteen machines at process stage 4. The research framework was performed by querying the specific piece of data from the massive manufacturing database using an SQL program. Then data were prepared in the appropriate format for the mining algorithms.

For the yield clustering results, the final testing yield of the slider was clustered into low and high yield groups by using the K-Mean clustering algorithm. The average yield of the high group was 95.89% (499 lots) and the average yield of low group was 65.06% (158 lots). The yield cutting point was 90%.

The p-value of all process stages were tested by using the machine-oriented K-W testing. The machine-oriented testing represented the process stage performance because all machines in the same process stages performed the same function without preemption. The results were not significant. Thus there were no defective process stages and no defective machines. The system automatically switched to review the K-W testing under material and method in the highest machine number process stage using algorithm 2 (i.e., stage 4 was selected). As a result, the method-oriented testing results were not significant ($p = 0.66$), whereas the material-oriented testing results were ($p < 0.0001$). This implied that materials have the potential to be a root cause for low yield.

The multivariate chart generated the yield vectors following algorithm 3. The yield vectors of each transaction were transferred to perform the a priori association rules in algorithm 4. The a priori association rules generated a set of Z (defective material sets) rules associated with the S set (low yield group). The results showed that type A material was associated with the low yield portion based on 30% support (Sup) and 100% confidence (Con) whereas materials B and C did not show any association (i.e., they showed 0% support). Materials B and C were pruned because their percentage support did not meet the criteria (i.e., 20% minimum).

The manufacturing was conducted for 23 out of 24 h a day and low yield occurred for 15 h. The CBM function showed a constant level of material type A using algorithm 5. The CBM of material type A was 0.65 and that provided the confidence to be the real root cause of defect because it was higher than specification (> 0.50).

The yield among material types were benchmarked by using the RPN process ($O \times S \times D$) for wisdom conversion. The RPN of materials type A was 250 ($O = 5$, $S = 10$, $D = 5$) whereas material types B and C were 25 ($O = 5$, $S = 1$, $D = 5$). The wisdom was defined that material type A was defective. This information educated the production and material team to avoid material type A to minimize the yield impact.

The delivery time of results was 40 min. Products X and Y were also examined (Table 1). The delivery time of the proposed approach ranged from 40.0 to 40.5 min whereas the delivery time of the existing approach ranged from 72 and 168 h.

DISCUSSION

The proposed management modelling and data mining approach for defective diagnosis was applied to slider manufacturing to compare results with the existing approach. Based on nine cases, the results showed that 67% of defects were related to machines from several process stages, 22% related to materials, and 11% related to method types. There were three defective machines for product X and two defective machines for product Y in case 4. Those multiple defects were segregated by multivariate chart algorithm (i.e., algorithm 3) during yield vector generation. This algorithm showed a powerful diagnosis to segregate

Table 1 Summary of results of cases on products X and Y.

Cases	Product X				Product Y			
	p-value	CBM	Wisdom (Defective)	Significant K-W Test	p-value	CBM	Wisdom (Defective)	Significant K-W Test
1	< 0.0001	1	Mac 11 Stage 4	Mac	< 0.0001	0.69	Mat C	Mat
2	< 0.0001	0.8	Met 1	Met	< 0.0001	0.74	Mac 5 Stage 1	Mac
3	0.0007	0.88	Mac 5 Stage 1	Mac	0.0018	0.63	Mac 1 Stage 8	Mac
4	< 0.0001	0.56	Mac 1 Stage 4	Mac	< 0.0001	0.81	Mac 5 Stage 8	Mac
		0.62	Mac 2 Stage 4			0.5	Mac 9 Stage 8	
		0.7	Mac 9 Stage 4					

Mac = machine; Mat = material; Met = method

a source of defects for consequent algorithms (algorithm 4 and algorithm 5). The yield among suspect factors (machines, materials, and methods) was benchmarked by using the RPN number for converting to useful wisdom. The useful wisdom was efficiently applied to manage daily manufacturing, i.e., production planning without defective factors, appropriate preventive maintenance scheduling (i.e., process stages 1, 4, and 8 were suggested for preventive maintenance in order to reduce a chance of defects because they had a higher rate of defect occurrence than other process stages).

The results of the proposed approach show the same results as the existing approach, and it can deliver results faster than the existing approach based on the automatic decision. The delivery time of the proposed approach was within an hour for data retrieving from the massive database, calculating and reporting, whereas the existing approach took 72–168 h due to time-consuming laboratory tools and manual interpretative methods. The time reduction of analysis was important for manufacturing management. The short time of analysis was able to reduce manufacturing costs. However, the key requirement for the proposed approach was more case problems for training on the data mining system. Specifically, the CBM needs an a priori association for the rule generation in order to support other cases.

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