A Set Theory-Based Approach for Efficient Diagnosis of Semiconductor Test Equipment

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The operational efficiency of semiconductor factories relies heavily on robust processes and reliable equipment performance. Plant managers need their manufacturing equipment to predictably produce the required units to run a smooth operation. When equipment is down, capacity to deliver is threatened and penalties are manifested in terms of lost production time and buildup of work-in-process inventory. This paper explores the use of a set theory-based inference engine to facilitate diagnosis of equipment failures, thus reducing equipment downtime. The model discussed in this paper requires a particular data structure to aid in the documentation of the observed symptoms and causes of equipment failure. The same data structure will also be used to support inference operation of the model. A system block diagram level of diagnostics is used to illustrate the methodology of inference algorithm.

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I. INTRODUCTION

Whenever factory equipment breaks down or when there are unusual occurrences that are not within the set operational parameters, it triggers a request for equipment inspection (Koh 2009). Technicians are called in to determine the cause of the problem and are tasked to bring the equipment back to its normal operating mode at the soonest time possible. After the technician has finished inspecting the equipment, the immediate question any factory supervisor will ask the equipment technician is: “When will the equipment get fixed?” (Lei 2009) The answer to the question is simple. If the nature of breakdown or yield excursion is known, it will surely get fixed within a given specified period. However, if the nature or cause of failure is fairly new and unknown, the time it takes to repair the equipment would now depend on the level of expertise of the technician, engineer, manager or the companies offering vendor service support (Lei 2009). Very often, equipment failures on the production floor are repetitive events with similarly repetitive causes. Ideally, equipment failures should be fixed within a specified period of time. However, this is only possible if all the failure symptoms and causes are known. In many cases, ineffective documentation of failure events happens even if equipment maintenance is already a routinary and highly organized activity.

All equipment is generally accompanied with technical user manuals that contain numerous pages of diagrams but only a few pages on troubleshooting. The reason for this thin reference on trouble shooting is that equipment vendors are normally hesitant to give out voluminous troubleshooting information. Thick troubleshooting guides included in manuals are generally perceived negatively by the industrial market because it implies that the equipment is troublesome (Hakansson 1982). This is the main driver for the internal documentation of tremendous encyclopedic information about process and equipment troubleshooting occurrences for some complex equipment. Since equipment vendors insist on having minimal troubleshooting guides, then it is assumed that they have internal guides ready in case there are called on to service equipment breakdowns that are not indicated in the technical manual. Properly documented, the troubleshooting guide in a tabulation format generally consists of a column for troubles and a second column for the root causes and a third column for the procedure of repair and calibration (Bulos 2009). Ideally, the name and position of the technician logging the information onto the database should also be included (Bulos 2009) (Lei 2009).

The compiled information in the troubleshooting guide would also be useful in diagnosing future equipment failures, long after the technician or engineers have left the company (Koh 2009). However, users of this document should remember that voluminous data may lead to some difficulty in terms of diagnosing equipment failures. The users should also keep in mind that a single symptom could sometimes point to several root causes. In cases like these, short-listing the possible root causes would help in diagnosing the actual problem. The short listing is done through the trials of various fixes until the symptom vanishes. Sometimes when all known fixes have already been tried and the symptom still remains, this is usually a strong indication that a new type of failure cause, unknown before, is at hand.

The main objective of the troubleshooting process is to diagnose and provide a prognosis for any equipment failure (Bulos 2009). Therefore, for validation purposes, access to all of the associated symptoms attributed by the identified root causes must be available to the person performing the diagnostics. This way, the practice of trial and error on the fixes may be eliminated. The validation of the universal set of symptoms would now determine whether the problem at hand is old or new.

A typical diagnostic and problem solving flow chart is shown in Fig. 1. This diagnostic and troubleshooting practice process is not supported with availability of and access to information through a database system. Thus, the diagnostic procedure and problem solving often take a repetitive and iterative process as shown by the thick arrows forming a loop in Fig. 1.

Without the support of a database system, the diagnostic process is dependent on the limited knowledge of individual problem solvers and for the most part, unresolved problems have to be elevated to the higher management, resulting in further loss of time and waste of resources (Koh 2009). In some extreme cases, when the threshold of the resource allocation for the failure diagnosis has been reached, management makes decisions to either discontinue the product using the equipment; stop the process; or live with the problem (Lei 2009) (Koh 2009).

II. CONCEPTUAL FRAMEWORK: DIAGNOSTIC EXPERT SYSTEM

An expert system is a computer application that solves problems in specific task areas. Often, it refers to programs whose knowledge base contains the knowledge used by human experts (Engelmore and Feigenbaum 1993) and the system emulates the decision-making ability of humans (Jackson 1998). Expert systems are different from conventional computer programs. It is designed to solve complex problems by reasoning about the knowledge from the variable knowledge database developed by experts (Barzilay, et al. 1998).

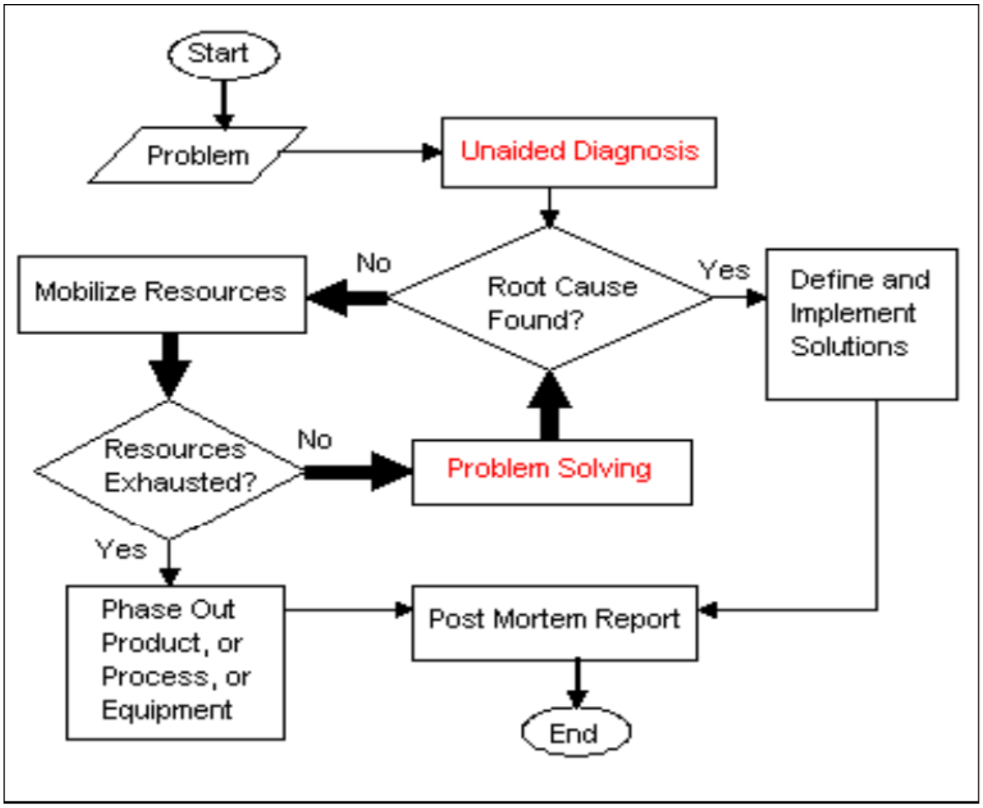

FIGURE 1. A Typical Diagnostic and Problem-solving Flowchart

Kiong, Rahman, Zaiyadi and Aziz (2005) discussed the uses and advantages of the expert system in agriculture, education, environmental management and medicine. In their study, they discussed the components of the expert system: knowledge base, inference engine and the user interface and how these components were used in setting up the technology for commercial application. They also discussed how the expert system was configured to solve specific task areas in these applications. They concluded that the implementation of the expert system in the fields that were studied is heavily influence by techniques and methods from an adaptive hypermedia. They also concluded that personalization, user modeling and ability to adapt towards the changing environment would be the greatest challenges to the practical application of the expert system.

In a study commissioned by the Asian Development Bank (ADB) in 1997, several scientists and researchers and experts were tasked to evaluate the use of the expert system on environmental impact assessment (EIA). Gray and Stokoe (1988) found only a few examples of expert systems application specifically for EIA, but noted that there were many more applications in natural resources management, particularly in the areas of forestry, hazardous wastes and weather forecasting. Page (1989) supported this finding by comparing the applications of expert systems in Canada and Germany. His study revealed that only a small number of applications are specific to EIA, but a number of systems are applied to natural resource management. However, these systems were still either in a prototype or demonstration stage.

The WTEC (World Technology Evaluation Center) lists seven major classes of applications for expert systems (The Applications of Expert Systems 1993) and one of the major applications is diagnosis and troubleshooting of devices and systems of all kinds. However, none of the approaches discussed within diagnosis and troubleshooting application mentioned the integration of the set theory-approach into the expert systems. The diagnostic and problem solving flow chart being proposed in this study is shown in Fig. 2. The processes in the activity loop that require resource mobilization are greatly reduced by diverting repetitive problems to the database loop. The thick lines indicate heavy activities within the database loop, as shown in Fig. 2.

The only problems getting into the loop that require resource mobilization are the new, and previously unidentified, ones. Equipment problems or failures usually lead to the loss of manufacturing capacity. Whenever there is a “lines down” situation, the technicians have to determine whether it is an equipment or process problem. These problems are often manifested through loss of capacity and issues in yield and quality (Koh 2009).

The conceptual framework will have two fundamental paths: First, the problem must be identified and determined whether it is a new or an old problem. When the symptoms are entered as key words into the database, the search engine should yield a set of candidate causes; Second, if the set of the entered symptoms is incomplete for the system to deduce the causes or if the symptoms are too much to include irrelevant causes, then a number of algorithms may be designed to filter input symptoms and infer relevant causes. The validation of the user’s complete premise will be necessary for the expert system to come up with its final conclusion.

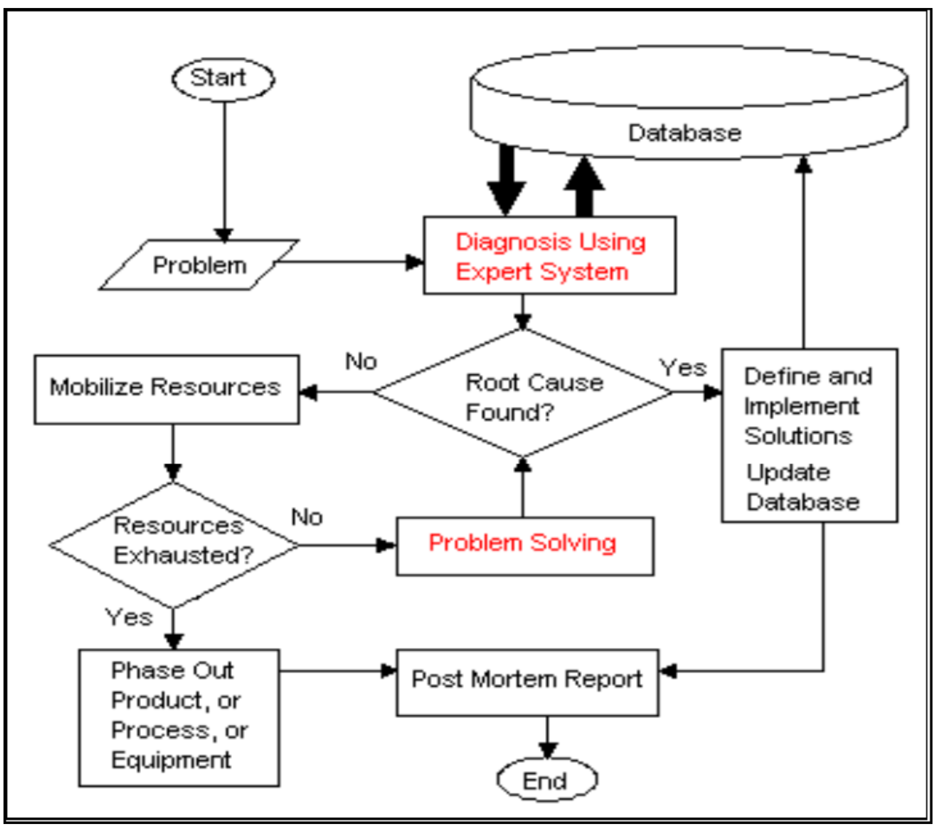

FIGURE 2. Diagnostic and Problem Solving Flowchart with the AID of Expert System

III. SET THEORY-BASED INFERENCE ENGINE

The expert system simulates the interaction between consultant and consultee during the diagnostics activity (Bulos 2009) (Lei 2009). Briefly, the interaction starts with consultee asking the consultant for possible causes on some observed symptoms. The consultant initially infers all possible causes associated with the observed symptoms. Every possible cause will then be examined to infer all the other symptoms associated with it. After the examination, the consultant will bring forth to the attention of the consultee all the other symptoms that were not observed for confirmation and verification. Once the consultee verifies the observed symptoms, the consultant will again work on the hypotheses to eliminate irrelevant causes and pronounce the relevant causes as the conclusion. The knowledge of domain expert may be stored as database of the "IF-THEN" statement. The "IF-THEN" rule function is being construed based on the following observations (Lim and Co 2002):

Every symptom has one or more causes;

Symptom = function (Cause1 and/or Cause2, and/or Cause3 and/or …..) (1)

Every cause must have all the symptoms it requires for it to be unique;

Cause = function (Symptom1 and Symptom2 and Symptom3 and …..) (2)

The symptoms and causes are related by relational matrix RM as

$$RM_{i,j} = \begin{cases} 1 & if\ cause, C_j\ manifest\ symptom, S_i \\ 0 & otherwise \end{cases}$$

Where CS_i = cause, $SMPT_j$ = symptom, $RM_{i,j}$ = relational matrix (Gmytrasiewicz and Hassberger 1990) where $RM_{i,j}=1$ if CS_i causes $SMPT_j$ to manifest, otherwise $RM_{i,j} = 0$. Hence, from "(1)" the following is defined in terms of sum axiom and families of set (Suppes 1972).

$$SMPT_j = \bigcup_{i=1}^{I} \{\{CS_i\} \mid RM_{i,j} = 1\} \tag{3}$$

From "(3)" the following may be formulated based on "(2)". Hence "(4)" is true if and only if no two causes have the same symptoms. It can be said that a singleton symptom set describes a cause.

$$\{CS_i\} = \bigcap_{j=1}^{J} \{SMPT_j \mid RM_{i,j} = 1\} \tag{4}$$

Having established "(3)" and "(4)", the inference rule for block diagram may be formulated. The rule is within the context of electronic system where the input and output are solely signals. The expression "(3)" may be called OR List and the expression "(4)" AND List.

IV. DIAGNOSTIC PROCESS MODEL AND ALGORITHM

4.1 Phenomenology of Diagnostic Process

To discuss the concepts, it will be good to start with the two fundamental statements about causes and symptoms.

1) AND Phenomenon

The first statement is given as follows:

Statement 1. *A cause manifests a definite set of symptoms.*

The corollary is that a set of causes has a definite number of symptoms. Not all the symptoms may be known but a critical set of symptoms should be adequate to be able to identify the cause. There may also be some known and unknown causes that might both have the exact same set of critical symptoms. If the known cause is fixed and the symptoms remain, then it is assumed that the problem is due to an unknown cause. However, since the cause is unknown, it must first be discovered. New symptoms must be identified to differentiate the newly discovered cause from the old causes. If fixing the known cause simply reduces the number of symptoms, then it is assumed that an unknown cause manifested itself with some common symptoms associated with the known cause.

When the cause is fixed, the expectation is that all symptoms associated with it must vanish. Therefore, a cause necessitates that all enumerated symptoms associated with it must exist. Several definite sets of symptoms must manifest a definite set of causes. Let us call this the AND phenomenon.

2) OR Phenomenon

The second statement is given as follows:

Statement 2. *A symptom may be manifested by one or more causes.*

The corollary is that a set of symptoms may have one or more causes. Not all causes may be known. An unknown cause may manifest only if all the known causes are already fixed and yet the symptoms remain.

A set of causes may manifest a single particular symptom. Fixing one of the causes in a set of causes may make the symptom disappear if that cause is the culprit. Several causes may need to be fixed, especially if these causes are also manifesting the symptoms. Let us call this the OR phenomenon.

4.2 Derivation of Method

1. One or more symptoms manifested. This isthe given set of symptoms, GS.
2. Causes that manifest the given set of symptoms are deducted by virtue of statement 2, the OR phenomenon. This is the set of given causes, GC.
3. All manifested symptoms are identified by the given set of causes, GC, by virtue of statement 1, the AND phenomenon. All these set of symptoms is called resultant symptoms, RS.
4. The resultant symptoms, RS are generally more than the given symptoms, GS. RS data may be reconsidered to validate GS, assuming GS is finalized. The difference between RS and GS would now result to the excluded symptom, XS. Therefore, RS – GS = XS.
5. The excluded symptom belonging to XS must point to set of causes that contain them. This set of causes for the excluded symptoms, XS, will be referred to as XC. Then the set of resultant causes, RC, may be computed by subtracting the excluded causes, XC, from given causes GC. Therefore RC = GC – XC.

Once RC is computed to be non-zero, it assumes a cause can be determined considering that all sets of symptoms and causes are known and cataloged in the database. Let us create a mathematical model and the corresponding algorithm to illustrate the process.

4.3 Comprehensive Algorithm

The comprehensive algorithm flow chart is illustrated in Fig. 3. The database support is made explicit. If all symptoms and the corresponding causes are in database, then corresponding fixes and the time required for fixing the troubles must also be accessible from the database. The information about the time it takes to fix the equipment will be very useful to the manufacturing team particularly when the team has to make decisions on what courses of action to take to minimize loss of capacity.

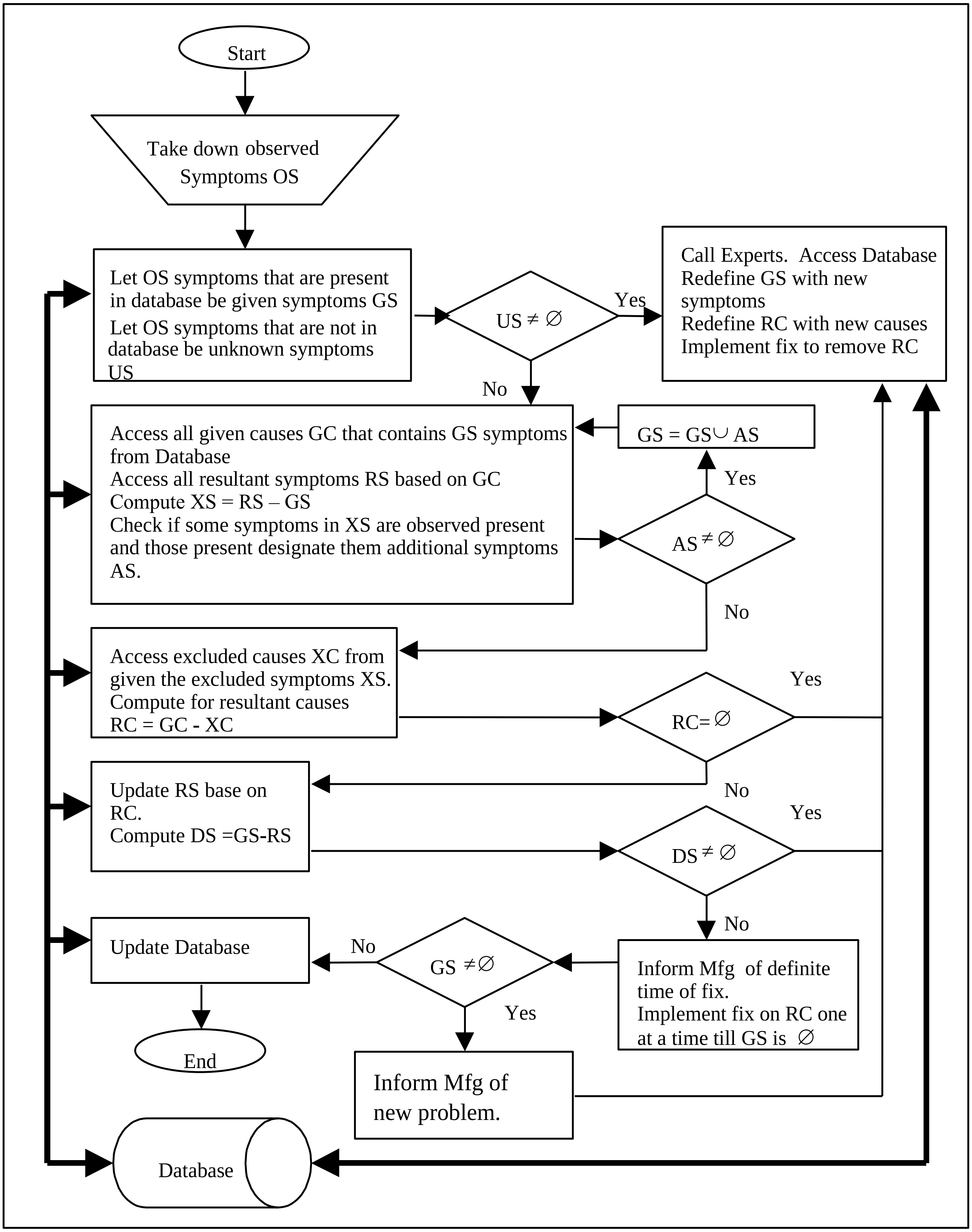

FIGURE 3. Troubleshooting Algorithm

In cases when expert intervention is deemed necessary, the database must be updated with the new symptoms and new causes. Ideally, however, even if there are no expert interventions, the updated information should still be logged into the database. These updates should consist of the statistics of the occurrences of different causes (Koh 2009) (Lei 2009) (Bulos 2009).

The future improvements on the system would mainly depend on the available data and the frequency distribution of causes weighted by the time of repair. Frequently observed causes that take the most time to fix must be prioritized in planning for continuous improvements on the factory floor (Koh 2009).

V. SEMICONDUCTON APPLICATION

5.1 Test equipment application

Table 1 shows an initial set of data for test equipment used in electronics manufacturing. It is a simple matrix wherein the algorithm developed can be applied on electronics test manufacturing process. Analysis of test failures is usually difficult, especially if the reasons for the failures are not device-related. Over time, the technicians and engineers will uncover new symptoms and causes. These discoveries should be properly documented in a database. A thorough and fast analysis requires the engineer or technician to have a good product background and a sound knowledge on both the hardware and software part of the tester. These set of skills will help guide him through the fault isolation process.

Let us start with few initial entries in Table 1 and assume that all the entries are valid. To facilitate deduction of the causes, it is necessary that each cause must have the unique symptoms by virtue of statement 1. Table 1 satisfies this criterion since each cause has set unique set of symptoms. No causes will have the exact duplicate symptoms with other causes. If duplication exists, then it is necessary to figure out the differentiating symptoms. This will serve as a trigger to search for unknown symptoms.

By abstracting Table 1, Table 2 can be constructed in terms of mathematical symbols. On the one hand, let say the symptom S3(high resistance) has a set of causes namely c1(tester calibration), c2(test board), c3(contact fingers), c5(device). Therefore we have S3{c1,c2,c3,c5}. On the other hand, let say C1 (tester calibration) has a set of symptoms namely, s1{high leakage}, s3{high resistance}, s4{high timing}, s5{misbinning}. Therefore, we have C1{s1,s3, s4,s5}.

TABLE 1. Initial Data for Test equipment Testing

Symptoms		Causes					
		1	2	3	4	5	6
		Tester Calibration	Test board	Contact Fingers	Stray Inductance	Device	Software Program
1	High leakage	Yes		Yes	Yes	Yes	
2	Fail Contact Test		Yes	Yes			
3	High Resistance	Yes	Yes	Yes		Yes	
4	High timing	Yes				Yes	
5	Misbinning	Yes					Yes
6	Fail Diode Test						Yes

TABLE 2. Abstract Tabulation of Table 1

Set of Symptoms	Set of Causes
C1{s1,s3,s4,s5}	S1{c1,c3,c4,c5}
C2{s2,s3}	S2{c2,c3}
C3{s1,s2,s3}	S3{c1,c2,c3,c5}
C4{s1}	S4{c1,c5}
C5{s1,s3,s4}	S5{c1,c6}
C6{s5,s6}	S6{c6}
Sn = set of causes with elements cn cn= cause Cn = set of symptoms with element sn sn = symptom	

When symptom S1 is reported, the probable causes are c1, c3, c4, c5. If all these causes are present then all symptoms S1, S2, S3, S4, and S5 must be present by virtue of statement 1. All these symptoms must be checked. Let us assume that S4 is validated. Then the only probable causes that are now common for both S1 and S4 are c1 and c5. However, C1 and C5 must have s1, s3, s4, and s5. Note s2 and s6 were eliminated.

Let us assume that S1, S4 and S5 symptoms are confirmed to be present. Then the remaining cause common to all S1, S4 and S5 is only c1. However, C1 requires s1, s3, s4 and s5. To finally confirm C1, s3 must exist. Otherwise, there may be other unknown causes that may require the identification of new symptom(s), for instance, a low plunger force (an unknown cause or other listed in Table 1) for tester calibration failure. By computational process, we have the following:

Let us assume that symptoms s1, s3, s4 and s5 are confirmed to be present.

Let GS be the given symptoms.

$$GS\{s1, s3, s4, s5\}$$

Let GC be the given set of causes based on GS.

$$S1 \cup S3 \cup S4 \cup S5 = GC\ \{c1, c2, c3, c4, c5, c6\}$$

Let RS be the set of symptoms based on GC.

$$C1 \cup C2 \cup C3 \cup C4 \cup C5 \cup C6 = RS\ \{s1,s2,s3,s4,s5,s6\}$$

Let XS be the excluded symptoms taken from the difference between RS and GS.

$$RS - GS = XS\ \{s2, s6\}$$

The XS symptoms allude to causes that are not relevant. These are excluded causes XC.

Let us compute them as follows:

$$S2 \cup S6 = XC\ \{c2, c3, c6\}$$

The resultant causes RC are the difference between GC and XC.

$$GC - XC = RC\ \{c1, c4, c5\} \neq \emptyset$$

If RC is null, that means no cause is identified. There is no conclusion and additional information is needed. If RC is not null, it still needs to be validated by computing for DS if a cause exists in the database.

To validate the RC, let us again compute RS based on RC instead of GC as follows:

$$RC = RS \{s1, s3, s4, s5\}$$

Then computing for the difference DS we have the following:

$$GS - RS = DS \{\} = \varnothing$$

The calculation reaches a solution RC that is not null. It means a cause solution can be determined from the given symptoms. The null result of DS confirms a perfect match in the set of symptom and set of causes.

Given GS{s1, s3, s4, s5}, the algorithm turn out is RC{c1, c4, c5}. The task is to prioritize the causes that have the shortest fix time. The causes c1, c4 and c5 manifest symptoms s1, s3, s4 and s5. Note that by the OR phenomenon, it is not definite whether c1 is the only cause or c1, c4 and c5 are the causes. By inspection, we note that $C1 \supset C5 \supset C4$, thus we can say that C1{s1, s3, s4, s5} is a super set of C5{s1, s3, s4} and C4{s1}. By statement 1, c1 is a definite cause because the elimination of c5 or c4 alone will not remove all the symptoms. During the updates on the database, the statistics of cause occurrences could be used as guide on which fixes to prioritize. The content of the database should be regularly validated specifically when adding new entries for symptoms and causes and when obsolete symptoms and causes data are deleted. The obsolescence of causes and symptoms data may be brought about by continuous improvement or upgrade of the system.

A number of algorithms may be created to perform various inference functions. Consider an algorithm to deduce a number of causes. Then, a series of set intersection operation may deduce a cause. For example if "high leakage" symptom is entered, expert system returns a list of causes as follows:

(High leakage)= {Tester Calibration, Contact Fingers, Stray Inductance, and Device}. (5)

An additional symptom may further reduce the element on the set of causes in "(5)" by set intersection operation.
Hence,

(High Timing) ={Tester Calibration, Device) (6)

By intersection of "(5)" and "(6)", we have

(High leakage)∩(High Timing)={Tester Calibration, Device) (7)

Finally, if "Missed-Binning" and "High Resistance" are also noted, then the result in "(7)" is reduced into one cause as follows:

(Missed-Binning)∩(High Leakage)∩(High Timing)∩(High Resistance) = {Tester Calibration) (8)

Equation (8) is known as Horn Clause. Based on the definitions in "(3)" and "(4)", "(8)" is a singleton set with one cause element. Hence, a cause may be taken as singleton symptom set.

Validation may be made by performing search with the result of "(8)" as key word. Another function may be introduced as:

Lookup ("Tester Calibration", "Cause") = {"Missed-binning", "High leakage", "High Timing", "High Resistance") (9)

The first argument is the key word for item to search and the second argument is the name of file where to look. The result in "(9)" is the inverse of "(8)". The user must validate the lists of symptoms in "(8)". All the symptoms must be validated as premises before "(8)" is accepted as conclusion.

The initial database in Table 1 will grow over time as new symptoms and causes are discovered and the database is upgraded and updated. Whenever the expert system fails to provide the prescription upon the input of a symptom, this new symptom should be noted. Then the search engine should return a "null" list. The "null" list means that the symptoms are not included in the existing database.

The new cause occurs when the prescription of expert system fails to solve the problem. For instance, "(8)" shows that Tester Calibration is the root cause for Missed-Binning, High Leakage, High Timing and High Resistance. If after Tester Calibration is done, and some or all these symptoms still persist, then there must be new cause. This time, an expert human being, not the system, does the diagnosis. When the new cause is identified, its corresponding new symptom(s) should also be identified. If it is hidden, then diagnostic test must be prescribed to reveal the new symptoms. Diagnostic test is used to uncover hidden symptoms that are the necessary premise to infer a conclusion.

5.2 Evaluation Result

A test evaluation run was conducted in a production test facility in Asia. A total of fourteen test equipments with the same models were identified. Seven out of the fourteen test equipments were grouped for diagnosis using the existing process shown in Fig. 1, while the other remaining seven test equipments will be diagnosed using the expert system database as shown in Fig. 2. Initial equipment diagnostics histories were entered to the expert system to establish the baselines. Technicians with roughly the same experience were used to manage each set of equipment.

Data was gathered for one quarter (13 weeks) and the results are shown in Figure 4. Each week, the average downtime for the seven test equipment was taken. The results showed a significant decrease in equipment downtime when the expert system database was used to aid the technician. It takes the technician a shorter time to diagnose and repair the problem. The 13-week average equipment downtime dropped from 4.6 hours to 2.4 hours.

It will be noted in Fig. 4 that between week6 and week10, the downtime using the expert system went up. Upon investigation, it was discovered the increase in the downtime was due to a new failure mechanism symptom encountered that did not yet exist in the expert database. The new cause for failure was determined and updated onto the system.

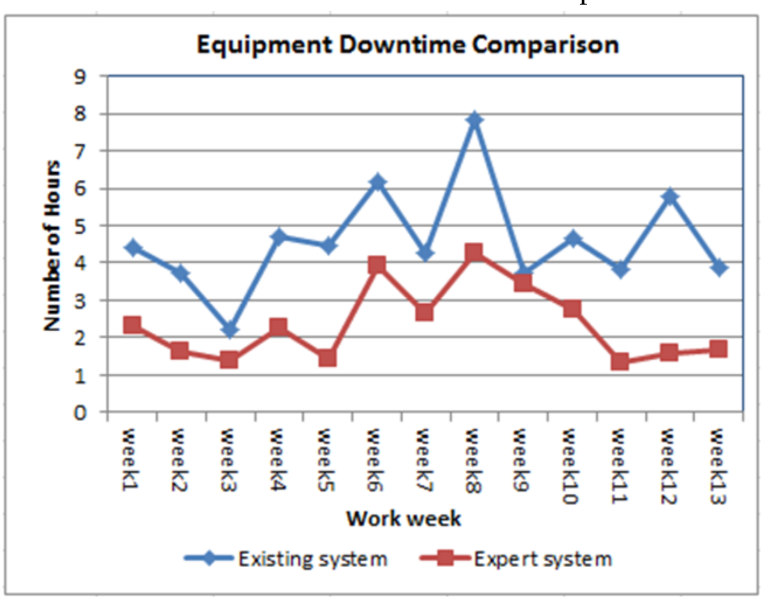

FIGURE 4. Equipment Downtime Comparison

5.3 Building Database as a Learning Process

In Fig. 5, the database may be managed in such a way that data grows through learning. The symptoms may be sorted in a descending order of frequency of occurrences while the causes sorted in decreasing length of time of fix. As continuous improvement is implemented, the longest and most frequent downtimes are eliminated. This input will shrink the active diagnostic data. Over time, as new discoveries accumulate and learning grows, then the active diagnostic data would expand accordingly.

VI. EXPERT SYSTEM DATABASE MANAGEMENT

The primary objective of an expert system is to provide quick solutions for old problems that occur repetitively in order to minimize manufacturing capacity losses. The reliability of the system depends on building up an expert system information database. In building up a useful database, several elements have to be considered.

<table>
<tr><td rowspan="2"></td><td colspan="5">CAUSES</td></tr>
<tr><td>Database Sorting</td><td>Long Period To Fix</td><td>Medium Period To Fix</td><td>Short Period To Fix</td><td>Unknown</td></tr>
<tr><td rowspan="4">SYMPTOMS</td><td>Most Frequent</td><td>Continuous Improvement</td><td colspan="3">This row for most frequent symptoms may be deleted once continuous improvement has eliminated their corresponding most frequent causes</td></tr>
<tr><td>Moderately Frequent</td><td rowspan="3">This column for longest period to fix causes may be deleted once continuous improvement has eliminated them.</td><td colspan="2" rowspan="2">This area is an active diagnostic data. It shrinks once continuous improvement eliminates long period and most frequent causes. It expands once new symptoms and causes are discovered by learning experience.</td><td rowspan="2">This column is the unknown causes data to be discovered by learning experience</td></tr>
<tr><td>Less Frequent</td></tr>
<tr><td>Unknown</td><td colspan="2">This row is the unknown symptoms data to be discovered by learning experience.</td><td>Learning</td></tr>
</table>

FIGURE 5. Managing Symptoms and Causes Database

First, the information must be highly reliable and secure. The contributed information and frequency of user log-ins could be used for performance evaluation. Analysis of data through personal observation by the users may provide information not only on the system but also about the thought processes of the individual user. Such information could be the basis for need analysis to be used for future training programs.

The reliability information may be derived from the statistics of failure occurrences. Such information could be the basis for the creation of continuous improvement program and the development of FMEA (Failure Mode Engineering Analysis) tables. FMEA is a commonly-used procedure in semiconductor manufacturing for product design and operations management for analysis of potential failure modes within a system for classification by the severity and likelihood of the failures. A successful FMEA activity helps a team to identify potential failure modes based on past experience with similar products or processes, enabling the team to design those failures out of the system with the minimum of effort and resource expenditure, thereby reducing development time and costs. It is widely used in manufacturing industries in various phases of the product life cycle. Failure modes are any errors or defects in a process, design, or item, especially those that affect the customer, and can be potential or actual. Effects analysis refers to studying the consequences of those failures (Langford 1995) (What is FMEA? 2006-2011). When the information in the database increases, diagnostics may now be segmented into categories such as: equipment, process, and continuous improvement.

The expert system based on set theory is appropriate for diagnostic applications since parameters are limited to known information. The accomplishment and growth of the expert system database is fully dependent on the diagnostic database administrator. The reliability of the database also depends on the sound management of information. The relational matrix must be truthful and accurate. The source of cause and effect relationships could be obtained from experience or observation, design model, and design of experiment. This relational matrix rests on good judgment of engineers and technicians.

From “(3)” and “(4)”, one can formulate the definitions of symptoms and causes. In particular, “(4)” requires unique set of symptoms. An algorithm may be required to check the uniqueness of each set of symptoms. For recognition purposes, the database may include authorship for the discovery of symptoms and causes, validation prescription, and diagnostic test. It may include the user’s log-in frequency and accommodate documentation of observation. Mobile handheld terminals may be used for easier access. Although expert system has grown more sophisticated in the past years, various opportunities in developing its inference engine are still open (Eom 1996).

VII. MANAGEMENT IMPLICATIONS

Company operations could not tolerate extended downtime of equipment. Each day that machines and equipment are non-functional would add to the production costs of the company. What most companies do to avoid a “stop production” situation is to purchase stand-by equipment for use just in case the main equipment breaks down. This is one way of ensuring that there will be minimal disruptions on the outputs. However, this practice puts a burden on capital expenditures and net income is weighed down because of the high depreciation expenses (Koh 2009).

Equipment breakdowns are inevitable but knowing how long it will take to repair it and put it back into running condition could ease the pressure on the management. Developing a system of digitizing the routine diagnostics of the equipment will definitely help in reducing the time for diagnosis. The determination of the problem is also standardized in a program or system. The proposed set theory embedded in the expert system will approach equipment problems in a systematic and standardized manner. This method eliminates the intervention of a human consultant not unless the problem is perceived to be a new one, thus reducing the dependence on human factors.

In terms of maintaining efficiency of operations, the system can easily diagnose failures based on the database created. This approach is very helpful in predicting the possible down time of equipment, provided that the symptoms exhibited during diagnostics is in the database. This information could be used for planning purposes and for drawing up contingency plans.

VIII. CONCLUSIONS AND RECOMMENDATIONS

It has been demonstrated that a set theory model can perform the deduction process in the derivation of causes from the given symptoms. When no conclusion is arrived at through the algorithm, it means the equipment problem has new and unknown causes. The algorithm works only within the domain of known set of causes and symptoms data.

Even if conclusions are arrived at, the algorithm can still detect unknown causes by noting whether all the symptoms have finally vanished and the suspected causes are fixed. Good in-depth analysis of failures and the speed with which it is accomplished requires an engineer with strong technical background and experience. Being able to accurately narrow down all the possible causes and pinpoint the actual failure source would take more time if the person handling the job is a non-experienced engineer. Companies would always lose the knowledge base acquired through years of experience whenever there is a movement of engineers. In order to minimize the impact of these talent losses, it is prudent to document their best-known methods and experiences and put this accumulated experience in a database. These documentations could be developed into several working algorithms that can be used by the new or incoming engineers. This method will also make it possible for management to streamline the operations and minimize dependency on the individual engineer's competence. Instead of wasting time and other valuable resources in trying to troubleshoot a certain failure, manufacturing staff may now start looking at the cost reduction opportunities in handling recurrent problems in terms of immediate solution delivery.

In the high-tech operations setting, all equipment are continuously improved to reduce manufacturing costs, thus companies are able to maintain their price-based competitive advantage. Properly managed, some investments in continuous improvement programs are able to pay itself back within one year (Koh 2009). One of the major reasons why most of these programs fail is that there were a number of poor assumptions made during the development of program. The proposed expert system database will aid in providing better data-based assumptions. Statistical data taken from the usage of the expert system can help the management team make decisions on which continuous improvement program to prioritize.

The development of expert system database could serve as venue for managers, engineers and technicians in their pursuit of career advancement and development in technical arena. Technicians could be trained to be more sensitive to detailed observations. The engineers' analytical skills are honed through multitudes of problem analysis. Thus, the manager's methods of validation are continuously challenged. Such venue creates an environment for knowledge production and knowledge workers to flourish.

Taking the risks to introduce the expert system should not be major concern for most companies. In fact, the introduction could effectively piggyback on the existing technology infrastructure of the company. Setting up the shared knowledge system will also not be too much of a problem since virtually every company has already set up shared databases.

The application of the set theory approach to the expert system is not a panacea but a tool to facilitate diagnostics of semiconductor equipment failures. This approach may be efficient but has its limitations. Future research can be done on overcoming these limitations. It may be worthwhile to examine the integration of the expert system with other technologies in the future and explore how these can be adapted in the operations environment.

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