A Study on Constructing Aircraft Maintenance Diagnosis System to Quality Related Customer Complaints

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ABSTRACT

Owing to the difficulties, complexity and personnel turnover, the airplane maintenance industry has faced insufficient ability to maintain a good level of airplane readiness. Therefore, this study intends to develop a quality diagnosis system for airplane maintenance industry. This diagnosis system first utilizes the self-organizing map (SOM) neural networks for clustering data based on CAFM 0020 form from the selected aircraft maintenance station. A CAFM 0020 documents all the corrective actions and defects. Subsequently, for each SOM group, decision tree is utilized to determine rules. It is evident that SOM grouped results are superior to ungrouped ones in terms of overall accuracy and coverage. Since the diagnostic rule is more detailed, it fosters the problem judgment time and reduces the cost for repetitive personnel training.

Keywords: data mining, CAFM 0020, SOM, decision tree analysis, quality diagnosis system

建構飛機維修客訴品質問題診斷之研究

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摘　要

飛機維修行業由於困難性、複雜性和人員流動面臨到維持良好飛機準備水平的能力不足，因此，本研究旨在為飛機維修行業開發一種質量診斷系統，該診斷系統首先利用 SOM 神經網絡對來自所選飛機維修站的 CAFM 0020 表格的數據進行聚類；CAFM 0020 記錄了所有糾正措施和缺陷，隨後對於每個 SOM 組以決策樹模型確定規則，顯然，就整體準確性和覆蓋範圍而言，SOM 分組結果優於未分組結果，藉由診斷規則更加詳細，可以縮短問題的判斷時間並減少重複人員培訓的成本。

關鍵詞：數據挖掘，CAFM 0020，自組織圖 (SOM)，決策數分析，質量診斷系統

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I. INTRODUCTION

In recent years, information technology has been successfully introduced to Air Force logistics and maintenance operations, such as Depot Maintenance Management System (DMMS), Depot Supply Management System (DSMS), and Maintenance and Repair System (MRS). However there was not an effective management system for Air Force to analyze the past data of "Weapon and Equipment Repair Compatibility Form (CAFM 0020)", and whenever the end user reflects the defects, it takes time to investigate the cause.

This study intends to determine the characteristics of defects and corresponding countermeasures, so that quality problems can be quickly diagnosed and responded, and to provide maintenance professionals with an improvement reference. Therefore, data mining technology is used and the study takes an aircraft repair station of the Air Force for example to investigate certain aircraft that completes maintenance. The contents of defects are extracted from customer complaint record in CAFM 0020 from past years, and grouped via self-organizing map (SOM), followed by decision tree analysis on cause induction and diagnosis. Finally, a countermeasure database will be constructed for the cause of each incident based on the diagnostic results.

II. LITERATURE REVIEWS

Data Mining is defined as obtaining meaningful information from the database and summarizing information to a structured mode, and serving as references when making decisions [1]. The use of mining tools can extract valuable information from huge data, and discovers beneficial information required by the industry quickly and accurately [2].

There are five steps of data mining including Data Manipulation, Define a Study, Reading the Data and Building a Model, Understanding the Model, and Prediction [3]. Most data mining functions include six types of tasks, which are the category, conjecture, prediction, association grouping, clustering, and description [4]. The method used in this study is the self-organizing maps and decision tree analysis. Both do not need basic assumptions, and have the ability to process and analyze large amounts of data. The two algorithms are described as follows:

2.1 Self-Organizing Map (SOM)

SOM perceives each piece of data has a considerable number of attributes, if certain data have similarities in n-dimensional space, there should also be similarities when converted to two-dimensional space [5]. The SOM network firstly sets various parameters, followed by entering the field factor of the customer complaint data as the training example value of the network. The SOM starts to calculate the distance between the input vector of the quality problem and output layer of processing unit. The closer the distance, the higher the similarity.

After calculating the distances between all output layer processing units and training examples of customer complaints, the shortest distance is selected, and the most representative quality-related problem in this group is the winning unit. The SOM adjusts the connection weights of all input layer and output layer processing units, and the degree of adjustment is fixed according to the proximity distance of the processing unit from the winning unit (near the center). The greater the proximity distance, the smaller the proximity coefficient, and the smaller the adjustment of the weight. When all the training examples of customer complaint materials are learned once in sequence, it is called a learning cycle, and for a learning cycle, the neighboring radius will be reduced once, the learning rate will be reduced once, and the learning will be repeated until the weights are steady. After the clustering study of customer complaint data is completed, the testing quality-related problem data is to be entered to determine which clustering problem the new customer complaint problem is similar to, and the associated set generated by the clustering problem is extracted as the final decision.

2.2 Decision Tree

Decision tree is to express classification results, and the inductions trees are easily interpreted. In the dendrogram calculation results of the decision tree. Each internal node represents a test on an attribute, each branch represents a result of a test, and each leaf node holds a class label [6]. When establishing a decision tree, a piece of data is entered from the root and then a test is used to choose which child node to enter the next layer. Although the test has different algorithms, the common objective of is to reduce the disorder in the child nodes. This process is repeated until the data reaches the leaf node. All the data that reaches a certain decision leaf section are classified in the same way, and there is a unique path from the root to each leaf section called classification rule.

The decision tree algorithm ID3 and C4.5 are developed from [7], and the C4.5 is an advanced improvement of ID3, which utilizes top-down recursive divide and conquer approach to construct decision trees. Information gain is used to select best attributes as tree nodes, and the attribute with maximum information profit is the segmentation condition for this node. This step is repeated until the clutter of the data cannot be effectively reduced. When developing C4.5 algorithm, it is proposed to use gain measure ratio as a selection criterion to measure the properties of the effect to mitigate excessive sub-tree.

A "fully-grown tree" usually cannot be directly used as a classification rule; the main reason is the training data may contain noise or outliers which lead to abnormality or error, so prune actions must be taken to make the decision tree more realistic. The standard of C4.5 tree pruning algorithm mentioned in [8] is based on the predicated error rate as judgment conditions. The method is testing subtree formed by each node from the bottom (the leaf nodes). If the subtree is replaced with a leaf node, whose predicted error rate is below the original subtree, modify subtree to leaf node. Based on the majority voting principle, the class with most original subtrees will be replaced with the class of new leaf nodes.

III. RESEARCH METHODS

The proposed method includes problem definition, data preparation, establishing exploration mode, result analysis and evaluation and building a response database.

3.1 Problem Definition

Currently there isn't an effective system to formulate CAFM 0020 record in Air Force, resulting in wasting of time and money on searching and reviewing the problems. In addition, due to complicated data types and problems, the cause of the abnormality cannot be found quickly. The problem to be solved in this study is to induce the reasons for the quality problems raised by the end users.

3.2 Data Preparation

The process does not turn entire contents of data into analysis mode. Firstly the conversion must be done. In order to ensure the correctness of the performance and results of data analysis, 3 preparatory actions will be done respectively including attribute definitions and data compilation, data clearing, and data conversion.

3.2.1 Attribute Definition and Data Compilation

The attributes of quality-related customer complaints can be divided into 4 categories, which are Man, Machine, Material and Method, known as 4M. The corresponding data of the reference characteristic factor mode under the four attributes are recorded as "no error occurred" or "error situation / repair process". If the attribute variable is "no error occurred", it is counted as 0, and numbers are arranged in order.

This study collected a total of 346 data from January 2006 to December 2008, and integrated to 40 types of quality problems. The variable numbers to 4 attributes are: 47 Man, 45 Machine, 41 Material, and 25 Method variables. The numbering is shown in Table 1.

Table 1. Attribute variables and judgment items

Vari-able	Man	Machine	Material	Method	Judgments
0	none	none	none	None	-
1	Nuts not tightened / General inspection	Screw hole reaming / cover removal	Defective nut /parts assembly	Improper opening & closing /test in plant	Loose cover
2	Excessive l ubrication /	Aging Reaming /	Wear and tear / parts	Improper activation /	Loose parts

	lubrication	Parts Assembly	removal	test in plant	
3	Seal not removed / degum	Glue Failure / Flight Test	Rubber Hardening / GI	Insufficient sealing / seal test	Poor sealing
4	Leak test not confirmed/ inspection	Poor seating / pipe test	B-cap wear / pipe removal	Pipeline not restored / pipeline assembly	Hydraulic oil Leak
5	Leak test not confirmed / GI	Poor connection / pipe test	B-cap wear / pipe removal	Pipeline not restored / assembly	Lub. oil leakage
6	Leak test not confirmed / inspection	Poor apron / pipe test	Pipe wear / pipe removal	Wrong tool / pipeline assembly	Fuel leakage
7	Undetected / Quality Assurance	Poor quality / parts assembly	Wear & tear / parts test	Improper test / test in plant	Mechanic failure
8	Inspection Missed / Quality Assurance	Block failure / accessory disassembly	Aging / Accessories assembly	Low parameters / accessory test	Damaged accessories
9	Incorrect tools / parts installed	Poor Quality / Part Test	Frequent wear / parts removal	Excessive exertion / test in plant	Part stripped
10	Uninsured / General Inspection	No safety hole / assembly	Loose insurance / Insurance	Wrong method/ test in plant	Poor insurance
11	No anti-slip / anti-slip	Non-slip off / general inspection	Positioning not planned / parts test	Unnamed positioning / test	Poor anti-slippery
12	Not tightened / parts tested	Insufficient angle adjust /inspection	Defective tools / parts assembly	Items not listed / test in plant	Improper parts installation
13	No rust treatment / general inspection	Insufficient coating / rust treatment	Effects of temperature and humidity / trial	Procedural error / trial	Parts rust corrosion
14	damaged / Assembly	Poor gelling / sealing	Inadequate forming / trial	lamination poor/ test in plant	De-lamination
15	Not tightened / trial	close tube angle / pipe installation	Insufficient clearance / adjust	Unclear standards / test in plant	Pipes Interfere
16	Insufficient lubrication / general inspection	Not lubricated /lubrication	Poor lubrication / parts test	Lub. not wiped up / trial	Parts too tight and stuck
17	Undetected / Quality Assurance	Wear & tear / machinery	Stress damage / parts removal	Improper operation / test in plant	Cracked parts

18	Incorrect inspection / General inspection	coating scratch / wire removal	Aging crack / line test	wrong procedure / test in plant	Pipes collide
19	Improper operation / General inspection	Frequent disassembly /pipe installation	Loose parts / pipe test	Wrong model# /pipeline removal	Poor pipe connection
20	Not checked / QA	Obsolete/ parts assembly	Model difference / parts test	Non-compliant / test	Wrong part model
21	Installation not monitored / QA	block failure / accessory assembly	Poor contact / test	Wrong procedures / accessory test	Cockpit instrument mal-function
22	Removal not inspected/ inspection	Spring failure / part test	Frequent disassembly / assembly	Improper use / parts removal	Poor safety pin
23	Poor wrapping/ general inspection	Wrapping ripped / wiring	Interference with mechanism/ trial	Cable harness too long / test in plant	Poor harness
24	Circuit Breakage / General Inspection	Bulb burnout / part test	Lamp not tighten / accessory assembly	Broken fuse / test	Control panel light mal-function
25	Not checked / GI	Paint not fully removed / removal	Cleaning not thorough / cleaning		Paint residue
26	Incorrect rust inspect/ QA	Corrosion untreated / finishing	corrosion not obvious/test in plant		Structural corrosion
27	Poor connection / fly test	Improper disassembly / installation	Pipe aging / piping test		Broken oxygen hose
28	Missing spray / inspection	Spraying distance /painting	Paint peeling / fly test		Poor paint job
29	Missed cabling / GI	Signal line breakage / cabling test	Poor contact / wire assembly	-	Poor trans-mitting/ receiving
30	Moisture proof fail/ parts removal	Humid climate / trial	Replacement not proper / parts assembly	-	Moisture-proof sand defect
31	Not checked / GI	Missing dust cover / parts removal	No connectors/ PA	-	Poor dust protection
32	Friction with parts / inspection	Insufficient pounds / NDI	Poor quality / parts assembly	-	Steel rope peeling
33	Poor visual inspection/	Paint dust adhesion /	Not found /		Parts not clean

	trial	cleaning	cleaning		
34	Incomplete Inspection / General Inspection	Original machine not installed / test in plant	Missing parts / Parts assembly	-	Missing part
35	Improper tools/ GA	Improper operation/ PA	Poor Quality / Parts test	-	Parts deform
36	Incorrect inspection / ENG inspection	Original equipment failure / ENG test	poor maintenance /ENG test	-	ENG parts failure
37	Wrong labeling / GI	Unlabeled / labeling	Poor material / fly test	-	Poor labeling
38	Not adjusted / capped	Flight Vibration / Flight Test	Poor adjustment / pipe test	-	Pipeline interfere
39	Not found/ ENG main -tenance	Oil leakage / ENG test run	Parts wear / ENG inspection	-	ENG Oil leak
40	Installation not tight / QA	Flight Vibration / Flight Test	Poor seating / parts assembly	-	Parts leaking oil
41	Unfound / General Inspection	Defective clip / assembly	-	-	-
42	Clearance not adjust / clearance	Wrapping touching pipeline /GI	-	-	-
43	Degum poor/test	Sealing off / sealing	-	-	-
44	Improper operation / assembly	Loose steel rope / parts testing			
45	Improper assembly/ PA				
46	Poor wrap/ cabling				

3.2.2 Data Cleaning

The variable "none" means no possible causes for the attribute, and is marked as 0, during data mining, the variables are still taken into account, but if more than 3 out of 4 attributes are 0, the data will be deleted. After a series of data screening, cleaning and filtering, a total of 312 empirical data are used.

3.2.3 Data Conversion

The data is converted into the format required based on the characteristics. The repair part of the “error condition / repair process” is used to correspond to the belonging workstation. The workstation is numbered, and the 4 attributes of each data are brought in to perform cluster analysis.

3.3 Building Mining Model

Firstly, SOM is used for multi-variant cluster analysis, it is anticipated that desirable clusters, definition and explanation generated could be used as the pre-operation of the decision tree analysis. It is also desired that SOM would be used to enter variables to the workstations based on customer attributes, and then generate clusters via SOM network learning. The study will analyze the clustering data similar to the workstation. The neural network-like software tool used in the research is Neural Works. It is a complete neural network-like construction environment produced by Neural Ware. The software only requires setting the data source, defining the variables, the learning rate and other parameters. After calculation, the learning process will gradually converge to a stable state to obtain the final cluster results, and then repeat the experiment to get the best cluster efficiency used as the target variable for the decision tree analysis.

For clusters established, decision tree will classify the data according to the target variables and present the classification in a tree structure. The decision tree tool used in this study is See5 produced by RuleQuest, which is in accordance with the traditional C4.5 data mining tools. It is expected the main cause to be diagnosed and understood by See5.

3.4 Analysis and Evaluation of Results

The results are summarized and discusses with domain experts to interpret the appropriate reasons and meanings. Verification is conducted to determine whether results are reasonable and recommendation is provided for improvement. For the evaluation of the classification decision tree, the ten-fold cross validation mode (10-fold) in [8] is used. The ten-fold cross validation square law divides data into ten groups (Subset), each subset forms a fold data group with the other nine subsets. Each fold data group contains nine training groups and a test group. Each test group is generated through a decision tree to predict the result. The process is repeated 10 times, and the average error rate of 10 folds is treated as the evaluation index. This study uses a cross-validation framework for decision tree evaluation. At the end of the study, all collected data is analyzed using this framework, and an accuracy scale is established to evaluate the validity of the classification.

3.5 Building a Response Database

Finally, the results from data mining are discussed with field experts to construct the relative response countermeasure database. The method of construction is the use of customer complaints reflected in the CAFM 0020 to conceive responding approach. In addition, professional judgment may be combined to modify more accurate solutions to make the database more effective in solving problems.

IV. CASE ANALYSIS

The case study is based on an empirical analysis of actual quality problems in the aircraft maintenance station of the Air Force. It is hoped that the knowledge can be used to diagnose the cause of the abnormality from the end user complaints. The goal is to achieve accurate diagnosis and rapid responding to end user. The final diagnosis results can be further established as a countermeasures database, so as to avoid repeated learning, redundant time consuming and extra costs. When the aircraft enters a repair facility, it follows sequential stations to execute each stage of repair, as in Fig. 1.

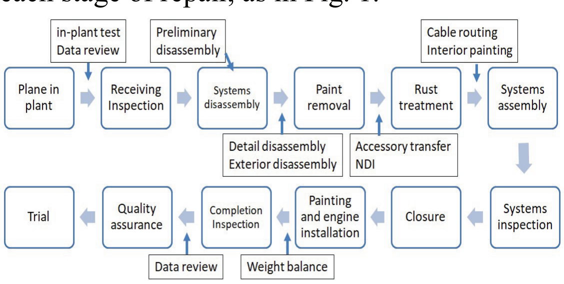

Fig.1. The detail process of aircraft maintenance

The research method for this study included 5 steps which are SOM cluster analysis, See5 decision tree analysis of customer complaints, classification of the analysis, incorporating field experts' opinions for future improvement, and complete quality problem diagnosis. The research process to diagnose customer complaints is elaborated in the followings.

4.1 SOM Cluster Analysis

Firstly the 312 repair jobs are compiled into workstation numbering shown in Table 2.

Table 2. Workstation numbering

No	Workstation	Repair jobs(attribute variable)
0	none	Attribute variable "none"
1	Receiving	Test in plant, ENG inspection
2	Dis-assembly	Cover, accessories, parts, parts, pipelines, and wires removal
3	Paint off	Paint off, degum, clean, NDI
4	Final repair	Corrosion treatment, structural repair, wiring harness
5	Assembly	parts, pipeline, circuit, clearance adjustment, safety pin, lubrication, anti-slippery, sealing
6	Test	Accessories, equipment, parts, pipeline, circuit, seal test
7	Closure	Capping , cleaning, painting, labeling, ENG maintenance
8	ENG install	ENG assembly, ENG trial
9	Quality Assurance	General inspection, quality assurance, acceptance test
10	Test Flight	Fly trial

The attribute variables are converted to workstation record. Take one aircraft completed maintenance for example, the CAFM 0020 reflected by end user are converted to a table as in Table 3.

Table 3. Workstation cluster analysis – take CAFM 0020 for one aircraft as an example

No	Man	Machine	Material	Method	Problem type
1	Circuit break / GI Station 9	Block fail / assembly/ station 5	Poor contact/ test / Station 9	None 0	accessories damaged
2	Excess seal not removed seal removal/Station 9	Poor gelling/ sealing /station 5	Rubber Hardening /Inspection/ station 9	Poor adhesive / test/ station 1	accessories delamina-tion
3	Incorrect rust inspection /QA/ Station 9	None 0	Corrosion not clear/ test/station	Wrong Procedure/ test/station	Parts rust corrosion

			1	1	
4	Not tightened/ parts test/ station 6	Spring failure / part test/ station 6	defect nut/ assembly /station5	None 0	Loose cover
5	None 0	Sealing off / sealing / station 5	Poor forming /Trial/ station 9	Poor seal / seal test/ station 6	Poor sealing
6	Circuit Break/ General Inspection/ Station 9	Block fail / accessory assembly/ station 2	Ageing / Parts station 5	Low settings / test/ station 6	Cockpit instrument mal-function
7	Nuts not tight/general inspection/ Station 9	Body fail/ accessary disassembly/ station2	None 0	Improper operate / test /station1	Loose cover
8	Disassembly without inspection/ inspection/ Station 9	Improper operation / parts assembly/ station 5	Model difference / part test station 6	Improper use /parts removal station2	Improper parts installation

After converting CAFM 0020, the data clustering was performed by using 2D network topology. The parameter is set as the values listed in Table 4. In this case, 4 variables including Man, Machine, Material, and Method are defined, and learning times are set at 300 to determine the stable condition of learning times. The network topology matrix is defined as 5 * 2 since there are 5 input vectors, which are Man, Machine, Material, Method, and Problem Type and 2D topology is used. The initial neighborhood size is set at 7 since there are 8 clusters and final adjacent size is set at 1. The initial rate and initial neighborhood size are randomly picked numbers and commonly set as the values shown in Table 4.

Table 4. 2D SOM network parameter settings

Parameter name	Parameter value
Number of input units	4
Learning times	300 times
Network topology matrix	5 * 2
Initial learning rate	0.1
Initial network weight	-0.01 ~ 0.01
Initial neighborhood size	7
Final adjacent area size	1

Fig. 2 shows the SOM learning convergence. The steady state is determined by the total distance, which is calculated to judge the convergence. When learning number reach over 200, the variation will be stable.

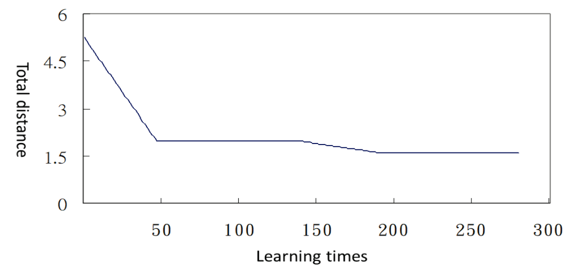

Fig.2. SOM convergence

A total of 63 data was generated in the first group, whereas Man attribute mainly clusters in quality control station, Method attribute cluster in receiving station, and other attributes generally cluster in disassembly, paint off, and final repair processes. A total of 101 data was in the second group, whereas Machine and Material attributes mostly cluster in assembly and test stations, Method attribute cluster in receiving station, and Man attribute cluster in quality control station. The third group obtained a total of 148 data. The 4 attributes mainly cluster in closure, engine installation, quality control and test flight stations, while Method attribute is still affected by receiving station.

4.2 Classification of Decision Tree

For decision tree analysis, quality problems will be target variables and the attribute (man, machine, material, and method) of each quality problem will be used for decision tree analysis. In this study, classification is done by the programing tool See5, which compiled data of the 3 groups clustered by SOM. The final result will be present in text form “IF…THEN”.

Firstly, for 63 data from the first group, 25 rules were obtained as in Fig. 3. The number on the left in the brackets is the number of examples (the number appears n/x, n represents the total number of examples, x is the number of misjudgments), and the number on the right is the probability of occurrence. If there is only one quality problem in each group, it will be deleted. One data does not represent the problem. After analysis, the Man attribute is considered to be utmost important in the first group, while the attributes of Method, Machine, and Material are considered to be of secondary importance.

Therefore, the Man attribute is used as the starting branch nodes of the tree. The average error rate by ten-fold cross validation is 7. 5 %.

1.IF man = improper operation / general inspection THEN judgment = loose cover (4, 0.833)
2.IF man = not tightened / tested THEN judgment = loose parts (4, 0.833)
3.IF man = unaware / quality assurance THEN judgment = loose parts (1,0.677)
4.IF machine = poor connection / piping test AND man = connection not tight / quality assurance THEN judgment = leak hydraulic oil (5 / 1,0.714)
5.IF method= pipeline not restored/pipeline installed THEN judgment = hydraulic oil leak (2, 0.750)
6.IF material = mechanical loss / ENG test THEN judgment = leakage oil (4, 0.833)
7.IF machine = durable wear / mechanical machine THEN judgment = mechanism failure (2,0.750)
8.IF man = unfulfilled inspection /general inspection THEN judgment = poor insurance (3, 0.800)
9.IF man = visually unscheduled / test THEN judgment = poor slip resistance (2, 0.750)
10.IF method = pressed job program / feed sample THEN Analyzing = improper component (4,0.833)
11.IF man = disassembly without inspection/GI THEN judgment= improper parts /device (1,0.677)
12.IF man = incorrect rust inspection/QA THEN judgment = rust corrosion of parts (3, 0.800)
13.IF material = long-term aging / attachment THEN judgment = broken line (2, 0.750)
14.IF method = Excessive force/test AND material = frequent wear/part removal THEN judgment = poor safety pin (3, 0.800)
15.IF man = dressing failure / line Complete THEN Analyzing = Defective harness (2,0.750)
16.IF man = not inspected /general inspection THEN judgment = residual paint not removed (2, 0.750)
17.IF method = program error / test THEN judgment = structural corrosion (2, 0.750)
18.IF machine = steel rope loosening / attachment test THEN judgment = steel rope fluff (3 / 1,0.600)
19.IF machine = poor quality / attachment THEN judgment = defective parts (2, 0.750)
20.IF man = not proofreading / quality assurance THEN judgment = missing parts (2, 0.750)
21.IF material = Bad tool / Part THEN judgment = Part deformation (2,0.750)
22.IF machine = near-pipe angle / pipeline mounted AND machine = flight vibration / flight test THEN judgment = pipeline interference (3, 0.800)
23.IF method = no activating / test THEN judgment = Pipe interference (1,0.667)
24.IF method = pipeline not restored/ pipeline install THEN judgment = ENG oil leakage (1,0.667)
25.IF man = improper inspection / ENG detection THEN judgment = ENG oil leakage (1,0.667)

Fig.3. Data mining rules in first group

The decision tree analysis was done on the 101 data in the second cluster, 24 diagnostic rules were summed, and two important attributes are Machine and Material, while secondary attribute is Method. Problems of Machine, Material and Method can also be found by the rules obtained as in Fig. 4. The average error rate by 10-fold cross validation is 6.7 %.

1.IF machine = spring failure / part testing AND man = not tightened / part testing THEN judgment = loose cover (3,0.800)
2.IF machine = improper operation / part test THEN judgment = loose cover (4, 0.833)
3.IF machine = aging reaming / components THEN judgment = loose parts (6, 0.875)
4.IF material = frequent wear AND man = unfound/ QA THEN Analyzing = loose parts (6 / 1,0.750)
5.IF material = Insufficient forming / THEN judgment test = Poor sealant of machine (2,0.750)
6.IF machine = bulk failure / attachment means THEN Analyzing = accessory damage (7,0.899)
7.IF material = poor contact / circuit installation THEN judgment = accessory damage (7, 0.899)
8.IF method = low parameter / attachment test THEN judgment = attachment damage (1,0.667)
9.IF material = Frequent disassembly / components THEN judgment = Smooth parts (5,0.857)
10.IF material = Insufficient adjustment / AND man on the pipeline side = Not adjusted / capped THEN judgment = pipelines collide (6, 0.875)
11.IF material=poor lubricate/mechanical test THEN judgment = machine too tight/ jammed (3, 0.800)
12.IF machine = durable wear / machine THEN judgment = mechanical crack (2,0.750)
13.IF machine = poor seating / piping test AND man = improper connection / parts installation THEN judgment = poor pipe connection (7/2, 0.667)
14.IF machine = poor joint / pipeline test THEN judgment = poor pipeline connection (2, 0.750)
15.IF method=not compliant/test AND man=no check /QA THEN Analyzing=part# not match (2,0.750)
16.IF material = aging / attachment THEN judgment = malfunction of cabin instrumentation (6, 0.875)
17.IF material = poor quality / Part test AND method = excessive force /test THEN Analyzing = poor safety pin (9 / 3,0.636)
18.IF material = frequent wear / part removal THEN judgment = poor safety guard pin (3, 0.800)
19.IF material = poor contact / circuit installation THEN judgment = control panel light off (2, 0.750)
20.IF machine = body failure / attachment removal THEN judgment = bad reporting (8, 0.900)
21.IF material = bad contact of the connector / test THEN judgment = bad reporting (2, 0.750)
22.IF machine = humid climate / out again THEN Analyzing = damp sand moisture (5,0.857)

23.IF machine = paint dust adhesion / cleaning THEN judgment = poor dust prevention (2, 0.750)
24.IF machine = Poor apron / pipe test THEN judgment = mechanical oil leakage (3,0.800)

Fig.4. Data mining rules in second group

Finally, 148 data from the third group is analyzed, and 37 diagnostic rules are induced. The order of important attributes extracted by the decision tree is Machine, Material, Man and Method. The rules obtained are as shown as Fig. 5. The average error rate is 10 % by 10-fold cross validation.

1.IF machine = seals off / sealant AND method = delamination not obvious / test THEN Analyzing = mechanical failure sealant (5,0.857)
2.IF material = poor seating / machine THEN judgment = fuel leakage (3 / 1,0.600)
3.IF man = not noticed / quality assurance THEN judgment = mechanism failure (4,0.833)
4.IF machine = durable wear / machine THEN judgment = mechanism failure (2,0.750)
5.IF material = bad contact of the connector / test THEN judgment = damaged accessory (6, 0.875)
6.IF machine=body failure/parts AND method = low parameter/ test judgment =part damage (9/2, 0.727)
7.IF man = line break / general inspection THEN judgment = damaged accessories (3, 0.800)
8.IF man = improper tools / general inspection THEN judgment = parts sliding teeth (3, 0.800)
9.IF material = pin / safety AND man = unfulfilled inspection / general inspection THEN judgment = bad insurance (4, 0.833)
10.IF machine = not marked / marked with THEN judgment = poor slip resistance (2,0.750)
11.IF material = model difference / part test THEN judgment = improper part machine (7/2, 0.667)
12.IF method = improper use / parts removal THEN judgment = improper parts installation (9, 0.909)
13.IF machine = rust untreated / repaired THEN judgment = rust corrosion of parts (5, 0.857)
14.IF machine = poor gelation / sealing AND machine = sealing off / sealing THEN judgment = machine delamination (5,0.857)
15.IF machine = flight vibration / flight test AND material = interference with mechanism / test THEN judgment = collision of pipeline (7, 0.899)
16.IF machine = wrapped bandage / whole line THEN judgment = broken line (2,0.750)
17.IF method=pipeline not restored/installation THEN judgment = poor connection (3, 0.800)
18.IF method=low parameter/accessory testing AND machine=body failure/removal THEN judgment = malfunction of cabin instrumentation (7, 0.899)
19.IF man = line disconnection / GI THEN judgment = malfunction of cabin instruments (1,0.667)
20.IF machine = poor operation / parts installed THEN judgment = poor safety guard pin (3, 0.800)
21.IF man = Incorrect inspection / inspection THEN judgment = Poor wiring harness (5, 0.857)
22.IF material = pipe wear / pipe removal THEN judgment = broken oxygen hose (5, 0.857)
23.IF man = poor installation / flight test THEN judgment = broken oxygen hose (1,0.667)
24.IF machine = paint not returned / painted THEN judgment = poor finish (5, 0.857)
25.IF man = installation is not monitored /QA THEN judgment=bad reporting (3, 0.800)
26.IF material = temperature / humidity / THEN judgment = moisture-proof sand (4, 0.833)
27.IF material = proper replacement / installation THEN judgment = moisture proof sand (1,0.667)
28.IF staff = visually unscheduled / test THEN judgment = poor dust resistance (2, 0.750)
29.IF material = harness without plug / parts assembly AND Material = unfound / cleaned THEN Analyzing = parts dirty (5,0.857)
30.IF material = Machining wear / ENG test THEN judgment = ENG machine failure (3,0.800)
31.IF man = not checked / ENG maintenance THEN judgment = ENG parts failure (2, 0.750)
32.IF material = paint peeling off / fly test THEN judgment = bad mark (5/2, 0.571)
33.IF method = standard undecided / test THEN judgment = bad mark (2, 0.750)
34.IF man = gap unadjusted / gap THEN judgment = pipeline interference (6, 0.875)
35.IF machine = original failure / ENG test THEN judgment = ENG oil leakage (5, 0.857)
36.IF machine = improper disassembly/pipe install THEN judgment=parts leak oil (9/3, 0.636)
37.IF method =wronly installed parts/pipeline THEN judgment = parts leak oil (1,0.667)

Fig.5. Data mining rules in third group

The above 3 groups are authenticated to obtain the average error rate of each group, the overall average error rate is calculated as 8.066 %, the rule numbers from each group adds up to be 86. Thereby differences appeared between grouped and ungrouped. It also means that the decision tree classification analysis followed by clustering has a lower error rate than direct analysis, and the generated rules are also more thorough and detailed, as shown in Table 5.

Table 5. Comparison of results between grouped and ungrouped

method / item	grouped	ungrouped

total average error rate	8.066%	27.3%
patterns generated	86	58

Lastly, the reasoning of the decision tree is analyzed, and the quality problems recorded in CAFM 0020 from the end user is used to define and construct a database of countermeasures corresponding to the individual quality problems, together with the professional knowledge by field experts, to revise implementation rules and solutions. The result is used as a reference for future improvement.

This study takes loose cover and damaged parts for examples to construct countermeasure database, as shown in Table 6 and Table 7.

Table 6. Example of "loose cover" and countermeasure database

Reason	Countermeasures
1.Frequent disassembling cover seating and mounts during assembly caused reaming, wearing and loosening.	When restoring surface, check conditions of cover screws. If damage or reaming, replace and restore immediately.
2.Machenics did not press the gasket in securing clip cap, or flatten and tighten the cotter pin, resulting in loose cover.	At completion stage, mechanics should check condition, and a double check should be done by senior worker.
3.When locking cover, improper operating/ tools resulted in stop spring failure or spring clasp malfunction, generating loose cover.	The maintenance technical training should be done every month to strengthen the skills and inspection mechanism to avoid errors.
4.When installing covers, gasket sealant squeezed into torx seating cause gasket failure and unable to fix screws.	Enhance inspection of the cover screw seat before trial. If similar conditions found or gasket damaged, replace immediately.
5.High vibration generated when deploying landing gears. Frequent operations caused the rivet malfunction.	The cover plate and rivets in high vibration area be inspected thoroughly. If concerning about loose rivet, replace a new one.

Table 7. Example of "damaged parts" and countermeasures database

reason	countermeasure
1. The aging and poor quality of accessories resulted in abnormality, non-functioning, abnormal sounds or noises.	Enhance worker and inspector's ability to predict reliability. If abnormality found, refer to MTBF value and repeat inspection
2. Due to the low setting of test parameters when the aircraft is in the factory for testing on the professional bench, resulting in an adverse effect after the flight.	Electrician is required to conduct power-on test and set parameters according to the technical manual. If malfunction found, immediately replace a new one
3. Frequent assembly/ disassembly of the switches or internal circuit causing elastic fatigue, poor connector, or disconnection	During inspection and acceptance test, strengthen functional test, and check the connection of parts to avoid affecting quality.
4. During installation test, due to insufficient inspection methods, no improper conditions found in time, no new parts replaced.	Specialization training to enhance testing skills, and to improve inspection level to reduce occurrence of human negligence.

The approach is used to construct a thorough diagnosis system for the 40 quality-related customer complaints to help staff deal with future similar problems, thus reducing possibility of misjudgment and effectively responding to end users. The knowledge can be archived to reduce repeated learning.

V. CONCLUSIONS AND RECOMMENDATIONS

In this study, firstly data was grouped via SOM neural network, followed by the decision tree classification, after which the error rate is 8.066%. It reduced 19.23% from ungrouped error rate of 27.3 %.

According to the diagnosis results of this study case, the abnormity is mainly due to Machine, Material and Man attributes. It shows that the skills of machine operation control and material assembly still need to be strengthened. In addition, the Man attribute shows room for improvement on the inspection mechanism and strictness of online workers and QA personnel.

The specific effects of handling quality-related customer complaints are as follows:

(1) Effectively summarizing the causes of abnormalities in its repair process. The actual average error rate and the results of class verification are sufficient to show that the rules concluded are effective.

(2) It helps quality-problem handlers reduce

time and scope diagnosing the incident, define the cause quickly and respond to end users, and handle damaged parts in a timely manner.

(3) It archives the previously analyzed knowledge, so that it is no longer affected by personnel shifting. It enables new successors to utilize knowledge, reduces repeated learning, and assists maintenance and quality inspection personnel in the station.

It is suggested future study focus on the association rule, utilize CAFM 0020, and collect relevant data for analysis, in order to determine which combination of abnormal factors during repair process will result in defects. It is also suggested that visual data can be used to enter the expert system, so that diagnostic personnel can accurately determine the causes, in order to take more appropriate preventive and corrective measures. Finally, there are many data mining methods and algorithms. The application of data mining technology is based on SOM neural network and decision tree analysis. It is suggested that follow-up researchers can conduct more in-depth research on other mining technologies and attributes.

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