

Equipment Fault Prognosis Based on Temporal Association Rules

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Abstract

Equipment fault prognosis is important for reliability, operational safety, and efficient performance of equipment. Temporal fault data model is built according to the principles of the Apriori traditional association rules algorithm based on the characteristics of fault data. An Improved Apriori algorithm and frequent temporal association rules algorithm are proposed in this study by converting fault data to temporal item sets matrix. Equipment fault trends are predicted by mining the frequent temporal association rules of fault data based on the algorithm, which provides good support for equipment maintenance and management. At last an example is given to prove the feasibility and practical application of proposed algorithms.

Keywords: fault prognosis, temporal association rules, apriori algorithm, data mining, frequent Item sets

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1. Introduction

Mechanical equipment is becoming large-scale, complex, precision and multifunctional increasingly with advances in technology and manufacturing methods. For safe and reliable operation of such equipment its maintenance is critical and essential. Equipment maintenance mode was initially practiced as run-to-failure maintenance incipiently. Slowly it developed as time-based preventive maintenance and gradually transformed to condition-based maintenance [1]. The equipment fault prognosis was problematic in condition-based maintenance. The research on equipment fault prognosis advanced in recent years. A Duration-Dependent Hidden Semi-Markov Model was proposed by Wangning et al. which was using for the problem of equipment operational state identification and equipment fault prognosis [2]. The probability theory and Support Vector Machine were used by Caesarendra et al. through emulational and experimental fault data to forecast the attenuation process of equipment fault [3]. A fault prognosis method was developed by Tran VT et al. based on Regression Trees and time series analysis [4]. CHEN et al. proposed a robust fault diagnosis system included a set of individual neural networks based on structured genetic algorithm by Fourier transform and full spectrum to diagnose the whirl mechanical equipment [5];

This paper proposes an equipment fault prognosis method based on temporal association rules. The frequent temporal association rules of temporal item sets matrix are mined based on improved Apriori algorithm and frequent temporal association rules algorithm. Both algorithms convert the fault data to temporal item-sets matrix. The probability of equipment failure is calculated out and the fault trend is predicted, which can serve as useful managerial information. Finally, a validation example was provided to prove the feasibility of the method developed through this study.

2. Fault Data Model

With the rapid development of manufacturing, the structure of Mechanical equipment is more complex, and the function is more diversified. Therefore, the possibility of equipment fault is far greater. The characteristics of fault data are as follows [6, 7]:

1. Large data. According to the passage of equipment life and the advances in sensor technology, volumes of fault data are recorded and accumulated.
2. Dynamic. With the multifunctional equipment increased, whose fault mechanism

has the characteristics of diversity and sudden. Fault data contain much dynamic information because of keeping running of the equipment.

3. Redundancy. A large number of status parameter, fault information, base attribute etc. are recorded during equipment failure, some of which are superfluous.
4. Fault data are desultory.

Grouping the fault record table from database by recording equipment ID, failure time, and by excluding the invalid data, a temporal fault data model is built according to the principles of the A priori traditional association rules algorithm [8, 9] based on the above characteristics of fault data. Temporal fault data model is shown in Table 1.

Table1. The Temporal Fault Data Model

Transaction(ID)	Items(Fault Data)
T1	$\langle R_1, Ta_1 \rangle, \langle 1, Ta_2 \rangle, \langle R_3, Ta_3 \rangle, \langle R_5, Ta_4 \rangle$
T2	$\langle R_1, Tb_1 \rangle, \langle R_2, Tb_2 \rangle, \langle R_6, Tb_3 \rangle, \langle R_1, Tb_4 \rangle$
T3	$\langle R_2, Tc_1 \rangle, \langle R_3, Tc_2 \rangle, \langle R_5, Tc_3 \rangle$
T4	$\langle R_2, Td_1 \rangle, \langle R_4, Td_2 \rangle, \langle R_7, Td_4 \rangle, \langle R_4, Td_5 \rangle$
T5	$\langle R_2, Te_1 \rangle, \langle R_3, Te_2 \rangle, \langle R_4, Te_3 \rangle, \langle R_5, Te_4 \rangle, \langle R_6, Te_5 \rangle$
T6	$\langle R_2, Tf_1 \rangle, \langle R_3, Tf_2 \rangle, \langle R_5, Tf_3 \rangle, \langle R_6, Tf_4 \rangle$

The data organization of temporal fault data model must satisfy two properties:

Property 1: Each transaction has unique equipment identity, whose item data maps the equipment fault data. Therefore, it is impossible for two different transactions to exist with same equipment identity.

Property 2: The data items in transaction are expressed by two-tuples $\langle i, t \rangle$, which is described as temporal item. In this paper, parameter i represents the item which is fault code in this paper, and t is the timestamp of temporal item.

In order to find out frequent itemsets with frequent temporal association rules algorithm, and in order to establish the relationship among the fault codes, the temporal fault data shown in Table 1 has been converted to the form of bitmap shown as Table 2. $\langle 1, T \rangle$ means that the equipment malfunctioned at time T , and $\langle 0, 0 \rangle$ means that the equipment has malfunctioned at no time. More than one temporal item may appear in a cell as the same equipment may malfunction many times at different instants of time.

Table 2. The Temporal Fault Data Model in the Form of Bitmap

	R_1	R_2	R_3	R_4	R_5	R_6	R_7
T1	$\langle 1, Ta_1 \rangle$	$\langle 1, Ta_2 \rangle$	$\langle 1, Ta_3 \rangle$	$\langle 0, 0 \rangle$	$\langle 1, Ta_4 \rangle$	$\langle 0, 0 \rangle$	$\langle 0, 0 \rangle$
T2	$\langle 1, Tb_1 \rangle, \langle 1, Tb_4 \rangle$	$\langle 1, Tb_2 \rangle$	$\langle 0, 0 \rangle$	$\langle 0, 0 \rangle$	$\langle 0, 0 \rangle$	$\langle 1, Tb_3 \rangle$	$\langle 0, 0 \rangle$
T3	$\langle 0, 0 \rangle$	$\langle 1, Tc_1 \rangle$	$\langle 1, Tc_2 \rangle$	$\langle 0, 0 \rangle$	$\langle 1, Tc_3 \rangle$	$\langle 0, 0 \rangle$	$\langle 0, 0 \rangle$
T4	$\langle 0, 0 \rangle$	$\langle 1, Td_1 \rangle$	$\langle 0, 0 \rangle$	$\langle 1, Td_2 \rangle, \langle 1, Td_5 \rangle$	$\langle 0, 0 \rangle$	$\langle 1, Td_3 \rangle$	$\langle 1, Td_4 \rangle$
T5	$\langle 0, 0 \rangle$	$\langle 1, Te_1 \rangle$	$\langle 1, Te_2 \rangle$	$\langle 1, Te_3 \rangle$	$\langle 1, Te_4 \rangle$	$\langle 1, Te_5 \rangle$	$\langle 0, 0 \rangle$
T6	$\langle 0, 0 \rangle$	$\langle 1, Tf_1 \rangle$	$\langle 1, Tf_2 \rangle$	$\langle 0, 0 \rangle$	$\langle 1, Tf_3 \rangle$	$\langle 1, Tf_4 \rangle$	$\langle 0, 0 \rangle$

Therefore, the equipment fault relational data can be converted to Matrix D, shown as follows:

$$D_{m \times n} = \begin{bmatrix} f(T_{00}) & f(T_{01}) & \cdots & f(T_{0n}) \\ f(T_{10}) & f(T_{11}) & \cdots & f(T_{1n}) \\ \vdots & \vdots & \ddots & \vdots \\ f(T_{m0}) & f(T_{m1}) & \cdots & f(T_{mn}) \end{bmatrix} \quad (1)$$

Where, $f(T_{ij}) = \begin{cases} (1, T_{ij1}), (1, T_{ij2}), \dots, (1, T_{ijS}) & (R_j \in T_i) \\ (0, 0) & (R_j \notin T_i) \end{cases}$

$i = 0, 1, 2 \dots m; j = 0, 1, 2 \dots n;$

Further, R_j is fault code, T_i is equipment identity, $(R_j \in T_i)$ means that the equipment T_i had a failure R_j at time $T_{ij1}, T_{ij2}, \dots, T_{ijS}$, S is the number of times that the equipment T_i had the failure R_j , T_{ijS} is failure time, $(R_j \notin T_i)$ means that the equipment T_i had the failure R_j at no time.

The relationship between equipment and fault code has been described distinctly through converting fault database to a matrix shown by (1). This fault data model will decrease the number of times scanning database, and also reduce the requirements of the computer configuration. Further the model will improve the operational efficiency of Apriori Algorithm.

3. Concepts of the Temporal Fault Data Model

Definition 1. Temporal Itemsets Matrix

In the matrix, each row represents a transaction (T_i), and each column represents a item(I_j). When i -th transaction contains the j -th item, the value is $\{(1, T_{ij1}), (1, T_{ij2}), (1, T_{ij3})\}$, T_{ijS} is the timestamp of temporal item, S is the number of items that T_i contains. On the other hand, When i -th transaction doesn't contain the j -th item, the value is $(0, 0)$. Equation (1-1) is a temporal itemsets matrix.

Definition 2. Temporal Candidate Itemsets Matrix

Temporal candidate itemsets matrix is built based on association rules algorithm after pruning the temporal itemsets matrix, deleting the rows and columns that do not meet the requirements and recalculating the matrix.

Definition 3. Temporal Association Rules

Consider that A and B are subsets of itemset I , and $A \subset I, B \subset I$, and $A \cap B = \emptyset$. Let itemset B occur after time t when itemset A occurred in the same transaction. Temporal association rule is an implication like as follows:

$$A \rightarrow B: \Delta T = t;$$

Definition 4. Temporal Support

The ratio of the number that equals to the Temporal association rules $A \rightarrow B: \Delta T = t$ and the number of all transactions. Temporal Support is shown as:

$$\frac{|A \rightarrow B: \Delta T = t|}{|D|}$$

$|D|$ represents the number of all transaction in the temporal itemsets matrix.

Definition 5. Temporal Confidence Level

The ratio of the number that is equal to the Temporal association rules $A \rightarrow B: \Delta T = t$ and the number of transactions that contains itemset A . Temporal Confidence Level is shown as:

$$\frac{|A \rightarrow B: \Delta T = t|}{|A|}$$

$|A|$ represent the number of transactions that contains itemset A in the temporal itemsets matrix.

Definition 6. Temporal Minimum Support Number

Temporal minimum support number is the minimum quantity of transactions that can match a specific itemset requirement. Its value can be calculated by expression as follows:

$$\text{Math.Ceiling}(\text{minSup} * m * t)$$

In this expression, minSup is temporal support, m is the number of all the transactions, t is the maintenance coefficient of equipment, which is determined by the maintenance status of the equipment.

Definition 7. Temporal Rule Pattern

Let itemset A be subsets of a frequent itemset, which is found out by Apriori association rule mining algorithm, and let itemset B be its complement. Let itemset B occurs after a time interval of ΔT when itemset A occurs, which is called temporal rule pattern, shown as follows:

$$A \rightarrow B$$

Definition 8. Maximum Same Temporal Association Rules

Time mode discriminant operation is expressed by the operator " \cap ", whose operation expression is " $\Delta T_1 \cap \Delta T_2 \cap \dots \cap \Delta T_i$ ", and the result of operation is the maximum of the number of the same element among $(\Delta T_1, \Delta T_2, \dots, \Delta T_i)$. For instance, $5 \cap 4 \cap 5 \cap 5 \cap 5 \cap 7 = 4$.

Time mode subtraction operation is expressed by the operator "-", whose operation is expressed as " $(A, T_a) - (B, T_b) = A \rightarrow B: \Delta T = (T_b - T_a)$ ".

Let there exist j records to support temporal rule pattern $A \rightarrow B$ in frequent temporal itemsets, that can be expressed as $\{(A, T_{a1}), (B, T_{b1})\}, \{(A, T_{a2}), (B, T_{b2})\}, \dots, \{(A, T_{aj}), (B, T_{bj})\}$, and $\Delta T_1 = T_{b1} - T_{a1}, \Delta T_2 = T_{b2} - T_{a2}, \Delta T_j = T_{bj} - T_{aj}$. If $\Delta T_1 \cap \Delta T_2 \cap \dots \cap \Delta T_j = \text{number}$, and the time is t' , then temporal association rule $A \rightarrow B: \Delta T = t'$ is maximum same temporal association rules of temporal rule pattern $A \rightarrow B$.

Definition 9. Frequent Temporal Association Rules It is the temporal association rules that the support of maximum same temporal association rules of one temporal rule pattern are not less than minimum support, and the confidence level of them are not less than minimum confidence level.

4. Basic Principle of the Algorithms

As the above known, the maximum same temporal association rule of each temporal rule pattern does not always meet the temporal minimum support among all temporal rule patterns of the frequent itemsets. Therefore, equipment fault prognosis can be converted to find out all frequent temporal association rules of the temporal itemsets matrix, and then predicting trend of equipment fault. The steps involved are outlined below.

(1) Find out all frequent itemsets of temporal itemsets matrix.

Apriori algorithm is the most classic association rule mining algorithm. The traditional mining algorithm has two disadvantages since the mining object is massive fault data [10, 11]. These are a) Scanning the database frequently, and exacerbating database overhead. b) The adaptability of algorithms is poor because of many iterations and massive data. An Improved Apriori algorithm is proposed by converting fault database to temporal itemsets matrix and then converting the operation of database into the handling of the matrix. The requirement for computer configuration are reduced, the efficiency and computed speed are raised.

(2) Obtaining the frequent temporal association rules.

After finding out all temporal rule pattern of each frequent itemset, frequent temporal association rules have been filtered out according to temporal minimum support and temporal minimum confidence level. On this basis strategic decisions have been made at last.

(3) Feedback Mechanism

Whether the feedback mechanism should be enabled which is based on current situation of the equipment and production status, also the experience of the workers is very

important. Temporal support, temporal confidence level and maintenance coefficient will be reset once the feedback mechanisms enabled.

Figure 1 shows the application process of the proposed algorithms in equipment fault prognosis.

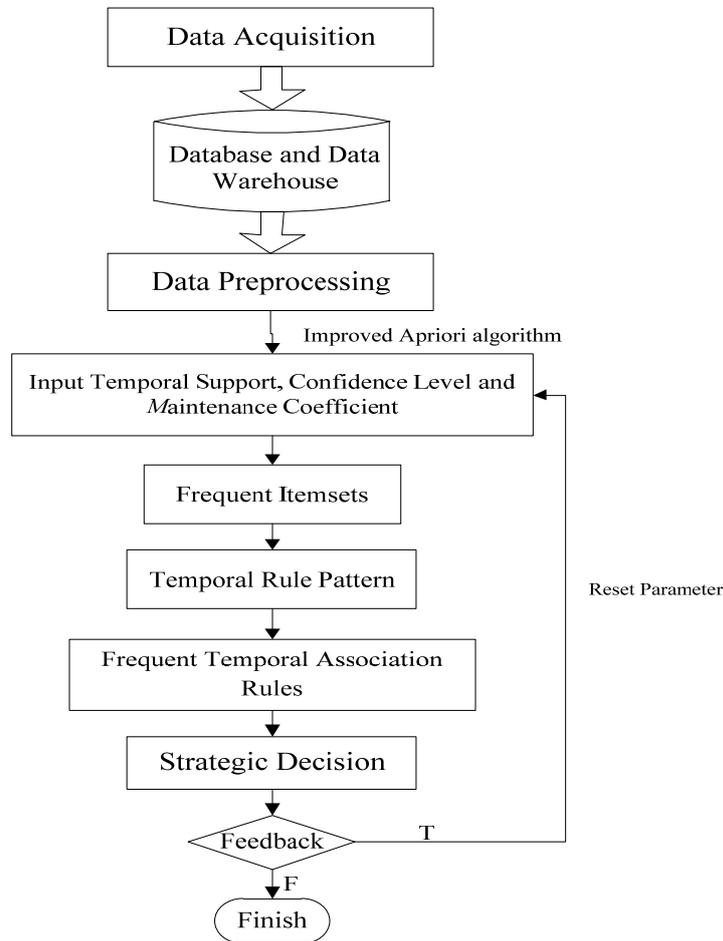


Figure 1. The Application Process of the Algorithms in Equipment Fault Prognosis

5. Algorithm Description

This section is going to describe the improved Apriori algorithm and frequent temporal association rules algorithm in detail.

5.1. Description of Improved Apriori Algorithm

The steps for finding out all frequent itemsets of temporal itemsets matrix based on improved Apriori algorithm are as follows.

(1) After preprocessing the fault data, converting the pure data to temporal itemsets matrix (M), in which the transactions represent different types of equipment, and items represent the fault codes. The value of temporal item is replaced by $d[i,j]$ when calculating the matrix. If the value of temporal item is (0,0), the value of $d[i,j]$ is 0, otherwise it's value is 1. This explanation is summarized as follows;

For (int i = 0; i < m; i++) { // Converting the fault data to temporal itemsets matrix;

For (int j = 0; j < n; j++) {

If ($R_j \in T_i$) {set $f(T_{ij}) = (1, T_{ij}1), (1, T_{ij}2), \dots, (1, T_{ij}S)$; set $d[i,j] = 1$; } //

Else {set $f(T_{ij}) = (0, 0)$; set $d[i,j] = 0$; };

(2) Temporal candidate itemsets matrix (M_0) is found out according to add a $(m+1)$ row and a $(n+1)$ column. The fault code number of each type equipment have been calculated through summing each row of matrix, and the equipment supporting number of fault code is calculated through summing up of each column of matrix, which are the values of $(m+1)$ row and $(n+1)$ column. At last, the matrix M_0 is generated after sorting descending order of the number of support. The above statements can be expressed as:

$$d[i, n+1] = \sum d[i, j] \text{ And } i = 1, 2, \dots, m; j = 1, 2, \dots, n; \text{ // calculating the column } (n+1)$$

$$d[m+1, j] = \sum d[i, j] \text{ And } i = 1, 2, \dots, m; j = 1, 2, \dots, n; \text{ // calculating the row } (m+1)$$

(3) Calculating the temporal minimum support number (minSupCount), whose value is equal to the product of temporal minimum support (minSup), the number of transaction (m) and maintenance coefficient (t), and the result is the smallest integer that is not less than the value.

$$\text{minSupCount} = \text{Math.Ceiling}(\text{minSup} * m * t)$$

(4) Finding out the Frequent K Itemsets ($L[k]$)

The inner product operation of corresponding columns needs to be applied when finding out the support number of the frequent K itemsets. So only the value of all items' cells is 1, the result is equal to 1, otherwise the result is 0. If the number of equipment's items is less than k , the number of the value of row's cells for the equipment is equal to 1 is also less than k . Therefore, the row can be deleted directly.

Support numbers have been arranged in descending order after deleting the trashy rows and recalculating the matrix. Then temporal candidate itemsets matrix (M_n) is found out after delete the columns that whose support number is less than minimum support number and recalculating the matrix.

Support number of each itemsets are calculated according to the inner product operation, which compared with minimum support number, and then frequent K itemsets ($L[k]$) are found out.

The above explanation can be expressed as follows:

For (int i = 0; i < m; i++);

If (d[i, n+1] < k) delete row[i]; // deleting the trashy rows;

Transactions move forward after delete row i;

m--; //the number of rows minus 1;

If (d[m+1, j] < minSupCount) delete column[j]; //deleting the trashy columns;

Items move forward after delete column j;

n--; // the number of columns minus 1;

Calculating the matrix again;

The support number of the itemsets is found out by the inner product operation;

L[k] = {C[k] | s >= minSupCount }; // frequent K itemsets (L[k])

5.2. Description of Frequent Temporal Association Rules Algorithm

In order to describe the algorithm, the following definitions are proposed according to temporal itemsets ((I, T)).

I represent itemset and T is the timestamp of temporal itemsets whose value is the timestamp of last temporal item. The operator is "#", the expression is written as "#(I, T)". If T is the maximum of all temporal items, the output is 1, otherwise it is 0;

The pseudo code of algorithm is as follows.

Input: Frequent Itemsets ($\text{List}\{L[K]\}$), Temporal Minimum Support, Temporal Confidence Level, maintenance coefficient;

Output: Frequent Temporal Association Rules;

1: For ($i = 1; \text{List}\{L[K]\} \neq \text{null}; i++$) {

2: For all pattern {; //loop all the temporal rule patterns

- “→”;
- 3: Temporal rule patterns are split into temporal itemsets (A) and temporal item (B) by
 - 4: For all records {
 - 5: If($\#(A, T_a) = 0$) {continue};
 - 6: $(A, T_a) - (B, T_b) = A \rightarrow B: \Delta T$
 - 7: If ($\Delta T < 0$) {continue};
 - 8: Else {save $A \rightarrow B: \Delta T$ } };
 - 9: $\Delta T_1 \cap \Delta T_2 \cap \dots \cap \Delta T_i$ //time mode subtraction operation;
 - 10: Calculating the temporal support of maximum same temporal association rules and comparing with temporal minimum support;
 - 11: Calculating the temporal confidence level of maximum same temporal association rules and comparing with temporal minimum confidence level;
 - 12: Output the frequent temporal association rules;

6. Examples Verification

The Table 3 shows preprocessed temporal fault data of an automobile enterprise. Equipment ID represents the type of equipment. Only ordinary equipment faults are listed in the table. It contains main engine parts fault of machine tool (P01), workbench parts fault of machine tool (P02), transmission parts fault of machine tool (P03), lifting workbench parts fault of machine tool (P04), auxiliary parts fault of machine tool (P05), process assembly parts fault of machine tool (P06), and safety protection parts of machine tool (P07).

Table 3. Temporal Fault Data

Fault Code Equipment ID	P01	P02	P03	P04	P05	P06	P07
2101080001	(1,48)	(1,5)	(1,20)	(0,0)	(1,32)	(0,0)	(0,0)
2101080005	(0,0)	(1,13)	(0,0)	(1,12),(1,31)	(0,0)	(1,22)	(1,23)
2101120006	(0,0)	(1,9)	(1,41)	(0,0)	(1,53)	(0,0)	(0,0)
2101980001	(1,6),(1,17)	(1,34)	(0,0)	(0,0)	(0,0)	(1,42)	(0,0)
2190000003	(0,0)	(1,17)	(1,15)	(1,51)	(1,27)	(1,9)	(0,0)
2190000059	(0,0)	(1,31)	(1,44)	(0,0)	(1,56)	(1,39)	(0,0)

Scanning fault database and converting the Table 3 to temporal itemsets matrix M:

$$M = \begin{bmatrix} (1,48) & (1,5) & (1,20) & (0,0) & (1,32) & (0,0) & (0,0) \\ (0,0) & (1,13) & (0,0) & (1,12), (1,31) & (0,0) & (1,22) & (1,23) \\ (0,0) & (1,9) & (1,41) & (0,0) & (1,53) & (0,0) & (0,0) \\ (1,6), (1,17) & (1,34) & (0,0) & (0,0) & (0,0) & (1,42) & (0,0) \\ (0,0) & (1,17) & (1,15) & (1,51) & (1,27) & (1,9) & (0,0) \\ (0,0) & (1,31) & (1,44) & (0,0) & (1,56) & (1,39) & (0,0) \end{bmatrix}$$

While calculating, the value of temporal item is replaced with 0, if its value is (0, 0), otherwise it is replaced with 1. Summing each row and column respectively, the matrix M_{0j} s generated after sorting in descending order by the number of support.

$$M_0 = \begin{bmatrix} (1,5) & (1,32) & (0,0) & (1,20) & (1,48) & (0,0) & (0,0) & 4 \\ (1,13) & (0,0) & (1,22) & (0,0) & (0,0) & (1,12),(1,31) & (1,23) & 3 \\ (1,9) & (1,53) & (0,0) & (1,41) & (0,0) & (0,0) & (0,0) & 3 \\ (1,34) & (0,0) & (1,42) & (0,0) & (1,6),(1,17) & (0,0) & (0,0) & 4 \\ (1,17) & (1,27) & (1,9) & (1,15) & (0,0) & (1,51) & (0,0) & 5 \\ (1,31) & (1,56) & (1,39) & (1,44) & (0,0) & (0,0) & (0,0) & 4 \\ 6 & 4 & 4 & 4 & 2 & 2 & 1 & \end{bmatrix}$$

Set the temporal minimum support as 40%, and maintenance coefficient as 1.5. Then the temporal minimum support can be calculated out.

$$\text{minSupCount} = 40\% * 6 * 1.5 = 3.6$$

The result is rounded off to 4.

Then the frequent 1 Itemsets (L[1]) would have been found out. Deleting the columns that their support number is less than 4, matrix M₁ was gained after calculating the matrix.

$$M_1 = \begin{bmatrix} (1,5) & (1,32) & (0,0) & (1,20) & 3 \\ (1,13) & (0,0) & (1,22) & (0,0) & 2 \\ (1,9) & (1,53) & (0,0) & (1,41) & 3 \\ (1,34) & (0,0) & (1,42) & (0,0) & 2 \\ (1,17) & (1,27) & (1,9) & (1,15) & 4 \\ (1,31) & (1,56) & (1,39) & (1,44) & 4 \\ 6 & 4 & 4 & 4 & \end{bmatrix}$$

Therefore, L[1] = {{P02},{P03},{P05},{P06}};

Next, Frequent 2 Itemsets (L[2]) would have been found out. Deleting the rows that the items number is less than 2 in last column, but there were no rows like that. We have M₂=M₁. The support number of candidate 2 itemsets has been calculated out.

$$\text{SupCount} (P02*P05) = [1,1,1,1,1,1]*[1,0,1,0,1,1] = 4;$$

$$\text{And, SupCount} (P02*P06) = 4; \text{SupCount} (P02*P03) = 4; \text{SupCount} (P05*P06) = 2;$$

$$\text{SupCount} (P05*P03) = 4; \text{SupCount} (P06*P03) = 2;$$

Therefore, L[2] = {{P02,P05},{P02,P06},{P02,P03},{P05,P03}}.

Frequent 3 Itemsets (L[3]) would have been found out. Deleting the rows that items number is less than 3 at last column, and deleting the columns whose support number is less than 4, Matrix M₃ has been gained after calculating the matrix M₂.

$$M_3 = \begin{bmatrix} (1,5) & (1,32) & (1,20) & 3 \\ (1,9) & (1,53) & (1,41) & 3 \\ (1,17) & (1,27) & (1,15) & 3 \\ (1,31) & (1,56) & (1,44) & 3 \\ 4 & 4 & 4 & \end{bmatrix}$$

The support number of candidate 3 itemsets has been calculated out.

$$\text{SupCount} (P02*P05*P03) = 4;$$

Therefore, $L[3] = \{\{P02, P03, P05\}\}$; and frequent 3 Itemsets is the maximal frequent itemsets.

All the frequent itemsets are found out.

$$L[1] \cup L[2] \cup L[3] \\ = \{\{P02\}, \{P03\}, \{P05\}, \{P06\}, \{P02, P05\}, \{P02, P06\}, \{P02, P03\}, \{P05, P03\}, \{P02, P03, P05\}\}$$

Finding out all temporal rule pattern of each frequent itemset, all frequent temporal association rules would have been filtered out based on frequent temporal association rules algorithm. As space is limited, this paper is going to consider and present only frequent 3 Itemsets as an example.

All the temporal rule pattern of frequent 3 Itemsets are:

$$P02P05 \rightarrow P03, P05P02 \rightarrow P03, P02P03 \rightarrow P05, P03P02 \rightarrow P05, P03P05 \rightarrow P02 \text{ and} \\ P05P03 \rightarrow P02.$$

Temporal item $((P02, P05), 32)$ and $(P03, 20)$ have been obtained by splitting the temporal rule pattern $P02P05 \rightarrow P03$ in the first record of temporal itemsets matrix M_3 .

$$\#((P02, P05), 24) = 1; \\ ((P02, P05), 24) - (P03, 12) = P02P05 \rightarrow P03: \Delta T = -12$$

The record should have been abandoned as $\Delta T < 0$. Continuing the operations, on similar manner, ΔT of other records is found less than zero, so there are no maximum same temporal association rules and support number is less than 4.

Similarly, the support number of $P05P02 \rightarrow P03, P03P02 \rightarrow P05, P03P05 \rightarrow P02,$ and $P05P03 \rightarrow P02$ is less than minimum support number 4. So these rule pattern should be abandoned.

For $P02P03 \rightarrow P05$. The temporal association rules of each record are:

$$1, P02P03 \rightarrow P05: \Delta T = 12; 2, P02P03 \rightarrow P05: \Delta T = 12; 3, P02P03 \rightarrow P05: \Delta T = 12; \\ 4, P02P03 \rightarrow P05: \Delta T = 12; \\ 12 \cap 12 \cap 12 \cap 12 = 4;$$

There were four records in matrix to support temporal association rules $P02P03 \rightarrow P05: \Delta T = 12$, which is not less than 4.

Set the temporal minimum confidence level is set at 70%, and the temporal confidence level of temporal association rules $P02P03 \rightarrow P05$ is 100%, which is more than temporal minimum confidence level.

The output of temporal association rules $P02P03 \rightarrow P05$ can be described as follows: This type of equipment will malfunction by fault P05 in 12 time units after it is malfunctioned by fault P02, and then fault P03.

7. Conclusion

Equipment fault prognosis is an important method for improving stability and reliability of the machinery. This study proposed an equipment fault prognosis method based on temporal association rules. The fault data is converted to temporal itemsets matrix by Apriori traditional association rules algorithm under the consideration of characteristics of fault data. All the frequent temporal association rules of temporal itemsets matrix are found according to improved Apriori algorithm and frequent temporal association rules algorithm to provide a reliable basis to managers to make maintenance decisions. The results of this study will help in predicting the trends in equipment faults, reducing costs of equipment maintenance and improving the operational efficiency of equipment. The feedback mechanism of the algorithms however, is found defective and efficiency of the algorithms needs further improvement. Additional research is required for improving the feedback mechanism, precision and efficiency of the algorithms.

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