Modeling of Decision Making Process for Product Service Failure Diagnosis

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Abstract

Product malfunctions in service are addressed by service centres that diagnose the problem and make decisions on component repair or replacement actions. Feedback in the form of service centre performance in diagnosing and repairing product service failures is an important indicator of percentage of ‘First-Time-Right’ repairs, which can be improved by analytical modeling of decision making process related to fault diagnosis and repairs done by best service centres. This research proposes to develop a analytical model of service centres’ decision making process as IF-THEN decision rules which link repair actions with product pedigree. The proposed analytical model is based on Rough Sets theory and identifies decision rules which give statistically significant association between product pedigree and repair actions. Analysing the decision making process of service centres is important in developing pre-alerting fault diagnostic rules, recommending best practice diagnoses and sending feedback to OEM for potential changes in design and manufacturing. A case study from automotive warranty demonstrates the methodology.

Keywords: Product service failures; Diagnosis; Decision Rules; Design Parameters; Process Variables; Operating Conditions; Repair Actions; Service centres’ performance evaluation; Best practice diagnostics; Rough Sets

1. Introduction

Product malfunctions in service such as warranty and No-Fault-Found (NFF) failures result in customer dissatisfaction and significant costs of warranty and product returns to many industries such as automotive [1][2], aerospace[3], cellphone [4] etc. Product service failure is loss or non-conformance of an expected functional performance due to malfunctioning of a subsystem or component. Following the occurrence of failure, a service centre diagnoses the failure and decides on a repair action (RA). To tackle product failures in service, manufacturers take two major contingency actions: (i) modify design and manufacturing to eliminate or reduce the failure; and (ii) improve performance of service centres to increase percentage of ‘First-Time-Right’ diagnoses and repairs. Though warranty and repair data have been analyzed to provide feedback to OEM for design and manufacturing modifications, it has not been used systematically to improve service centres’ diagnosis and decision making process on repairs actions. This research proposes, as first crucial step, to obtain an analytical model of the decision making process of service centres for diagnosis and repair actions from repair data. The model for the decision making process can then be utilized to (i) generate pre-alerting that will speed-up service centres’ diagnoses, whereby they will perform fewer diagnostic tests to confirm failure cause rather than doing full routine to isolate root cause; (ii) recommend best practices by modeling the decision making process of best service centres, which are identified based on Key Performance Indicators such as warranty cost, repeat visits, first-time-right repairs etc.; and (iii) send product feedback to OEM for design and process modifications. Figure 1 shows a framework for application of the methodology. It proposes to model the decision making process as IF-THEN decision rules linking product pedigree attributes with repairs actions, done for a specific failure.
Fig. 1. Proposed application framework of the synthetic model of Product Service Failure Diagnosis

Product pedigree provides data on (i) product configuration given as Design Parameters (DPs); (ii) manufacturing conditions or Process Variables (PVs); and (iii) usage or Operating Conditions (OCs). Product pedigree attributes are either causal or correlated to failures and repair actions. Hence they are used to develop decision rules that give a logical representation of decision making process of the service centres. The methodology described in this paper focuses on extracting the IF-THEN decision rules which classifies repair actions in terms of product pedigree.

Table 1 gives example of parameters used to describe product pedigree for automotive vehicles. Next section presents a brief literature review on warranty data analysis. This is followed by methodology and case-study in sections 3 and 4 respectively.

Table 1. Example of attributes used to describe product pedigree

| Product pedigree attributes | Example of attributes                        |
|-----------------------------|---------------------------------------------|
| Design Parameters (DPs)     | DP = {Engine type, Fuel type, Transmission type, Gross Vehicle Weight etc.} |
| Process Variables (PVs)     | PV = {Manufacturing plant name, manufacturing batch number, manufacturing month-year etc.} |
| Operating Conditions (OCs)  | OC = {Mileage, Road type, Usage Type etc.} |

2. Literature Review

Warranty data have been extensively analysed (i) to estimate component failure rates and field reliability; (ii) to model the effect of covariates such as environmental conditions and manufacturing parameters on reliability; (iii) to assess effect of design changes on component reliability using hazards plots and (iv) to generate early warning of warranty failures. A review on these topics is given by Karim and Suzuki (2005) [5] and Wu [6]. These methods provide feedback to OEMs for reducing or eliminating service failures by improving product reliability via changes in design and manufacturing. This research proposes a framework which allows using analysis of warranty and repair data for improvement in performance of service centres. Table 2 summarizes past works on warranty data analysis and highlights the contribution of current research.

Table 2. Related research on warranty data analysis using covariates

| Methods                                      | Contingency Actions | Feedback to OEM for Design & Manufacturing Changes | Improvement of performance of service centres |
|----------------------------------------------|----------------------|---------------------------------------------------|---------------------------------------------|
| Field Reliability                            | - Field Reliability  | Estimation [7][8]                                 | - Not applied                                |
| Estimation of sub-systems & components       |                      | - Effects of covariates on reliability [9][10][11] |                                             |
|                                               |                      | - Assessment of design changes on component       |                                             |
|                                               |                      | reliability [12]                                  |                                             |
|                                               |                      | - Early warning                                   |                                             |
|                                               |                      | - Prediction of warranty failures [13]            |                                             |

Proposed Methodology:

Analytical Model of Service Failure Diagnosis

Send feedback to OEM for design and manufacturing modifications

Table 3. Proposed approach for addressing specifics of the problem

| Aspect of the problem | Suggested Approach                          |
|----------------------|---------------------------------------------|
| Association between product pedigree and repair actions | Rough Sets based association rules identification is applied to generate IF-THEN decision rules. Mannar et al [14] lists the advantages of Rough Sets over statistical and Artificial Intelligence based methods. |
| Minimal sets of product pedigree | Generic Algorithm is applied to generate minimal sets of product pedigree attributes. |
| Removal of casual decision rules | Chi-Square test of independence and Fisher’s Exact test determines statistical significance of decision rules. Rules which are not statistically significant are casual rules. |

3. Methodology

The objective of the proposed methodology is to identify IF-THEN decision rules linking product pedigree with repair actions performed for a given product service failure. In order to do so, the following specifics are to be considered:

- **Association between product pedigree and repair actions** – This must be identified in absence of predesigned fault causal models such as fault trees, Ishikawa diagrams, FMEA etc.
- **Minimal sets of product pedigree** – In real scenario, attributes used to describe product pedigree are numerous. Therefore it is necessary to express the decision rules in terms of minimal sets of attributes by eliminating redundant ones that are not associated with a given repair action.
- **Removal of casual decision rules** – Casual decision rules must be removed through verification of statistical significance of rules.

A summary of the approach taken by the methodology to address the aforementioned aspects is presented in Table 3.

The decision rules use Condition Attributes (C) obtained from product pedigree to classify repair actions (RA), which are treated as decision classes. The set of condition attributes is given by

\[
C = DP \cap PV \cap OC
\]
The methodology is based on Rough Sets theory [15]. The input is 'Nw' warranty failures pertaining to a particular warranty, \( W = \{ W_1, W_2, \ldots, W_n \} \). Each warranty failure is associated with a repair action (RA) and product pedigree data pertaining to DPs, PVs and OCs. Let us refer to the warranty failures dataset as \( D_w \). Figure 2 shows an example of a warranty failures dataset.

![Figure 2. Example of warranty failure dataset \( D_w \)](image)

The rest of this section describes in details the steps for identifying the decision rules. The key concept is to identify groups of 'indiscernible' or equivalent warranty failures, which have same values for a subset of condition attributes \( B \subseteq C \). Then strength of association between an equivalent warranty failures can be generated using this concept.

3.1. Notations

\( N_{RA} \) No. of distinct repair actions in \( D_w \)

\( RA \) Set of distinct repair actions in \( D_w \)

\( W_a \) Set of values attained by an attribute \( a \in C \)

\( f_a \) Function which maps warranty failures in \( W \) to \( W_a \)

\( \theta_{RA} \) Formula of \( B \) is combination of attribute-value pairs connected by the logical AND ('\&') operator

\( \theta_b \) Set of distinct formulae of \( B \subseteq C \) in \( D_w \)

3.2. 'Indiscernibility' and Warranty Failures Groups (WFG)

The concept of 'indiscernibility' is adapted from Rough Sets theory [16]. In the context of the current methodology, it implies that two warranty failures \( W_i \) and \( W_j \) are similar or equivalent to each other if they cannot be distinguished based on their values for a given subset of condition attributes, \( B \subseteq C \). For example, based on values of condition attributes, \( B=\{\text{Engine}, \text{Production Month}, \text{Usage Type}\} \), warranty failures \( W_i \) and \( W_j \) are indiscernible. A set of indiscernible warranty failures forms a Warranty Failures Group (WFG) denoted as \( I_{B,k} \). It creates a unique partition in the set, \( W \). Warranty Failures Group is similar in concept to equivalence classes or B-partitions of the set \( W \). Pawlak [16] describes B-partitions as equivalence classes, union of which gives the full set of objects. A WFG for \( B \subseteq C \) is given by

\[
I_{RA} = \{ (W_i, W_j) \in W \times W | f_a(W_i) = f_a(W_j) \forall a \in B \}
\]

A set of multiple Warranty Failures Groups generated by \( B \subseteq C \) is represented as

\[
I_B = \{ I_{B,1}^{(1)}, I_{B,2}^{(2)}, \ldots, I_{B,k}^{(k)} \}
\]

where \( |I_{B}| \) is cardinality of the set \( I_B \) or the number of WFGs obtained from \( B \subseteq C \). Also it is notable that for each \( I_{B,k} \) there exists a condition formula given by

\[
\Phi_{RA} = [a_1 \wedge f_{a_1}(W_i)] \wedge [a_2 \wedge f_{a_2}(W_i)] \wedge \ldots \wedge [a_m \wedge f_{a_m}(W_i)]
\]

where \( B=\{a_1, a_2, \ldots, a_m\} \) and \( W_i \) is a member of \( I_{B,k} \).

Figure 3 presents a flowchart showing the steps of the method of identifying IF-THEN Decision Rules. This is followed by a detailed discussion of each of the steps shown in the flowchart.

**3.3. Method of Identifying IF-THEN Decision Rules**

**Step 1:** Generate Warranty Data System (WDS) consisting of the 5-tuple as follows: \( WDS = (W, C, RA, V_a, f_a) \), where \( a \in C \)

**Step 2:** Calculate degree of dependency \( \delta_b (RA) \) of warranty repair actions or decision classes, \( RA \) on the set condition attributes \( C \)

**Step 3:** Apply Genetic Algorithm to generate minimal subsets of condition attributes \( C_R \subseteq C \) based on fitness function \( f(B) = \delta_b (RA) \times \frac{|C| - |B|}{|C|} \)

**Step 4:** For each minimal set, generate the IF-THEN rules and verify their statistical significance

![Fig. 3. Steps of generating IF-THEN Decision Rules](image)
The steps outlined in Figure 3 are detailed as follows:

**Step 1: Generate Warranty Data System**

The Warranty Data System (WDS) is a 4-tuple expressed as \( W DS = (W, C, RA, V, f_a) \)

(5)

Warranty Failures (W) is a sample of \( N_w \) warranty failures analyzed to generate IF-THEN decision rules. Each member of this set (\( W_i \)) is a warranty failure for which a repair action (RA) has been performed. The following product pedigree attributes are also known for each warranty failure (\( W_i \)):

- Product configuration or Design Parameters (DP)
- Manufacturing conditions or Process Variables (PV)
- Product usage or Operating Conditions (OC)

The union of DP, PV and OC gives the full set of condition attributes C. Therefore, \(|C| = |DP| + |PV| + |OC|\). Besides, when more than two repair actions are present in the warranty failure dataset \( D_w \), decision rules are identified for one repair action at a time. For \( i^{th} \) repair action, we label \( RA_i \) as \( RA_1 \) and all other \( RA_j \in RA - \{RA_i\} \) as \( RA_2 \). Therefore the list of warranty failures, \( W \) can be represented as

\[
W = \left[ \begin{array}{c}
C_1 \quad C_2 \quad \ldots \quad C_{|C|} \\
\vdots \\
C_{|C|} \quad C_2 \quad \ldots \quad C_1
\end{array} \right]_{|C| \times |C|} \quad \text{RA}_1 \\
\text{RA}_2
\]

Each, \( ra_k \in \{RA_1, RA_2\} \), where \( k = 1, 2 \ldots N_w \). Decision Rules linking formulae \( \phi_{k, b} \) of condition attributes \( B \subseteq C \) with \( RA_i \) can be represented as follows

\[
\Delta_{w,b,k} = \{\phi_{k, b} \rightarrow RA_1, \phi_{k, b} \rightarrow RA_2, \phi_{b, k} \rightarrow RA_1 \}
\]

(6)

Additionally, if any condition attribute in \( C \) is a continuous variable (e.g. vehicle mileage, product age etc.), then it is discretized by equal width interval binning method [17].

**Step 2: Calculate degree of dependency \( \delta_{b}(RA) \) based on set of condition attributes C**

The degree of dependency measures the capability of the set of condition attributes \( C \) to distinguish between the different repair actions or decision classes \( \{RA_1, RA_2\} \) . Based on condition attributes \( C \), set of equivalent warranty failures groups \( I_{C, i} = \{I_{C_1, i}, I_{C_2, i}, \ldots I_{C_{|C|}, i}\} \) is generated applying equation 2.

Each warranty failure group \( I_{b, i} \) has a corresponding condition formulae \( \phi_{b, k} \). Based on the sample warranty failure data, both \( I_{C, i} \) and \( \phi_{b, k} \) are associated with one or more repair actions. This can be represented as follows

\[
I_{C, i} \rightarrow RA_{b, i} \subseteq RA
\]

(7)

\[
\phi_{b, k} \rightarrow RA_{b, i} \subseteq RA
\]

(8)

Equations 7 and 8 are also applicable for a subset of condition attributes \( B \subseteq C \) . Decision classes or repair actions \( RA_{b, i} \) associated with a warranty failures group \( I_{b, i} \), can be obtained by applying the following expression

\[
RA_{b, i} = \bigcup_{k=1}^{|C|} \{RA(W_k)\}
\]

(9)

where \( RA(W_k) \) is the repair action done for \( W_k \) and \( RA(W_k) \in RA \). As an example, decision classes or repair actions associated with the warranty failures groups obtained from \( B = \{\text{Engine}, \text{Production Month, Usage Type}\} \) for warranty dataset \( D_w \) is shown in Table 5.

**Table 5. Example of Warranty Incidents’ Groups generated by \( B=\{\text{Engine, Production Month, Usage Type}\} \), for dataset \( D_w \)**

| Serial Number | Warranty Incidents’ Group \( (I_{b, i}) \) | Related Decision Classes or Repair Actions \( (RA_{b, i}) \) |
|---------------|--------------------------------------------|------------------------------------------------------------|
| 1             | \{W1, W2, W3\}                            | (Spark Plug)                                               |
| 2             | \{W4, W5\}                                | (Starter Motor)                                            |
| 3             | \{W6, W7\}                                | (Starter Motor)                                            |
| 4             | \{W8\}                                    | (Spark Plug)                                               |
| 5             | \{W9\}                                    | (Spark Plug)                                               |
| 6             | \{W10\}                                   | (Spark Plug)                                               |
| 7             | \{W11, W12, W13\}                         | (Spark Plug, Starter Motor)                                 |

Based on equation 9, decision rule induced by \( I_{b, i} \) is reliable and unambiguous if and only if \(|RA_{b, i}| = 1\) whereas it is ambiguous and unreliable if \(|RA_{b, i}| > 1\). Now, the lower approximation of a decision classes or repair actions \( RA \) generated from \( B \subseteq C \) is defined as

\[
B_{\text{low}}^{RA} = \bigcup_{\phi_{b, k} \rightarrow RA_1, \phi_{b, k} \rightarrow RA_2} \{I_{b, i} | \text{cardinality}(RA_{b, i}) = 1\}
\]

(10)

In other words, lower approximation, \( B_{\text{low}}^{RA} \) is the union of all warranty failures groups which are associated with one and only one repair action. Additionally, the boundary region of a decision class or repair action \( RA \) is defined as

\[
B_{\text{bnd}}^{RA} = \bigcup_{\phi_{b, k} \rightarrow RA_1, \phi_{b, k} \rightarrow RA_2} \{I_{b, i} | \text{cardinality}(RA_{b, i}) > 1\}
\]

(11)

In other words, boundary region, \( B_{\text{bnd}}^{RA} \) is the union of all warranty failure groups which are associated with more than one repair actions. The dependency of repair actions \( RA \) on condition attributes \( B \subseteq C \) is a measure of the capability of members of \( I_{b, i} \) to uniquely determine one and only one \( RA_j \in RA \). Based on this logic the dependency \( \delta_{b}(RA) \) is calculated as

\[
\delta_{b}(RA) = \frac{|B_{\text{low}}^{RA}|}{N_w}
\]

(12)

Dependence on the full set of condition attributes \( C \) is obtained as

\[
\delta_{b}(RA) = \frac{|C_{\text{RA}}|}{N_w}
\]

(13)

For the example given in Table 4, \( B^{RA} = \{I_{b, 1}, I_{b, 2}, I_{b, 3}, I_{b, 4}, I_{b, 5}\} \). Hence degree of dependency of \( RA = \{\text{Spark Plug, Starter Motor}\} \) on \( B = \{\text{Engine, Production Month, Usage Type}\} \) is calculated as

\[
\delta_{b}(RA) = \frac{|B_{\text{low}}^{RA}|}{N_w} = \frac{|I_{b, 1}| + |I_{b, 2}| + |I_{b, 3}| + |I_{b, 4}| + |I_{b, 5}|}{N_w} = \frac{3 + 3 + 3 + 1 + 1}{16} = 0.75
\]

In this case, \( RA_{b, i} \) is obtained applying equation 9.
Step 3: Apply Genetic Algorithm (GA) to generate minimal subsets or reducts of condition attributes

Genetic algorithm is applied in this step to generate minimal subsets or reducts $C_k \subseteq C$ such that $\delta_k(RA) = \delta_k(RA)$. This ensures that dimensionality reduction is achieved without significant loss of degree of dependency. Candidates solutions, $B \subseteq C$ are evaluated based on the fitness function

$$F(B) = \delta_k(RA) \times \frac{|C| - |B|}{|C|}$$

(15)

The best solutions maximize the fitness function. The degree of dependency $\delta_k(RA)$ is calculated as described in Step 2.

The second part of the fitness function, $\frac{|C| - |B|}{|C|}$ ensures that candidate solutions with smaller cardinality gets a higher fitness score and longer solutions are suitably penalized. Parameters applied to run the GA are as follows:

- Chromosome pool size $= 100$
- Number of generations $= 50$
- Probability of crossover $= 0.30$
- Probability of mutation $= 0.05$

Step 4: Verify statistical significance of rules obtained from minimal sets of product pedigree or condition attributes

Each minimal set $C_k$ obtained by step 3, gives warranty failure groups $I_{c_k}$ through equations 2 and 3. The purpose of this step is to test statistical independence between $I_{c_k}$ and repair actions, RA. The null hypothesis $H_0$ assumes that $I_{c_k}$ and RA are independent. At a significance level of 5%, if probability of obtaining the given warranty dataset under the conditions of $H_0$ is less than 0.05, then the null hypothesis is rejected and the association between $I_{c_k}$ and RA is deemed to be statistically significant and not casual. In this paper, this test is implemented as Chi-Square test of independence for contingency matrix with all cell values greater than 5.

Parameters applied to run the GA are as follows:

- Chromosome pool size $= 100$
- Number of generations $= 50$
- Probability of crossover $= 0.30$
- Probability of mutation $= 0.05$

Step 5: Publish decision rules which are statistically significant

IF-THEN decision rules are obtained for statistically significant $I_{c_k}$ applying equations 4 and 6.

4. Case Study

The methodology for identifying decision rules, described in previous section is demonstrated with a case study from automotive warranty failure. The data used in the case study pertains to 'engine not starting' problem of a passenger car, reported by customers to service centres during warranty period. A total of 940 cases are considered initially. Table 7 show the list of condition attributes considered in the case study. It is found that 12 different components were replaced for the 'engine not starting' complaint. Initial Pareto analysis shows that in 92.5% of the total number of cases 2 particular components Starter Motor and Alternator were diagnosed as faulty and were replaced. Therefore, the rest of the cases is treated as noise and 869 cases are used to identify decision rules. This gives two decision classes or repair actions.

Table 7. List of condition attributes (C) in case study on automotive warranty failure causing 'engine not starting' problem

| Condition Attributes | List of Condition Attributes |
|----------------------|-----------------------------|
| Design               | Fuel Type, Steering Type, No. of cylinders, Air Ventilation |
| Parameters           | System, Un-laden Vehicle Weight, Gross Vehicle Weight, Cubic Capacity, No. of cylinders, Wheel Base, Manufacturing Plant |
| Process Variables    |                                            |
| Operating Conditions | Road Type, Mileage (in km), Usage Type, Region |

RA = {Starter Motor, Alternator}, The method for identifying the decision rules has been implemented in R Statistical Computing platform (version 3.0.1) and uses PostgreSQL 9.1 to store the warranty dataset. The algorithm yielded 2 minimal sets of condition attributes for the case-study: (i) $C_{R1} = \{Road\ Type, \ Mileage, \ Usage\ Type, \ Air\ Ventilation\ System, \ Gross\ Vehicle\ Weight, \ Region\}$; and (ii) $C_{R2} = \{Road\ Type, \ Mileage, \ Usage\ Type, \ Air\ Ventilation\ System, \ Un-laden\ Vehicle\ Weight, \ Region\}$. Let us describe the statistical significance testing and selection of decision rules using $C_{R1}$. This minimal set gives 58 warranty failures groups ($I_{c_1}$) and formulae ($\theta_{c_1}$). $I_{c_1}$ partitions W into 2 subsets: (i) $I_{c_1}$ and (ii) its complement, $I_{c_1} = W - I_{c_1}$. The statistical significance testing is described using the following 4 scenarios:

- **Scenario I:** $H_0$ is accepted via Chi-Square test of independence for large sample.
- **Scenario II:** $H_0$ is rejected via Chi-Square test of independence for large sample
- **Scenario III:** $H_0$ is accepted via Fisher’s exact test for small sample size
- **Scenario IV:** $H_0$ is rejected via Fisher’s exact test for small sample size

For each case, a $2 \times 2$ contingency matrix is developed whose cells are calculated as shown in table 7. The test statistic and the p-value are calculated based on the contingency matrix.

Table 7. Generic representation of contingency matrix

| RA | Starter Motor | Alternator |
|----|---------------|------------|
| WC | $I_{c_1}$     | $I_{c_1}$  | |
| $I_{c_1}$ | $n_1 = (I_{c_1} \cap (W | RA(W) = A))$ | $n_2 = (I_{c_1} \cap (W | RA(W) = B))$ | |
| $I_{c_1}$ | $n_3 = (I_{c_1} \cap (W | RA(W) = A))$ | $n_4 = (I_{c_1} \cap (W | RA(W) = B))$ | |

Table 8 gives example of cases I and II and table 9 works out cases III and IV.

Table 8. Statistical significance testing for Cases I and II using Chi-Square test of independence for contingency matrix with all cell values greater than 5

| Case | Starter Motor | Alternator |
|------|---------------|------------|
| WC   | $I_{c_1}$     | $I_{c_1}$  | |
| $I_{c_1}$ | 84            | 6          | |
| $I_{c_1}$ | 688           | 91         | 757 |
| Test Statistic | 1.5717 | 10.9581 |
| p-value   | 0.2099 | 0.0009 |
| Test Result | Accept $H_0$ | Reject $H_0$ |
For \( C_{(2)} \), 5 warranty failure groups out of 58 are identified to be having statistically significant association with repair actions. Applying equations 4 and 6, IF-THEN decision rules are generated. These rules are listed in table 10.

Table 10. Statistically significant IF-THEN decision rules generated based on given vehicle pedigree attributes and repair actions.

| Serial Number | Rule Description |
|---------------|------------------|
| Rule_1 | (Road Type=PM) \land (Mileage \leq M_1) \land (Usage Type=P) \land (Air Ventilation System=AVS) \land (Gross Vehicle Weight=935 units) \land (Region=N) \Rightarrow Repair Action=Starter Motor OR Alternator |
| Rule_2 | (Road Type=PM) \land (Mileage \leq M_1) \land (Usage Type=T) \land (Air Ventilation System=AVS) \land (Gross Vehicle Weight=935 units) \land (Region=N) \Rightarrow Repair Action=Alternator |
| Rule_3 | (Road Type=PM) \land (Mileage \leq 1384 km) \land (Operation=P) \land (Air Ventilation System=AVS) \land (Gross Vehicle Weight=935 units) \land (Region=W) \Rightarrow Repair Action=Starter Motor OR Alternator |
| Rule_4 | (Road Type=PM) \land (Mileage \leq M_1) \land (Usage Type=P) \land (Air Ventilation System=AVS) \land (Gross Vehicle Weight=935 units) \land (Region=S) \Rightarrow Repair Action=Starter Motor OR Alternator |
| Rule_5 | (Road Type=PM) \land (Mileage \leq M_2) \land (Usage Type=P) \land (Air Ventilation System=AVS) \land (Gross Vehicle Weight=935 units) \land (Region=S) \Rightarrow Repair Action=Starter Motor |

As evident from table 10, Rules 2 and 5 point to a single repair action and hence have 100% accuracy. The other rules have varying degrees of accuracy which is expressed as conditional probability of the repair action given that the vehicle pedigree satisfies the rule. Table 11 lists the conditional probabilities of the repair actions given each of the 5 rules listed in table 10.

Table 11. Conditional probability of repair actions given IF-THEN Decision Rule

| Rule | Prob[RA=Starter Motor\mid Rule=Rule_] | Prob[RA=Alternator\mid Rule=Rule_] |
|------|--------------------------------------|--------------------------------------|
| Rule_1 | 0.6522 | 0.3478 |
| Rule_2 | 0.4 | 0.6 |
| Rule_3 | 1 | 0 |

Based on the values of the conditional probabilities, the manufacturer can decide which rules to be issued for pre-alerting service centres or using as feedback for design and manufacturing modifications.

5. Conclusions

The approach presented in this paper gives a systematic methodology to synthetically model the decision making process of service centres for diagnosis and repair of service failures. The index presented here such as conditional probabilities of repair action given IF-THEN decision rules can be used to evaluate the accuracy of classification of a decision rule. The results can be adopted by OEMs to (i) send pre-alerting to service centres for same service failure; (ii) recommend best practices when the rules are identified from repair data obtained from best service centres; and (iii) send feedback to OEM for product quality improvement.

The current research can be extended by developing a robust method for automatic generation of rules for multiple failures, each having multiple repair actions done.

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