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Development of Electronic Component Life Prediction Model Using Rough Set Theory in Case Study of Relay

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Despite the greatly increasing use of relays for various circuits, equipment, and electrical networks in a power system, little is known about how to select suitable relay products to ensure the reliability of relay life. Accordingly, there is a need to develop a model for predicting reliability and thus improve life expectancy. In this work, we identify the relationship between the initial relay performance information and the reliability life through long-term tests. A reliability prediction model for relay lifetime based on rough set theory is developed by the following steps: Firstly, the parameters affecting relay life are obtained. Secondly, discrete data values are divided into attribute values and a decision-making table is constructed. Third, a relative importance index based on attribute values is defined. Fourth, decision-making rules are formulated. Finally, decision-making rules are acquired by the analysis of actual relay parameters. Experimental results confirm the effectiveness of the proposed prediction model. The method can be applied not only to the relay product screening of an actual working system, but also to the reliability life prediction or product screening of other products.

1. Introduction

With the increasing use of electrical energy, a large number of electrical products are now being applied.(1) Among them, relays working as core devices in control circuits are widely employed in many electrical fields such as space stations, artificial satellites, and new energy vehicles.(2) For this reason, the reliability of relays is a key issue for industry.(3) Therefore, relay life prediction is very meaningful for electrical systems.

The reliable life required for relays depends on the area of application.(4) For example, the working life of a horn relay in a vehicle system must be at least a million operations. On the other hand, the working life of a headlight relay must be at least 500000 operations.(5) In some devices, such as space stations, offshore oil platforms, and artificial satellites, an extremely high relay reliability is required. If the actual service life of a device is 3 years, when selecting a relay,

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workers only need to ensure that the service life of the relay is greater than 3 years to ensure the reliability of the device.[6] A screening test is traditionally used to test relay reliability, but it usually takes a long time and has a high cost. The methods used to evaluate product operating lives in recent years can be divided into two types. One is based on sampling detection theory, from which the overall life distribution and the average life, median life, and other reliability characteristics are inferred.[7] However, such methods may only be suitable for the life prediction of batch products.[8] The other type of method applies a degradation mechanism to individual products and can reflect the different lifetimes of products in the same batch.[9]

Reliability life prediction from the performance parameters of an individual relay is usually based on condition monitoring.[10] Some methods such as neural networks,[11] the grey model,[12] regression analysis,[13] and the improved grey neural network model[14] have been applied to predict the reliable life of relays. The relationship between relay parameters and degradation has been analyzed using degradation parameters, from which a relay life prediction model was established.[15] Although the prediction was effective for the example in the study, it was necessary to process a large amount of data.

Selecting products with a reliable life longer than the system service life is a key issue in industry. For this purpose, qualitative prediction algorithms have been commonly used, including the Bayesian method, evidence theory, and rough set theory.[16] Liu *et al.*[17] proposed a Bayesian model averaging method for the life evaluation of a rubber seal storage device. The results showed that the device achieved a small negative log likelihood value with goodness of fit and low complexity. Bai *et al.*[18] used D-S evidence to acquire the reliability allocation of a multistate IR system with cognitive uncertainty. Alternatively, using rough set theory, the number of input variables of a large centrifugal compressor impeller was reduced to more accurately predict the impeller service life.[19]

Rough set theory is effective for the qualitative evaluation of uncertain information. For instance, it has been used to resolve the uncertainty in failure mode and effect analysis.[20] Also, it can be applied to improve the reliability of maintenance equipment in a manufacturing process. The fluctuation of pollutant concentration considering complex morphological characteristics in surface water has been predicted using rough set theory.[21] In view of the uncertainty in the rock mass, rough set theory was used to evaluate the importance of index parameters.[22] Li *et al.*[23] applied rough set theory to extract the characteristic parameters of relay state performance and thus establish decision rules for relay life prediction. However, the relay life cannot be accurately predicted only from a single initial state index.

2. Reliability Prediction Model

2.1 Fundamentals of rough set theory

Rough set theory was used to find the correlation between the initial state information and reliable life of relays.[24] In this theory, knowledge is regarded as information with the ability to classify objects in a research domain. A knowledge information system S represented by multiple groups can be expressed as

$$S = \langle U, A, V, f \rangle, \tag{1}$$

where U, called the universe, is a non-empty finite set of objects representing a set of N relay samples, A is a non-empty finite set of attributes representing the union of condition and decision attribute sets in the relay life, V is a set of property values representing the union of values in relay sample attributes, and f is an information function that can assign an information value to each object attribute. The following equations are satisfied:

$$A = C \cup D, \tag{2}$$

$$V = \bigcup_{a \in A} V_a, \tag{3}$$

$$\begin{cases} f : U \times A \to V, \\ \forall a \in A, x \in U, f(x, a) \in V_a, \end{cases} \tag{4}$$

where C is the condition attribute, D is the decision attribute, and V_a is the value range of attribute a.

Suppose that U is a given universe, $X \subseteq U$, P is an equivalence relation on U, and U/P represents the set of all equivalent classes of P. If $R \subseteq P$ and $R \neq \phi$, then $\cap R$ is also an equivalence relation that represents the intersection of all equivalence relations in R, and is called the indistinguishable relation on R, denoted by ind(R).

The following two subsets can be obtained:

$$\begin{cases} \underline{P}(X) = U\{Y \in U / P \mid Y \subseteq X\}, \\ \overline{P}(X) = U\{Y \in U / P \mid Y \cap X = \phi\}, \end{cases} \tag{5}$$

where $\underline{P}(X)$ is the lower approximation set of set X and $\overline{P}(X)$ is the upper approximation set of set X. $\underline{P}(X)$ is defined as the positive field of set X and is represented by $POS_P(X)$.

$$POS_p(X) = \underline{P}(X) \tag{6}$$

The core of attributes is the set of all necessary attributes of attribute set A and is depicted as core(A). red(A) is used to represent all reduction sets of A.

$$\text{core}(A) = \cap \text{red}(A) \tag{7}$$

This equation indicates that the intersection of all reductions of A constitutes the core of A. $|X_f|$ (f = 1, 2, 3, ..., p) is the number of elements in set U/C with equivalent classes of U reduced to C; $|Y_t|$ (t = 1, 2, 3, ..., q) is the number of elements in the set divided into the equivalence class of decision attribute D by universe U after attribute reduction. Then, the credibility of the decision based on rough set theory is expressed as

$$\alpha_{X_f}(Y_t) = \frac{|Y_t \cap X_f|}{|X_f|}, \tag{8}$$

where $|Y_t \cap X_f|$ is the number of elements in the intersection of sets Y_t and X_f.

2.2 Establishment of relay life decision-making rules

The prediction of relay life can be divided into two steps: one is the establishment of decision-making rules, corresponding to knowledge acquisition; the other is the matching of decision-making rules, corresponding to the use of the knowledge process. The application of the two steps in relay life prediction is described in detail as follows.

(a) Establishment of relay life decision-making rules

The establishment of rules to decide the relay life is carried out by the following three steps:

1. Establish an information system for relay life prediction.

The data in a relay life test is regarded as information system *S*. It is often given in the form of a relation table, i.e., a decision table, in rough set theory. Each row of the decision table corresponds to a specific object and each column represents an attribute value. In relay life prediction, the values of attributes including condition and decision attributes are in continuous intervals in the real number field. These attribute values should be discretized to form the original decision table.

2. Reduce the decision table.

There are *n* conditional attributes in the original decision table. A reduction process is performed to remove irrelevant and redundant conditional attributes. The calculation can thus be simplified and interference from random information can be effectively avoided.

3. Establish the decision-making rules.

Using the decision table, the decision-making rules for every object can be established. The credibility index of rules is used to evaluate their advantages and disadvantages.

(b) Matching of relay life decision-making rules

Life prediction involves performing a rule-matching process based on the condition of relay attributes, which are interval values rather than determined real numbers. To match relay life decision rules, the distance measurement method is applied as follows.

Suppose the predicted relay life is *a*, whose conditional attribute values are $\{C_1(a), C_2(a), ..., C_l(a)\}$. The conditional attribute values of rule set *r* are $\{C_1(r), C_2(r), ..., C_l(r)\}$. The number of mismatches between the conditional attribute values of all rules in the rule set and the conditional attribute values of *a* is counted, and the least number of rules is selected to form the candidate rule set. If there is only one rule in the candidate rule set, this rule is used as the matching rule. Otherwise, the similarity between each candidate rule and *x* is measured using a distance formula [Eq. (9)], and the nearest rule is used as the matching rule.

$$d(a,r) = \sqrt{\sum_{i=1}^{l} \left\{ \frac{[C_i(a) - C_i(r)]}{[C_{imax} - C_{imin}]} \right\}^2} \tag{9}$$

Here, C_{imax} and C_{imin} are the maximum and minimum values of C_i, respectively, and l is the number of condition attributes in the condition rule. After determining the rule, the decision attribute value a is classified into the decision category. Once the decision category of the predicted object is determined, the life grade of the product can be calculated as the prediction result using Eq. (9).

3. Relay Life Prediction Based on Rough Set Theory

3.1 Relay life prediction model

Firstly, the decision table for the life of individual relays is established using rough set theory. The relay performance parameters in the early life are defined as conditional attributes. The relay operating life is defined as a decision attribute. Secondly, using the decision table, a set of association rules between the initial relay performance parameters and the operating life are extracted. Thirdly, the individual relay life is predicted from the initial relay performance parameters.

The detailed steps for relay life prediction are listed as follows.

Step 1: Collect the life data and related parameters for relay life prediction. The ambient temperature C_1, the initial relay performance parameters $C = \{C_2, C_3, ..., C_N\}$, and the operating life D in the early stage are obtained through life tests of relay samples.

Step 2: Divide the discrete data values into attributed values and construct the decision-making table. Take C as the conditional attribute and D as the decision attribute. A decision table of individual relay operating lives is established using rough set theory.

Step 3: Reduce the number of relative attributes. A set of association rules are extracted from the initial relay performance characteristics and individual relay operating lives.

Step 4: Analyze the actual relay parameters and verify the decision-making rules. Using the decision-making rules, measure only the initial relay performance parameters to predict the relay life.

A flowchart of the relay life prediction model is shown in Fig. 1.

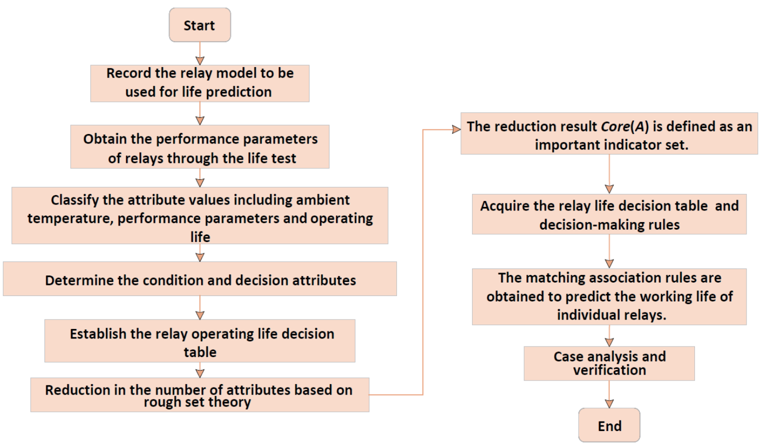

Fig. 1. (Color online) Flowchart of relay life prediction model.

3.2 Selection of relay life test data

In this study, an operation test platform using 12 electromagnetic relays of the same type was setup to carry out reliability life tests. The tests were divided into three groups (−20, 20, and 55 °C). In practice, the initial performance characteristics of each sample will vary with the sample itself. The relay life is defined as the number of contacts, where the contact point status is either on or off when the relay works normally. The major performance parameters of the relay include temperature, bounce time, dynamic fluctuation time, dynamic peak voltage drop, and static contact voltage drop. Each platform was equipped with eight electromagnetic relay samples. Through the electromagnetic relay life test on each platform, the initial state information and operation number were recorded. The operation test platform is shown in Fig. 2.

The entire test platform has 12 individual test platforms, and each individual platform was equipped with eight electronic relay samples. To verify the universality of the experimental results, one of the eight samples from each test platform was randomly selected for analysis. In this test, the ambient temperature was regarded as a crucial attribute, and the effects of the actual working conditions on the relay life were also considered in the prediction process. The results are shown in Table 1.

From Table 1, it can be seen that under the same ambient temperature conditions, the lifetime varied among the relays. For example, at −20 °C, the life of sample 1 is 685 (×10k times), while that of sample 2 is 834. At 20 °C, the life of sample 6 is 230, while that of sample 7 is 955. At 55 °C, the life of sample 10 is 579, while that of sample 12 is only 378.

By analyzing these results, we found that relay contact faults account for more than 90% of the total relay faults. This implies that the operating relay life strongly depends on the relay contact performance. Moreover, we found that early performance parameters such as bounce time, dynamic fluidization time, dynamic peak voltage drop, and static contact voltage drop are important factors.

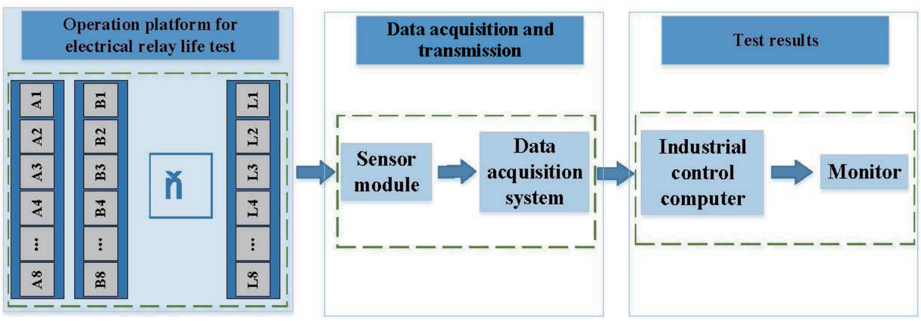

Fig. 2. (Color online) Structure of relay test platform.

Table 1
Results of measured relay life.

Ambient temperature (°C)	−20				20				55			
Relay sample number	1	2	3	4	5	6	7	8	9	10	11	12
Operating life (10k)	685	834	750	792	245	230	955	926	437	579	542	378

In this study, two early performance parameters, dynamic fluctuation time and static contact voltage drop, were compared using relay samples 6 and 7. Comparisons of the dynamic fluctuation time and static contact voltage drop between relay samples 6 and 7 at 20 ℃ are shown in Figs. 3(a) and 3(b), respectively.

From the above charts, there is clearly a significant correlation between the individual relay life and the working ambient temperature, which is also related to the early relay life behavior. This reveals that a relay with good early performance has a longer life. However, many factors that affect the initial relay performance may not affect its life. Therefore, it is necessary to eliminate some of the early performance factors to achieve accurate prediction results.

4. Experimental Results and Verification

4.1 Experimental results

The first eight relays, i.e., x_1–x_8, were selected to establish life decision rules, and the remaining four relays, i.e., x_9–x_{12}, were used for relay life prediction. We extracted the data from the final life of relays x_1–x_8 for 100,000 life tests. The average statistics obtained for the performance parameters and life data are summarized in Table 2. Note that the unit of the operating life is 10k times.

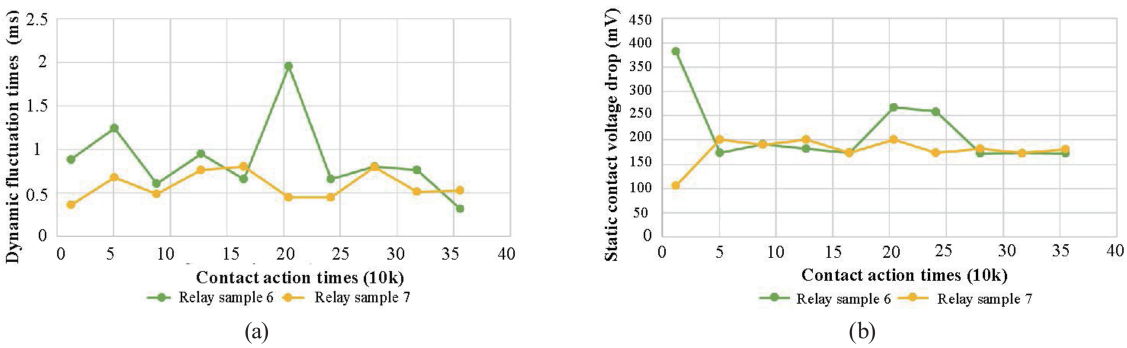

Fig. 3. (Color online) Comparison of dynamic fluctuation time and static contact voltage drop for samples 6 and 7. (a) Dynamic fluctuation time. (b) Static contact voltage drop.

Table 2
Performance parameters and life data.

Relay sample	Ambient temperature (℃)	Bounce time (ms)	Dynamic fluctuation time (ms)	Dynamic peak voltage drop (*V*)	Static contact voltage drop (*V*)	Operating life (10k)
x_1	−20	0.57	0.44	1.143	0.870	685
x_2	−20	0.48	0.70	1.010	0.882	834
x_3	20	0.48	0.53	0.510	0.166	245
x_4	20	0.57	0.90	0.580	0.264	230
x_5	20	0.45	0.57	0.743	0.135	955
x_6	20	0.56	0.51	0.437	0.175	926
x_7	55	0.58	0.59	1.418	0.966	437
x_8	55	0.30	0.88	1.286	1.001	579

All attribute values in Table 2 were discretized and assigned to three levels, i.e., 1–3, as shown in Table 3. In this study, the ambient temperature and early performance parameters of relay samples were taken as conditional attributes, and the operating life of samples was taken as the decision attribute. The results of the attribute assignment are shown in Table 4. On the basis of Table 4, the reduction in the number of conditional attributes relative to the number of decision attributes was carried out using rough set theory, and a reduced decision table was obtained. The specific reduction algorithm is as follows.

$$\begin{aligned}
U &= \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\} \\
U/ind(C_1) &= \{\{x_1, x_2\}, \{x_3, x_4, x_5, x_6\}, \{x_7, x_8\}\} \\
U/ind(C_2) &= \{\{x_1, x_4, x_6, x_7\}, \{x_2, x_3, x_5, x_8\}\} \\
U/ind(C_3) &= \{\{x_1, x_3, x_5, x_6, x_7\}, \{x_2, x_4, x_8\}\} \\
U/ind(C_4) &= \{\{x_1, x_2, x_7, x_8\}, \{x_3, x_4, x_6\}, \{x_5\}\} \\
U/ind(C_5) &= \{\{x_1, x_2, x_7, x_8\}, \{x_3, x_4, x_5, x_6\}\} \\
U/ind(C) &= \{\{x_1\}, \{x_2\}, \{x_3\}, \{x_4\}, \{x_5\}, \{x_6\}, \{x_7\}, \{x_8\}\} \\
U/ind(D) &= \{\{x_1, x_2\}, \{x_3, x_4, x_7, x_8\}, \{x_5, x_6\}\}
\end{aligned} \tag{10}$$

Table 3
Performance parameter assignment.

Attribute	Value range	Assignment	Attribute	Value range	Assignment
Ambient temperature C_1 (°C)	[−35, 0)	1	Dynamic peak voltage drop C_4 (V)	[0, 0.6)	1
	[0, 35]	2		[0.6, 1.0]	2
	(35, 70]	3		(1.0, +∞)	3
Bounce time C_2 (ms)	[0, 0.5)	1	Static contact voltage drop C_5 (V)	[0, 0.4)	1
	[0.5, 0.8]	2		[0.4, 0.8]	2
	(0.8, +∞)	3		(0.8, +∞)	3
Dynamic fluctuation time C_3 (ms)	[0, 0.6)	1	Operating life D (10k)	[0, 600]	1
	[0.6, 1.0]	2		[600, 900]	2
	(1.0, +∞)	3		(900, +∞)	3

Table 4
Decision-making results for operating life.

U	C_1	C_2	C_3	C_4	C_5	D
x_1	1	2	1	3	3	2
x_2	1	1	2	3	3	2
x_3	2	1	1	1	1	1
x_4	2	2	2	1	1	1
x_5	2	1	1	2	1	3
x_6	2	2	1	1	1	3
x_7	3	2	1	3	3	1
x_8	3	1	2	3	3	1

In summary, it can be concluded that

$$
\begin{aligned}
pos_C(D) &= \{x_1\} \cup \{x_2\} \cup \{x_3\} \cup \{x_4\} \cup \{x_5\} \cup \{x_6\} \cup \{x_7\} \cup \{x_8\} \\
&= \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}.
\end{aligned} \tag{11}
$$

The relationship between the attribute sets D and C is $k = \gamma_C(D) = |posC(D)| / |U| = 1$. The attribute set C = {ambient temperature, bounce time, dynamic fluctuation time, dynamic peak voltage drop, static contact voltage drop} is sufficient for classifying the operating lives of individual relays. Accordingly, the product sample $\{x_1, x_2, ..., x_7, x_8\}$ is classified as sufficient and can be reduced relative to D.

Next, each condition attribute (C_1, C_2, C_3, C_4, C_5) is analyzed to establish whether it can be reduced relative to D.

$$
\begin{aligned}
&pos_{(C-\{C_1\})}(D) = \{x_3\} \cup \{x_4\} \cup \{x_5\} \cup \{x_6\} = \{x_3, x_4, x_5, x_6\} \\
&pos_{(C-\{C_2\})}(D) = \{x_1\} \cup \{x_2\} \cup \{x_4\} \cup \{x_5\} \cup \{x_7\} \cup \{x_8\} = \{x_1, x_2, x_4, x_5, x_7, x_8\} \\
&pos_{(C-\{C_3\})}(D) = \{x_1\} \cup \{x_2\} \cup \{x_3\} \cup \{x_5\} \cup \{x_7\} \cup \{x_8\} = \{x_1, x_2, x_3, x_5, x_7, x_8\} \\
&pos_{(C-\{C_4\})}(D) = \{x_1\} \cup \{x_2\} \cup \{x_4\} \cup \{x_6\} \cup \{x_7\} \cup \{x_8\} = \{x_1, x_2, x_4, x_6, x_7, x_8\} \\
&pos_{(C-\{C_5\})}(D) = \{x_1\} \cup \{x_2\} \cup \{x_3\} \cup \{x_4\} \cup \{x_5\} \cup \{x_6\} \cup \{x_7\} \cup \{x_8\} \\
&\qquad = \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}
\end{aligned} \tag{12}
$$

a) $pos_{(C-\{C_1\})}(D) \neq pos_C(D)$, indicating that C_1 cannot be reduced separately relative to D
b) $pos_{(C-\{C_2\})}(D) \neq pos_C(D)$, indicating that C_2 cannot be reduced separately relative to D
c) $pos_{(C-\{C_3\})}(D) \neq pos_C(D)$, indicating that C_3 cannot be reduced separately relative to D
d) $pos_{(C-\{C_4\})}(D) \neq pos_C(D)$, indicating that C_4 cannot be reduced separately relative to D
e) $pos_{(C-\{C_5\})}(D) = pos_C(D)$, indicating that C_5 can be reduced separately relative to D

From the above deduction, C_1, C_2, C_3, C_4 are found relative to D. Accordingly, the important indexes that affect the operating lives of individual relays were confirmed to be the ambient temperature, bounce time, dynamic fluctuation time, and dynamic peak voltage drop. As a result of the above reasoning and reduction processes, the decision-making table for the operating lives of individual relays was thus obtained as Table 5, which was simplified from Table 4.

The relay life decision rules related to C_1, C_2, C_3, C_4 are expressed in Fig. 4. From Eq. (8), the reliability of each decision rule in the above example is 1, which reveals that the above decision rules are deterministic. The relay operational life decision rules can thus be deduced, as shown in Table 6. In practice, "1" is regarded as the initial reliability of the decision rules.

For example, Rule 1 states that if the ambient temperature is in the range [−35, 0) ℃, the average bounce time of the relay is in the range [0.5, 0.8] ms, the average dynamic fluctuation time is in the range [0, 0.6) ms, the dynamic peak voltage drop is in the range (1.0, +∞) *V*, and the

Table 5
Decision-making table.

U	C_1	C_2	C_3	C_4	D
x_1	1	2	1	3	2
x_2	1	1	2	3	2
x_3	2	1	1	1	1
x_4	2	2	2	1	1
x_5	2	1	1	2	3
x_6	2	2	1	1	3
x_7	3	2	1	3	1
x_8	3	1	2	3	1

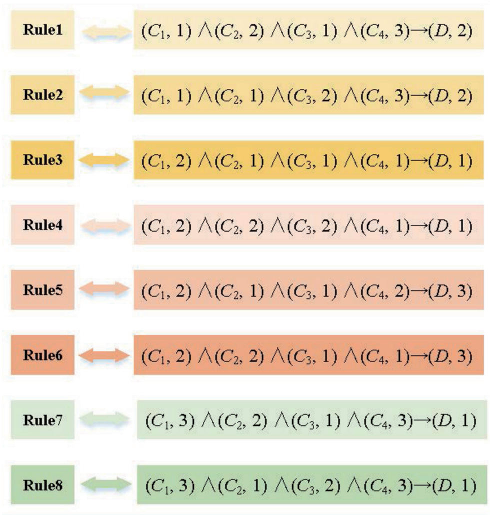

Fig. 4. (Color online) Relay life decision rules.

Table 6
Decision rules for relay operational life.

Rule	Range of ambient temperature	Range of average bounce time	Range of average dynamic fluctuation time	Range of dynamic peak voltage drop	Range of operating life (×10k)	Reliability of rule
1	[−35, 0) °C	[0.5, 0.8] ms	[0, 0.6) ms	(1.0, +∞) V	[600, 900]	1
2	[−35, 0) °C	[0, 0.5) ms	[0.6, 1.0] ms	(1.0, +∞) V	[600, 900]	1
3	[0, 35] °C	[0, 0.5) ms	[0, 0.6) ms	[0, 0.6) V	[0, 600)	1
4	[0, 35] °C	[0.5, 0.8] ms	[0.6, 1.0] ms	[0, 0.6) V	[0, 600)	1
5	[0, 35] °C	[0, 0.5) ms	[0, 0.6) ms	[0.6, 1.0] V	(900, +∞)	1
6	[0, 35] °C	[0.5, 0.8] ms	[0, 0.6) ms	[0, 0.6) V	(900, +∞)	1
7	(35, 70] °C	[0.5, 0.8] ms	[0, 0.6) ms	(1.0, +∞) V	[0, 600)	1
8	(35, 70] °C	[0, 0.5) ms	[0.6, 1.0] ms	(1.0, +∞) V	[0, 600)	1

operating life of the relay is in the range [600, 900] (×10k), then the reliability is 1. In this way, the relay operating life can be qualitatively predicted from the ambient temperature and early performance parameters, such as the bounce time, average dynamic fluctuation time, and dynamic peak voltage drop.

4.2 Model verification

Using the relay life rules in Sect. 4.1, the operating lives for relays x_9–x_{12} were predicted. The performance results are shown in Table 7.

According to the distance measurement method expressed in Eq. (9), only rule 8 matches relay x_{12}. Therefore, it can be inferred that the life level of relay x_{12} is 1, which is consistent with the actual life of 378.

Table 7
Performance prediction results of relays x_9–x_{12}.

Relay sample	Ambient temperature (°C)	Bounce time (ms)	Dynamic fluctuation time (ms)	Dynamic peak voltage drop (V)	Operating life (10k)
	Actual value/ attribute assignment	Actual value/ attribute assignment	Actual value/ attribute assignment	Actual value/ attribute assignment	Actual value/ attribute assignment
x_9	−20/1	0.54/2	0.48/1	1.027/3	750/2
x_{10}	−20/1	0.41/1	0.81/2	1.009/3	792/2
x_{11}	55/3	0.58/2	0.47/1	1.220/3	542/1
x_{12}	55/3	0.42/1	1.01/3	1.241/3	378/1

5. Conclusions

In this study, a liability prediction model for relay lifetime using rough set theory was developed successfully. Experimental results showed that the individual relay lifetime is related to its initial performance information. The key factors hidden in the existing data can be obtained from a set of relay life decision rules. The major contributions in this study are threefold: (1) The number of relay performance parameters can be reduced by rough set theory, and the key initial performance parameters can be obtained. (2) On the basis of attribute reduction using rough set theory, a group of decision-making rules for the relay life were well established directly from the early relay life states. (3) By analyzing the long-term life test data using different types of relays, the relay life was confirmed to be related to the early performance. The ideas and method used in this study can be applied to screen relays in practical working systems and to select devices with good performance for systems requiring high reliability. This innovative method and similar methods can also be applied to the reliability life prediction or product screening of other products to solve reliability problems in practical engineering.

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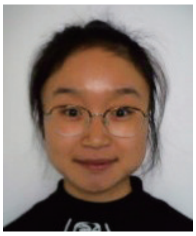

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