A new life prediction method of Intelligent meters based on adaptive weighting coefficients

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Abstract — In order to achieve the purpose of predicting the batch life index of intelligent meters in using, this paper analyzes the history failure data of the products, comprehensively considers the stresses such as temperature and humidity, then proposes an improved Weibull distribution statistical analysis method based on adaptive weighting coefficient, which is applied to the batch life prediction of intelligent meters. The prediction error of stage failure rate is less than 0.0002 fit.

1. INTRODUCTION
In the field of reliability engineering, product life prediction methods based on condition monitoring value and failure data driven are two kinds of methods with more reference value in theory and practice [1]; while methods based on reliability prediction or accelerated life test are generally used for reliability evaluation in product design stage [2], and the results are basically unable to be effectively correlated with field actual data. The residual life prediction method based on condition monitoring is based on a specific physical characteristic model, which is often used to predict the residual life of mechanical products [3], and needs to implant sensors for long-term monitoring of reliability sensitive quantities. For intelligent meters, because there is no special sensor inside, it is impossible to collect a large number of historical data of reliability sensitive quantity of single meter.

The field reliability data of intelligent meters is rich, and the statistical regression method based on data driven is the basis of applying historical fault data to study the remaining life of batch meters [4,5]. Through the statistical analysis of the historical fault data of products [6], the failure time model is established to predict the remaining life of batch products, which is a logical and economic feasible way in theory and practice. The prediction method based on historical fault data is favored by many scholars because it does not need to establish the specific failure physical model of the product [7, 8] But on the other hand, it can only be carried out on the whole machine, so it only has the evaluation function, but can’t consider the influence of different failure modes and different influence factors on the fault data. Therefore, its pertinence, accuracy and supporting role in fault cause analysis have great room for improvement [9]. Because of the above reasons, this paper creatively proposes a more practical life prediction method of intelligent meters, that is, the life prediction method of intelligent meters based on adaptive weight coefficient and multiple influence factors. Based on the traditional Weibull distribution model, this method takes the historical fault data of products as the research object, and considers
different failure modes and different failure mechanism, and corresponding correlation of different influence stress (factor). This method can more truly reflect the influence of influence factors on the parameters of the failure time model, and the life prediction results obtained by this method can be more accurate, and the obtained failure time law can be used as the basis of failure analysis, so as to continuously improve the design of products and improve the reliability of products.

2. FITTING PREDICTION METHOD OF BASIC WEIBULL DISTRIBUTION

2.1. Calculation of stage failure rate and cumulative failure rate

The phase failure rate is defined as:

$$\lambda(t_i) = \frac{n_i}{N_{i-1} \times \Delta t}$$

(1)

The cumulative failure rate at the end of the month is defined as:

$$F(t_i) = \frac{(N_0 - N_i)}{N_0}$$

(2)

Among them, the total number of batch intelligent meters is $$N_0$$, the service time before failure of each intelligent meter is $$t_i$$, the number of stage failures $$n_i$$ and the number of stage residual $$N_i$$ in each month.

2.2. Data distribution fitting based on Weibull model

Whether a group of data conforms to Weibull distribution in mathematics can be tested by graph estimation and calculation. In this paper, we use the combination of the two methods to test the distribution type.

If the classical formula of Weibull model is expressed by cumulative failure rate, it can be expressed as follows:

$$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^\beta}$$

(3)

Of course, according to this formula, failure rate $$\lambda(t)$$, failure probability density function $$f(t)$$ and reliability $$R(t)$$ can also be listed. In this paper, two indexes, $$F(t)$$ and $$\lambda(t)$$, are used to characterize the reliability level of batch intelligent meters and to predict the relevant data of remaining life.

In order to apply the historical failure data of batch intelligent meters to Weibull model for fitting test, transform equation (3), take two logarithms on both sides, and get:

$$\ln \left\{ \ln \left( \frac{1}{1 - F(t)} \right) \right\} = \beta \times \ln(t) - \beta \times \ln(\alpha)$$

(4)

If $$Y = \ln \left\{ \ln \left( \frac{1}{1 - F(t)} \right) \right\}$$, $$X = \ln(t)$$, then a new double logarithmic coordinate system, vibe coordinate system, can be formed[10].

First of all, process the historical failure data of batch intelligent meter, arrange the number of phase failures according to the successive phase time $$t_i$$, and then calculate $$X_i$$ and $$Y_i$$ according to formula (1) and formula (2), where $$Y_i = \ln \left\{ \ln \left( \frac{1}{1 - F(t)} \right) \right\}$$, $$X_i = \ln(t_i)$$.

A graphic method for calculating the parameters $$\alpha$$ and $$\beta$$ is to draw the values of the vectors $$X_i$$ and $$Y_i$$ into the orthogonal Weibull coordinate system, and obtain the distribution parameters $$\alpha$$ and $$\beta$$ of the linear model of Weibull fitting by line fitting[11].

2.3. Life prediction

After the parameters $$\alpha, \beta$$ of Weibull model are known, the next life performance of the intelligent meter batch can be predicted based on the model of this time point. In the future, the formula of phase failure rate is $$\lambda(t) = \left( \frac{1}{\alpha} \right) \alpha^\beta t^{- \beta - 1}$$, while in the future, the formula of cumulative failure rate of intelligent meter batch counting is $$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^\beta}$$ [12].
3. THE LIMITATION OF THE FITTING PREDICTION METHOD OF BASIC WEIBULL DISTRIBUTION

Since the prediction methods of Weibull distribution fitting are all based on the fault data of intelligent meters [13], they do not consider the difference of different circuit modules in the intelligent meter affected by different external stress [14]. Therefore, in order to make the failure time model better reflect the influence of temperature, humidity, salt spray, load, initial test data and other factors on the life of intelligent meters, these factors should be taken into account.

Generally, the failure distribution characteristics of different failure modes are different, and the stress type and degradation process of failure are also different. For specific failure modes, the degradation process is also related to the action time and strength of the stress [15,16]. Therefore, by obtaining the change characteristics of stress and the corresponding stress life model of intelligent meters (single failure mode), the distribution characteristics of each failure mode of intelligent meters can be more accurately mastered. Combined with the Weibull fitting method, the batch life of intelligent meters can be predicted more accurately.

4. IMPROVEMENT METHOD OF MULTI FAILURE MODE AND MULTI STRESS TYPE

4.1. Comprehensive prediction of multiple failure modes under the influence of multiple stresses

In this paper, a comprehensive life prediction method for intelligent meters based on adaptive weighting coefficient is proposed

1) The main failure mode types of intelligent meters are found out, and the main influence stress types are found by using FMEA method to form a cross matrix correlation relationship;

2) By querying the climate information of a certain area, the intensity time distribution of the main stress types is obtained by analyzing the data;

3) The relationship between the single stress and the affected single failure mode reliability index (i.e. the stress life model under the condition of single stress) is established.

Thus, the stage failure rate of a specific failure mode of the intelligent meter can be simply expressed as the following formula:

$$\lambda_i = \lambda_{i_0} \times \prod_{j=1}^{N} k_{ij}$$  \hspace{1cm} (5)

Where $$\lambda_{i_0}$$ is the basic failure rate predicted in Chapter 2 of this paper for the fault mode $$i$$ (i value is 1, 2, 3 , M), and $$k_{ij}$$ is the influence coefficient of the stress type $$j$$ (j value is 1, 2, 3 , N) to the fault mode $$i$$, ideally, $$k_{ij}$$ value is 1, that is, there is no influence.

Then the overall stage failure rate of a batch of intelligent meters can be expressed as follows:

$$\lambda = \sum_{i=1}^{M} \lambda_i = \sum_{i=1}^{M} \left( \lambda_{i_0} \prod_{j=1}^{N} k_{ij} \right)^{\beta_i}$$  \hspace{1cm} (6)

4.2. Temperature stress induced failure mode prediction

Temperature has an obvious effect on the clock module of intelligent meter. The mechanism of accelerated degradation at high temperature is as follows: at the initial time of $$T = T_0$$, the clock crystal oscillator works at frequency $$f_0$$, but with the effect of temperature stress $$T$$, frequency drift gradually begins to appear, which leads to the increase of timing error. When the crystal frequency drifts to the frequency of failure of timing, the system detects Abnormal timing failure. At this point, the time experienced is $$T_F$$, which is the life span of the product. The classical Arrhenius model is expressed as follows:

$$t_F = A \times e^{\frac{k}{T}}$$  \hspace{1cm} (7)

The above equation shows the relationship between life and temperature. The logarithm of both sides of equation (7) can be obtained as follows: the logarithm of time (life value) is positively linear with the reciprocal of temperature (Kelvin temperature).
Generally, the Weibull prediction method does not consider the difference of each time period, but in practice, the temperature and humidity of each time period are different, so it is necessary to analyze and forecast the data of each month.

Based on the above analysis, taking clock module as an example, the influence coefficient $k_{ij}$ of temperature on clock module fault can be defined as the failure rate adjustment coefficient $k_T$ caused by temperature difference, which also changes with the change of external temperature (different time periods). Therefore, the adjustment factor values $k_T(t, T)$ are calculated respectively with the month as the basic time period, where $t = 1, 2, 3 \cdots, 12$.

The basic Weibull model is used to directly predict the original stage failure rate of the clock module (which does not change with the average temperature of the month), and then according to the temperature adjustment coefficient of each month, the phase failure rate of different months (with different temperature) is calculated.

4.3. Humidity stress induced failure mode prediction

The effect of humidity on electronic products mainly refers to the failure mechanism such as thermal mismatch caused by water vapor penetrating into plastic interface and electrochemical corrosion and electrochemical migration caused by water vapor remaining on the surface of electronic products. The corresponding humidity adjustment coefficient $k_H(t, H)$ is related to humidity and action time.

Therefore, the stage failure rate of a specified area can be counted first; then, the average humidity level of each month in this region can be obtained by querying and calculating; then, the oblique line of the phase failure rate changing with the monthly average humidity can be linearly fitted in the coordinate with the humidity stress on the horizontal axis and the stage failure rate on the vertical axis, and the predicted failure rate under any humidity level can be obtained. The calculation method is similar to the adjustment calculation of temperature influencing factors.

5. APPLICATION OF IMPROVED PREDICTION METHOD

In this chapter, the temperature influence factor is taken as an example to illustrate the adjustment of the influence stress of the adaptive weighting coefficient on the life prediction of intelligent meters, and its prediction effect.

Taking a certain type and batch of electric energy meters as an example, the main calculation process is as follows:

1) Based on the actual data in 2017, the monthly failure number, monthly stage failure rate, logarithm of monthly stage failure rate, average temperature, reciprocal of average temperature, etc. of clock module failure mode of these meters are calculated as follows.

| Month | Monthly Failure number | $\lambda(t)$ | $\ln \lambda(t)$ | aver $T_K$ | $1/T_K$ |
|-------|------------------------|--------------|-------------------|------------|---------|
| Jan   | 210                    | 0.000537     | -7.524409         | 277.73     | 0.003600 |
| Feb   | 242                    | 0.000622     | -7.381957         | 279.28     | 0.003580 |
| Mar   | 254                    | 0.00065      | -7.332907         | 283.41     | 0.003528 |
| April | 286                    | 0.000736     | -7.213513         | 289.42     | 0.003455 |
| May   | 291                    | 0.00075      | -7.195432         | 294.39     | 0.003396 |
| Jun   | 318                    | 0.000820     | -7.105884         | 298.05     | 0.003355 |
| July  | 385                    | 0.000994     | -6.913698         | 302.39     | 0.003307 |
| Aug   | 371                    | 0.000958     | -6.949781         | 301.79     | 0.003313 |
| Sept  | 325                    | 0.000840     | -7.081318         | 297.28     | 0.003363 |
| Oct   | 274                    | 0.000709     | -7.251306         | 291.83     | 0.003426 |
| Nov   | 249                    | 0.000644     | -7.346336         | 286.07     | 0.003495 |
| Dec   | 221                    | 0.0005727    | -7.465054         | 280.15     | 0.003569 |
Fitting the functional relationship between the failure rate of the clock module and the monthly average temperature, and then obtaining the following formula:

\[ y = -1747.4x - 1.2003 \]  \hspace{1cm} (8)

Where \( y = \ln(\lambda(t)) \), \( x = 1/T_K \). The goodness of fit \( R^2 = 0.9277 \), which indicates that the relationship between failure rate and temperature is in accordance with Arrhenius equation.

\[ \text{Fig. 1 Relationship between logarithm of failure rate and temperature} \]

2) According to the temperature distribution, the following table shows that the annual average temperature is 16 ℃, and the corresponding \( 1/T_K \) is 0.00346. Based on the linear fitting formula (8) obtained in 1), \( y = \ln(\lambda(t)) = -7.249384 \), the adjustment coefficient \( T_K \) at this time is defined as 1, that is, the temperature has no obvious effect on the failure rate. According to formula (8), different temperatures can correspond to a different \( \ln(\lambda) \). By dividing \( \ln(\lambda) \) at different temperatures with \( \ln(\lambda) \) at 16 ℃, the adjustment coefficient of any temperature to 16 ℃ can be obtained. The table below is an example of the adjustment coefficient under typical temperature conditions.

\[ \text{Table 2 Variation of adjustment coefficient under typical temperature} \]

| T  | \( T_K \) | \( 1/T_K \) | \( \ln(\lambda(t)) \) | \( k_T \) |
|----|---------|-----------|-----------------|--------|
| 0  | 273     | 0.003663  | -7.609266       | 1.049643 |
| 10 | 283     | 0.003533  | -7.379571       | 1.017958 |
| 16 | 289     | 0.003460  | -7.249384       | 1       |
| 20 | 293     | 0.003412  | -7.165555       | 0.988436 |
| 30 | 303     | 0.003300  | -6.965665       | 0.960863 |
| 40 | 313     | 0.003194  | -6.778548       | 0.935051 |

3) Calculate the monthly adjustment coefficient in 2018: since the comprehensive average temperature of each month in 2015-2017 is used as the basis for predicting the failure rate of each month in 2018, that is, the monthly average temperature of the first three years is calculated, then converted into Kelvin temperature, and then the reciprocal is made. Then, the theoretical \( \ln(\lambda(t)) \) of each month in 2018 is calculated according to the fitting linear formula (8) obtained in 1), and Taking \( \ln(\lambda(t)) \) corresponding to 16 ℃ in Table 2 as the benchmark (i.e. when the adjustment coefficient is 1), the adjustment coefficient \( K_T \) of each month in 2018 is calculated in proportion.

\[ \text{Table 3 Theoretical monthly failure rate and } K_T \text{ value at average temperature in 2018} \]

| Month | T    | \( 1/T_K \) | \( \ln(\lambda(t)) \) | \( k_T \) |
|-------|------|-------------|-----------------|--------|
| Jan   | 3.89 | 0.003611    | -7.517943       | 1.037045 |
| Feb   | 7.01 | 0.003571    | -7.446530       | 1.027194 |
| Mar   | 9.92 | 0.003534    | -7.381344       | 1.018202 |
| April | 17.32| 0.003444    | -7.221465       | 0.996148 |
4) In the method without considering the temperature effect, the predicted monthly failure rate \( \lambda_0(t) \) in 2018 is converted into the logarithm \( \ln \lambda_0(t) \) of the monthly failure rate before adjustment, and then corrected by the adjustment coefficient \( K_T \) (such as the monthly values in Table 3) to obtain the logarithm \( \ln \lambda(t) \) of the adjusted monthly stage failure rate in 2018 considering the temperature effect, and then converted into the adjusted \( \lambda(t) \). It should be emphasized that the use of the adjustment factor \( K_T \) must be based on the logarithmic linear equation, instead of directly multiplying the failure rate before adjustment by \( K_T \) to obtain the adjusted failure rate. Table 4 below compares the failure rates before adjustment, after adjustment and actual stage, and describes the difference between the adjusted failure rate and the actual failure rate in the form of difference.

| Month | \( \lambda_0(t) \) | \( \ln \lambda_0(t) \) | \( k_T \) | \( \ln \lambda(t) \) | \( \lambda(t) \) | \( \lambda_a(t) \) actual | difference |
|-------|-----------------|-----------------|-------|-----------------|-----------------|-----------------|-----------------|
| Jan   | 0.000764765    | -7.175941961   | 1.037045749 | -7.441780103 | 0.000586241   | 0.000635427   | 0.00004919      |
| Feb   | 0.000764765    | -7.175941961   | 1.027194912 | -7.371091069 | 0.000629181   | 0.000610865   | -0.00001832     |
| Mar   | 0.000764765    | -7.175941961   | 1.018202936 | -7.306565171 | 0.000671118   | 0.000701755   | 0.00003064      |
| April | 0.000764765    | -7.175941961   | 0.996148779 | -7.14830582  | 0.000786195   | 0.000905575   | 0.00011938      |
| May   | 0.000764765    | -7.175941961   | 0.980471974 | -7.035809979 | 0.000879805   | 0.000863832   | -0.00001597     |
| Jun   | 0.000764765    | -7.175941961   | 0.971616301 | -6.972262186 | 0.00093753    | 0.000953802   | 0.00001627      |
| July  | 0.000764765    | -7.175941961   | 0.963216262 | -6.911983991 | 0.00099578    | 0.001068956   | 0.00007318      |
| Aug   | 0.000764765    | -7.175941961   | 0.964774748 | -6.923167596 | 0.000984706   | 0.000978433   | -0.00000627     |
| Sept  | 0.000764765    | -7.175941961   | 0.974087744 | -6.989997114 | 0.000921049   | 0.000942558   | 0.00002151      |
| Oct   | 0.000764765    | -7.175941961   | 0.99078112  | -7.109787817 | 0.000817068   | 0.000798565   | -0.00001850     |
| Nov   | 0.000764765    | -7.175941961   | 1.0043897   | -7.207442192 | 0.00074105    | 0.000764444   | 0.00002339      |
| Dec   | 0.000764765    | -7.175941961   | 1.027632223 | -7.374229239 | 0.00062721    | 0.000578644   | -0.00004857     |
Fig. 2 predicted values of failure rate with and without temperature coefficient and comparison with actual values

It can be seen from the data in Figure 2 above that the predicted failure rate of each month in 2018 is closer to the real data after the adjustment considering the influence of temperature. In Table 4, the maximum error between the adjusted monthly phase failure rate and the actual failure rate is in April, with an error of 0.00011938.

6. SUMMARY
This paper mainly expounds the goal, principle, connotation and mathematical model of intelligent meter life prediction. This paper studies the reliability evaluation and residual life prediction method of batch intelligent meters in use. Based on sorting out the failure mode types of intelligent meters, especially the technical accumulation of the relationship between different failure mechanisms and different influence stresses or factors, a life prediction method of intelligent meters based on adaptive weighting coefficient with multiple failure modes and multiple influence factors is proposed. In this paper, taking temperature and humidity stress as examples, the influence model combination Weibull distribution fitting prediction method is introduced. Based on the historical data of intelligent meters in field, the life prediction is carried out according to this method. The results obtained are obviously closer to the real data than the ordinary Weibull distribution method. Therefore, it can be better used to support intelligent meter manufacturers to carry out failure analysis and improve product reliability design level, and it can also better serve the power grid enterprises to make maintenance plans and timely replacement of batch intelligent meters.

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