

Introduction

Accurately mastering the quality status of equipment is the realistic demand to improve the level of equipment refined management and equipment support command decision. The quality status of equipment directly affects the timing and scale of equipment repair and life extension, the type and quantity of spare parts procurement, and the investment direction of funds.

Probability theory, evidence theory and other non-probabilistic methods are not suitable for modeling cognitive uncertainty, so the QMU method based on non-probabilistic measures also has some limitations.

Prediction Model

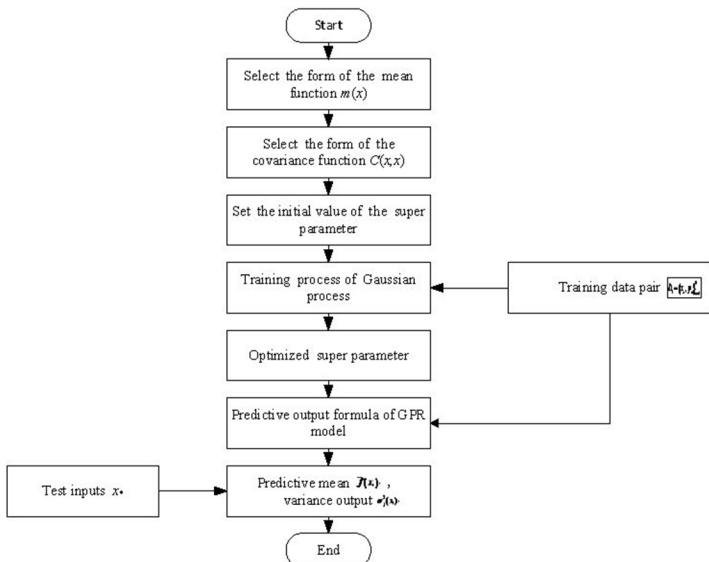


Figure 1. Performance parameter prediction process based on GPR model.

The main steps of performance parameter prediction based on GPR model are as follows:

Step 1: data set construction.

Step 2: determine the training data pair of independent variable and dependent variable, and establish the Gaussian process model.

Step 3: optimize the parameter value.

Step 4: use the established regression model to output the predicted value of the target parameters.

Basic Principles of QMU

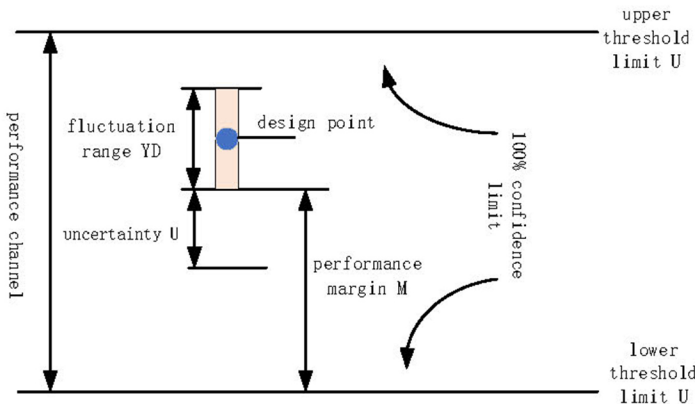


Figure 2. Schematic diagram of QMU basic principle.

Methods

Since the GPR model measures the uncertainty of the predicted value with the mean and variance, the margin M is defined as the difference between the mean value μ of the predicted value of the performance parameter and the performance threshold, that is, $M = \mu - PTL$ or $M = PTU - \mu$, the uncertainty U is quantified by the standard deviation σ of the predicted value of the performance parameter. Therefore, the confidence coefficient CF corresponding to the performance parameter is

$$CF = \frac{M}{U} = \frac{\min\{\mu - PTL, PTU - \mu\}}{\sigma}$$

Example verification

- (1) Data Set Construction
- Twenty-three device data sheets are combined into a new data sheet with 102 rows of 308 columns.
- (2) Model Training

Table 1. Prediction accuracy of some performance parameters of certain equipment

Parameter	Verification point	Actual value	Upper prediction	Lower limit	Minimum error interval
C63	2010.5	27.46	27.3384	27.0288	[-0.1216,-0.1948]
C51	2010.5	5.634	5.7911	5.6829	[0.0489,0.0641]
C155	2010.5	80.0	81.1317	79.0528	[-0.0537,0.2693]
C532	2010.5	14.46	14.2128	14.4332	[-0.0268,-0.0796]
C663	2010.5	27.4	27.3139	26.9162	[-0.0861,-0.1834]
C541	2010.5	27.43	27.2691	26.9583	[-0.1609,-0.23956]

- (3) Prediction process

$$\alpha_1 * x_1 + \alpha_2 * x_2 + \dots + \alpha_t * x_t + \beta * x_1^*$$

- (4) Results

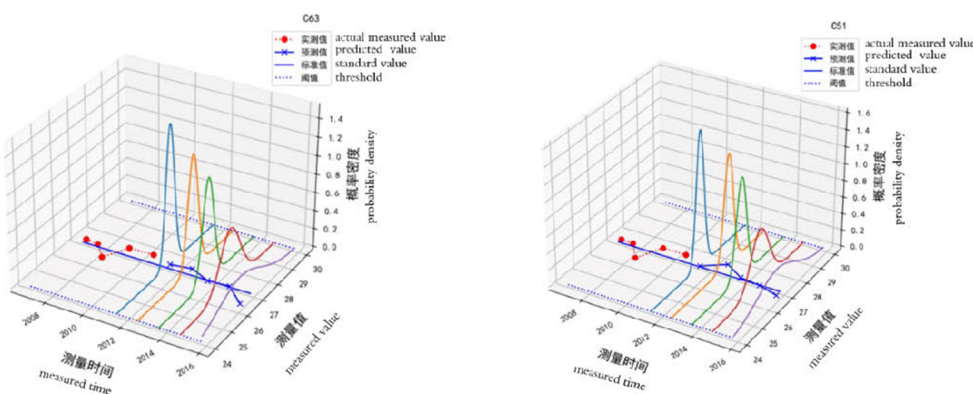


Figure 3. Prediction Results of Some Performance Parameters of Certain Equipment

Table 2. Evaluation result of equipment quality status

Time	Quality Status (Reliability)	Failure Probability
2011.4	0.9821	0.0179
2012.5	0.8355	0.1645
2013.6	0.8881	0.1119
2014.7	0.5146	0.0485
2015.8	0.2144	0.7856

Summary

- Based on the uncertainty measurement of GPR model, this paper gives the calculation method of CF value.
- An equipment quality status evaluation method combining GPR model and QMU is proposed.
- The equipment quality status evaluation methods proposed in this paper will optimize the parameter prediction model with the increase of test data, so as to improve the accuracy of evaluation.

References

[1] Liu Y, Zhang S R. Evaluation of Service Technology Status of Naval Power System Based on Expert Information[J]. Journal of Tianjin University of Science & Technology, 2023, 38(1): 70-74.

[2] Luo H J, Liu B J, Chen J H. Method of Equipment Health State Evaluation Based on Testing Data[J]. Computer Measurement & Control, 2020, 28(7): 265-268

[3] Liang T X, Peng Z M, Shen Z P, Xu Y, Zhang Y Z. System Reliability Assessment Based on QMU[J]. Science Technology and Engineering, 2017, 17(3): 121-128

[4] Zhang R, Liu T Y, Jin G. Remaining useful life prediction of lithium-ion batteries based on Gaussian process regression with self-constructed kernel[J]. Systems Engineering and Electronics, 2023, 45(8):2623-2633.

[5] Yao X J, Wu D. Prediction of mechanical properties of recycled concrete using bayesian optimization-based gaussian process regression method[J]. Science Technology and Engineering, 2023, 23(7): 2968-2975.

[6] Helton J C, Johnson J D, Sallaberry C J . Quantification of margins and uncertainties: example analyses from reactor safety and radioactive waste disposal involving the separation of aleatory and epistemic uncertainty . Reliability Engineering and System Safety, 2011; 96(9):1014-1033.

[7] Helton J C, Pilch M . Quantification of margins and uncertainties . Reliability Engineering and System Safety, 2011; 96(9):959-964.

[8] Schulz E, Speekenbrink M, Krause A . A tutorial on Gaussian process regression: modelling, exploring, and exploiting functions [J] . Journal of Mathematical Psychology, 2018, 85: 1-16 .

[9] Arthur C K, Temeng V A, Ziggah Y Y . Novel approach to predicting blast-induced ground vibration using Gaussian process regression [J] . Engineering with Computers, 2020, 36(1): 29-42 .