APEM journal
Advances in Production Engineering & Management
Volume 14 | Number 4 | December 2019 | pp 461–471
https://doi.org/10.14743/apem2019.4.341
ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

A new approach for product quality prediction of complex equipment by grey system theory: A case study of cutting tools for CNC machine tool

Pang, J.H.[a]**, Zhao, H.**[a]**, Qin, F.F.**[b,*]**, Xue, X.B.**[a]**, Yuan, K.Y.**[a]

[a]College of Mechanical and Electrical Engineering, Wenzhou University, Wenzhou, P.R. China
[b]School of Information Science and Engineering, Wenzhou Business College, Wenzhou, P.R. China

ABSTRACT

To compete in total global market, product quality has attracted the attention of manufacturers as an important mean of product differentiation. As effective product quality prediction method is the key technology for quality control system, a new prediction model and calculation method inspired by the grey system theory is proposed in this paper. Our practical evaluation shows that the quality of complex equipment was improved. Firstly, a new method of grey forecasting model for complex equipment was proposed, and the principle and method of grey predictive model with several variables were introduced. Secondly, this article discussed grey system theory model and showed how to use it in the forecasting process. Then, the quality prediction model and method using grey theory were set up with quality characteristics of cutting tools for Computer Numerical Control (CNC) machine tool. Finally, analysis of the test system showed that the applied predicting model and method were feasible and effective. This new method is also applicable to predict product quality of other complex electromechanical products which are composed a number of systems and subsystems.

ARTICLE INFO

Keywords:
Quality control;
Computer numerical control (CNC);
Machine tool;
Quality prediction;
Grey system theory

**Corresponding author:*
E-mail: helloqinfeifei8@sohu.com
(Qin, F.F.)

Article history:
Received 30 September 2019
Revised 9 December 2019
Accepted 13 December 2019

1. Introduction

Improving design and manufacturing quality are the reasons for the development of quality standard evaluation process of complex equipment production in the world. Complex equipment quality prediction is an important means for understanding the developmental tendency of electronic products. Product quality prediction using performance characteristics represents a difficult controllable variable in complex engineering environments. Due to quality characteristics, quality control, production technology and the technical conditions in engineering system practice, it is possible for errors to occur during product development and manufacturing processes [1]. The quality prediction phase is hence an important part of the manufacturing process, where emphasis is placed on managing resources and controlling operations to optimize costs and quality [2]. Therefore, a new quality predicting model and calculation method for complex equipment based on quality characteristics of engineering system should be identified for improving product quality under all foreseeable situations.

In this paper, a new model and calculation method has been perfected to predict production quality for complex equipment before actual implementation in manufacturing process [3]. Using analysis and prediction methods to do quality management and prediction work has become general knowledge in many fields [4]. Boosting quality prediction in manufacturing enterprises and advancing their quality management level have become the basic direction of complex equipment manufacturing industry [5]. This also helps product designers in their design decision-making by providing sufficient feedback information on capability and level of manufacturing quality [6]. Based on numerous survey results, this paper analyzed the current status of quality prediction in the manufacturing industry and proposed new quality prediction model and calculation method using grey system theory [7].

The application of grey system theory in complex equipment quality prediction is very important and useful. In this paper, we developed a fundamental model providing supports on product quality prediction of complex equipment associated with a particular sampling policy for a manufacturing system [8]. Real-time and accurate short-term quality forecasting had become a critical matter in intelligent engineering systems. In this paper, the current complex equipment quality prediction methods were systematically summarized, and the main contents of grey system were elaborated. In addition, the grey system theory model was used for complex equipment quality prediction. Finally, an ensemble data assimilation procedure was developed and evaluated for the quality prediction model.

Based on quality prediction models and methods have been discussed in many literatures and a lot of effective techniques and algorithms in the last 20 years. A methodology for sorting raw materials into homogenous groups with constant and optimized processing is presented to the most important factors causing unstable end-product quality by the fuzzy-c-means algorithm [9]. This paper has presented a simple data-based method in which measurements of other process variables are related to product quality, which were predicted recursively based on the measurements of reactor cooling rate [10]. A reliable model of a process both for the steady-state and unsteady-state regimes was established to predict the evolution of product composition with reliability of prediction and model reduction the neural model [11]. A novel offline modeling for product quality prediction of mineral processing was presented by using the least-squares support vector machine [12]. This paper has presented augmented reality and virtual reality as a successful tool in quality and defects management in construction industry [13]. A modeling approach to address the end-of-batch product quality prediction problem for batch processes was developed by using the three-way data set and the data set through the variable direction [14]. 20-lumped kinetics model and a linear partial least squares model was applied to the on-line aromatics yield prediction for a commercial continuous catalyst regeneration plat forming process [15]. An online product quality prediction method was developed based on offline clustering and online recognition of the operating modes a nonlinear dimension reduction method and multi-mode quality prediction method [16]. In order to predict software quality using a plain learner or a boosting algorithm which incorporates sampling, this paper presented the proposed techniques to several groups of datasets from two real-world software systems [17]. A novel online final product quality prediction scheme was proposed in this paper for the improvement of quality prediction in multi-phase batch processes, which explored the different effects of process variables in different phases on final product quality [18]. A developed model was used to predict final quality of products in a wide range of mineral content and temperature treatment data using principal component analysis and the influence of certain minerals [19]. This paper deals with the prediction of wafers quality in the semiconductor industry based on the pattern recognition principle by using a historical data of health indicators [20]. A survey of regularized linear regression methods using feature reduction and variable selection methods was presented to predict the water quality using the production equipment data and regression parameter optimization [21]. The potential of model predictive control on an offshore production unit starting was presented to control the gas-lift and ensure quality specifications of products of primary processing of petroleum through computer simulation [22]. A new methodology that utilizes a stochastic model to capture this complex relationship for better prediction that utilizes a linear model to represent the impact of tool wear was approved to capture the impact of quality degradation [23]. A novel Multi-Phase Support Vector Regression based soft sensor model for online quality prediction of glutamate concentration was presented by using the proposed soft sensor model for online product quality prediction [24]. An improved maximum likelihood estimation method was presented to reliability modelling of CNC machine tools with enlarging censored failure data [25].

On the basis of the reviewed documents, this paper has proposed the product quality prediction model and method of complex equipment via grey system theory, and tested and revised the method by the empirical method. The rest of this paper is organized as follows. Section 2 discusses the proposed quality prediction model of the research, and calculation method via grey system theory. Section 3 discusses and analyzes the results of experiments conducted in tooling system of CNC machine tool. Finally, some useful conclusions and future work are summarized in Section 4.

2. Materials and methods

2.1 Proposed quality prediction model

Aimed at process prediction in dynamic systems, a quality prediction model that meets the criteria for forecasting mechanism of time-varying quality characteristics is proposed in this article. Grey system theory is suitable for dynamic systems and is popularly applied in the prediction realm [26]. In this paper, a complex equipment quality prediction model was set up using the grey system theory which provided quality assurance of engineering systems. Here, an application example on the manufacturing process of complex equipment was used to validate the effectiveness of the prediction process and method.

The key to a successful prediction of manufacturing processes by mathematical method is the selection of an appropriate model and quality characteristics of engineering system [27]. A viable solution of prediction system will be essential based on technology of information sharing and transparency in different departments and business units [28]. Based on properties of complex equipment manufacturing process, the prediction model in quality control based on gray system theory is illustrated in Fig. 1. A nonparametric prediction algorithm for the forecasting of recurrent random events in complex engineering systems is expressed in the proposed quality prediction model. In the former stage, the main task of product quality prediction is feature selection and data preprocessing.

In addition, analysis and calculation are made through the grey system theory method, which formed the basis for system and quantitative analysis. Grey system theory is an effective method applicable to quality prediction when samples are small [29]. Then, on the basis of analyzing engineering system effluent quality prediction, we put forward a novel predictive method by grey system model GM (1, 1). The proposed forecast is a short-term quality prediction operation and is important for fault prevention of engineering machineries and prolonging their service life. The proposed quality prediction model is a fine prediction mode and method, which features automatic calculation and better reasonability and practicability. On the basis of above study, the proposed quality prediction model based on grey system theory is shown in Fig. 2.

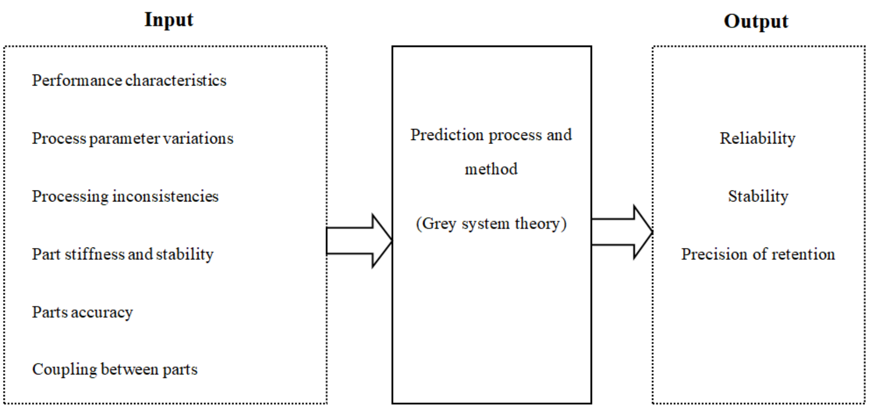

Fig. 1 Quality prediction process and method

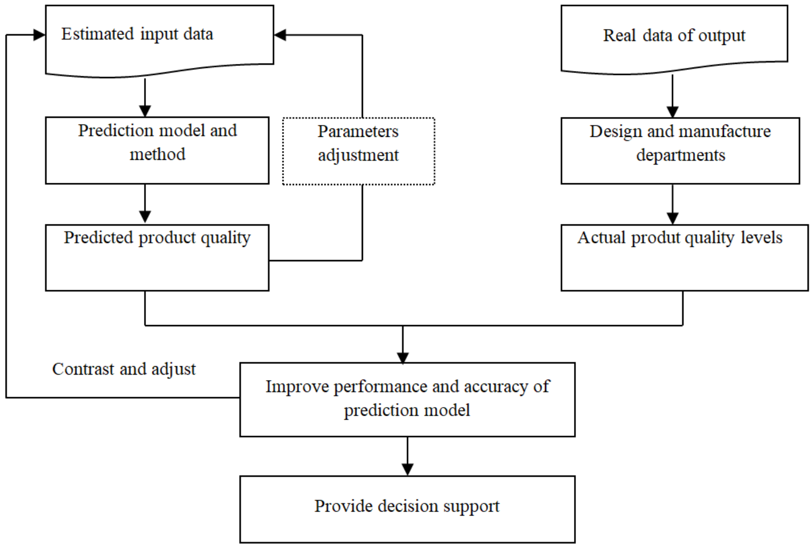

Fig. 2 Proposed quality prediction model via grey system theory

As seen in the Fig. 2, the complex equipment quality prediction is an intelligent system based on related research in this study. In some ways, the prediction system greatly improved the quality forecasting and delivered a better decision backing for quality management of the manufacturing industry [30].

2.2 Calculation method via grey system theory

Grey system theory was firstly developed in 1989 and has been used as a qualitative and quantitative analysis method in a system when available information is uncertain and incomplete [31]. This system has developed rapidly in recent years [32] and was successfully used in the field of quality assessment, risk forecasting, information decision, etc.

Generally speaking, grey system theory includes grey generating, grey relational analysis, grey forecasting, grey decision making and grey control [33]. Grey predicting is an important part of grey system theory. Grey forecasting is an important part of the grey system theory when information is imperfect [34]. The grey system model GM (1, 1) has been successfully applied to many fields of engineering system; moreover, it has been used in prediction realm [35].

Grey prediction model GM (1, 1) is applied to fit with the data sequence of performance characteristics in engineering system. Based on the grey system theory and method, a prediction model was devised to predict the quality level in the future was built. The relationship between the vibration and product quality prediction of complex equipment is analyzed with grey system theory and a new appraisal method for product quality prediction combining the qualitative and quantitative analysis by using the grey theory is composed here.

The process analysis show that the grey theory is of optimal prediction effect for product quality prediction of complex equipment. The grey model GM (1, 1) of grey system theory for product quality is put forward, and it provides scientific basis for the quantitative prediction result. The influence degree of the different variables for product quality prediction of complex equipment was analyzed by using grey model GM (1, 1). According to the prediction result of manufacturing complex equipment, we analyzed and predicted the product quality in the molding process of grey system theory. Due to currently shortage of grey system theory quality predicting, an adaptive quality forecasting method of grey model GM (1, 1) is presented here. The differential equation of GM (1, 1) is defined as:

$$\frac{d_x^{(1)}}{dt} + aX^{(1)} = u \tag{1}$$

where $X^{(1)}$ is defined as an accumulating sequence, and a, u are estimate parameters, which can be estimated by using least square method.

(1) *Construction of original sequence based on once accumulation method*. The original sequence is defined in this paper as the following:

$$X^{(0)} = (X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), \cdots, X^{(0)}(n)) \tag{2}$$

where $i = 1,2,\cdots,n$. Therefore, the original sequence can be generated by using once accumulation in the following equation:

$$X^{(1)}(i) = \sum_{m=1}^{i} X^{(0)}(m) \tag{3}$$

(2) *Evaluation of parameters a and u*
Based on the grey prediction model GM (1, 1), the numerical values of parameters a, u can be calculated by using the generalized least squares method. The matrix and some constants are defined as:

$$A = \begin{bmatrix} -[X^{(1)}(1) + X^{(1)}(2)]/2 & 1 \\ -[X^{(1)}(2) + X^{(1)}(3)]/2 & 1 \\ \vdots & \vdots \\ -[X^{(1)}(n-1) + X^{(1)}(n)]/2 & 1 \end{bmatrix} \tag{4}$$

where the uncertain matrix A is norm bound and time-varying. The original sequence is defined as:

$$y_n = \left[X^{(0)}(2), X^{(0)}(3), \cdots, X^{(0)}(n)\right]^T \tag{5}$$

Thus, an equation to identify parameters from experimental data can be expressed as:

$$\hat{\mathrm{a}} = \begin{bmatrix} \mathrm{a} \\ \mathrm{u} \end{bmatrix} = (\mathrm{A^T A})^{-1} \mathrm{A^T y_n} \tag{6}$$

(3) *Construction of the* GM (1, 1) *mode*
The GM (1, 1) model was constructed by using interactions and dependencies between these elements by the following forecast formula:

$$\hat{X}^{(1)}(i+1) = (X^{(0)}(1) - \frac{u}{a})e^{-ai} + \frac{u}{a} \tag{7}$$

where $\hat{X}^{(0)}(1) = \hat{X}^{(1)}(1), \hat{X}^{(0)}(i) = \hat{X}^{(1)}(i) - \hat{X}^{(1)}(i-1), i = 2, 3, \cdots, n$.

(4) *Verification of the accuracy of the prediction model*
Using the grey theory, our model accuracy can hence be compared, enhance verified with actual product quality feedback. By solving these equations, statistical expressions of expectation and mean square covariance about eigenvalues is given as following:

$$S_0 = \sqrt{S_0^2/(n-1)} \tag{8}$$

where S_0 represents mean square covariance of the prediction model system to be minimized in the next step:

$$S_0^2 = \sum_{i=1}^{n} [X^{(0)}(i) - \bar{X}^{(0)}]^2 \tag{9}$$

$$\bar{X}^{(0)} = \sum_{i=1}^{n} X^{(0)}(i)/n, \quad i = 2, 3, \cdots, n \tag{10}$$

(5) *Computation of mean-square deviation*
This simplifies the situation in the series $\varepsilon^{(0)}(i) = X^{(0)}(i) - \hat{X}^{(0)}(i)$ where the mean-square deviation was calculated. In general, the formula of the mean-square deviation is shown as followed:

$$S_1 = \sqrt{S_1^2/(n-1)} \tag{11}$$

$$S_1^2 = \sum_{i=1}^{n} \left[\varepsilon^{(0)}(i) - \bar{\varepsilon}^{(0)}\right]^2 \tag{12}$$

$$\bar{\varepsilon}^{(0)} = \sum_{i=1}^{n} \varepsilon^{(0)}(i)/n \tag{13}$$

Variance analysis revealed that the proposed method in this paper is more effective than traditional iterative methods. To test the exactness and robustness of the improved algorithm, a variance ratio is used here as a measure of efficiency as followed:

$$c = S_1/S_0 \tag{14}$$

The small probability of error can be computed in the same way:

$$p = \left|\varepsilon^{(0)}(i) - \bar{\varepsilon}^{(0)}\right| < 0.6745 \times S_0 \tag{15}$$

(6) *Determining the accuracy grade of prediction model*
In Table 1, we categorized the prediction accuracy of different model by its small error probability and variance ratio. Accordingly, the prediction model GM (1, 1) is in the Accuracy grade I category with its reliable forecast result.

Table 1 Grade specification of prediction accuracy

Accuracy grade	Precision grade	Values of small error probability	Values of variance ratio
Ⅰ	Very good	> 0.95	< 0.35
Ⅱ	Good	> 0.80	< 0.50
Ⅲ	General	> 0.70	< 0.65
Ⅳ	Unqualified	≤ 0.70	≥ 0.65

(7) *Forecasting using obtained prediction model*
Computation results were compared with experimental findings, verifying that this model can accurately predict product quality. If the resultant test is found to be acceptable, existing data can be transformed into numerical prediction for future data, which is calculated as:

$$\hat{X}^{(0)}(n+1) = \hat{X}^{(1)}(n+1) - \hat{X}^{(1)}(n) \tag{16}$$

$$\hat{X}^{(0)}(n+2) = \hat{X}^{(1)}(n+2) - \hat{X}^{(1)}(n+1) \tag{17}$$

where $X^{(0)}(n+1)$ and $X^{(0)}(n+2)$ are established by comparing predicted values with actual data. The predicted values should be arranged according to the given test set order. The forecast data of grey prediction GM (1, 1) were used as the input variable with real life results as output.

3. A case study

The application of grey system are introduced in this case study, the quality prediction problem of cutting tools for CNC machine tool of five axes simultaneous moving are also described. The grey system modeling is applied on evaluation of the structural and mechanical failure of CNC machine tool with the consideration of quality characteristics. To ensure better forecast accuracy, many satisfactory forecasting methods are assessed as the base of product quality prediction model of CNC machine tool. The cutting tools system is an important bridge that links the machine tool and the workpiece. The quality of cutting tools strongly influences the machining accuracy of the workpiece. This paper expounds the value of multiple quality characteristics to cutting tools in China manufacturing enterprises. The operation system of cutting tools for CNC machine tool is shown in Fig. 3.

The quality characteristics of cutting tools for CNC machine tool are obtained through static analysis and laboratory tests. The extraction of quality characteristics of cutting tools has great importance during the normal operation of CNC machine tool. As a result of this processing, the quality prediction is more useful for human and machine perception in further manufacturing process tasks. In this paper, we review the present research and key techniques for process quality, including the preprocessing methods, feature extraction and classifier design methods. Based on the proposed prediction GM (1, 1) model of grey system, the mechanical properties and quality characteristics of cutting tools for CNC machine tool in this article are listed in Table 2.

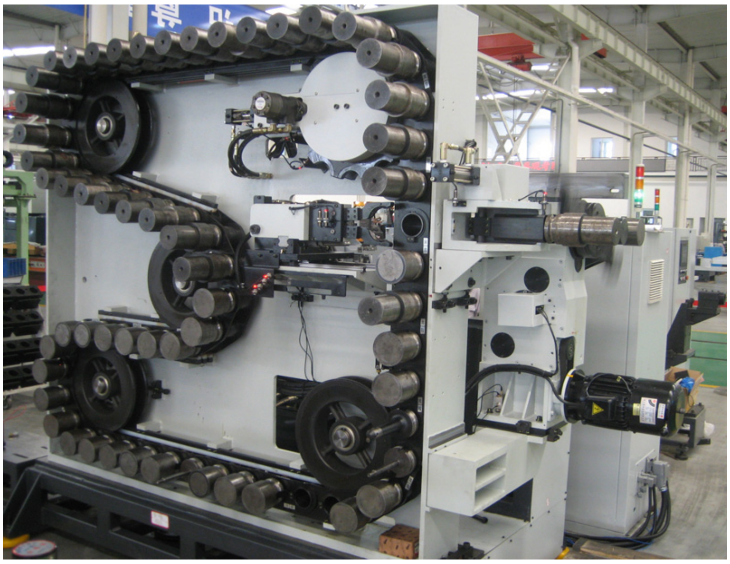

Fig. 3 Operation system of cutting tools for CNC machine tool

Table 2 Mechanical properties and quality characteristics of cutting tools

Number	MTBF	Hardness	Bending strength	Fracture toughness	Elasticity modulus
	hour	HRA	MPa	MPa· $m^{1/2}$	GPa
1	921.56	93.6	650	7.52	508
2	928.12	93.5	660	7.58	512
3	932.87	94.2	655	8.21	522
4	938.43	94.3	720	8.53	530
5	942.35	94.9	745	8.43	541
6	948.24	94.7	750	8.53	528

Moreover, the focus of this case study is on the quality prediction method of cutting tools of CNC machine tool based on the five quality characteristics, including mean time between failures (MTBF), hardness, bending strength, fracture toughness and elasticity modulus. The quality criterion of MTBF is used widely for qualitative assessment. One effective way of describing strength of cutting tools is in terms of hardness. Additionally, the bending strength of cutting tools was also explained. The fracture toughness of material was adequate to ensure operation quality of the cutting tools. The elasticity modulus of cutting tools can be obtained by using experimental testing with analysis and inference methods.

Table 2 compares quality characteristics of cutting tools based on key aspect of hardness, bending strength, fracture toughness and elastic modulus that affect the performance of machine tools. From the original sequence derived previously based on grey system GM (1, 1), we can get:

$$X^{(0)} = (X^{(0)}(1), X^{(0)}(2), \cdots, X^{(0)}(6)) = (921.56, 928.12, 932.87, 938.43, 942.35, 948.24)$$

Based on Eq. 3, the original sequence can be computed by using once accumulation as summarized below:

$$X^{(1)} = (X^{(1)}(1), X^{(1)}(2), \cdots, X^{(1)}(6)) = (921.56, 1849.68, 2782.55, 3720.98, 4663.33, 5611.57)$$

Then, the uncertain matrix A is given by Eq. 4 in the following:

$$A = \begin{bmatrix} -1385.62 & 1 \\ -2316.12 & 1 \\ -3251.77 & 1 \\ -4192.16 & 1 \\ -5137.45 & 1 \end{bmatrix}$$

Based on Eq. 5, the original sequence drawn from matrix A and the data from Table 2 are represented as shown below:

$$y_n = \begin{bmatrix} 928.12 \\ 932.87 \\ 938.43 \\ 942.35 \\ 948.24 \end{bmatrix}$$

Then, the numerical values can be mixed and matched to create the appropriate combination for grey system theory. That is the key to computation in practice. The calculation process from this simplified theory of this new method is hence reported as followed.

$$A^T A = \begin{bmatrix} 61825863.1394 & -16283.1050 \\ -16283.1050 & 5.0000 \end{bmatrix}$$

$$(A^T A)^{-1} = \begin{bmatrix} 0.00000011 & 0.00037016 \\ 0.00037016 & 1.40545883 \end{bmatrix}$$

On the other hand, a structurally simple equation to identify parameters from experimental data can be obtained by using Eq. 6:

$$\hat{a} = \begin{bmatrix} a \\ u \end{bmatrix} = (A^T A)^{-1} A^T y_n = \begin{bmatrix} -0.00530 \\ 920.73885 \end{bmatrix}$$

As mentioned above, the relationship between a and u is the following:

$$\frac{u}{a} = -58.71186551$$

So, the grey system GM (1, 1) is obtained based on Eq. 7:

$$\hat{X}^{(1)}(i+1) = 174615.0889 e^{0.0053i} - 58.71186551$$

Then, the accuracy of the prediction model can be checked in the following procedure. The mean square covariance about eigenvalues is expressed as:

$$\bar{X}^{(0)} = \frac{\sum_{i=1}^{n} X^{(0)}(i)}{n} = 935.2617$$

$$S_0 = \sqrt{S_0^2/(n-1)} = 9.728$$

The relation between the number of sampling points and remainder error is presented in this paper. Then, the choice is between original value and a processed value. The results of the computations by using grey system are tabulated in Table 3.

Table 3 Predicted value residual error of prediction model

Number No.	Original value $X^{(0)}(i)$	Predicted value $\bar{X}^{(0)}(i)$	Residual error $\varepsilon^{(0)}(i)$	Relative error (%)
1	921.56	921.5600	0	0
2	928.12	928.0817	0.038338	0.0041%
3	932.87	933.0144	-0.14443	-0.0155%
4	938.43	937.9734	0.456586	0.0487%
5	942.35	942.9588	-0.60876	-0.0646%
6	948.24	947.9706	0.269405	0.0284%

From the comparison sheet, the main factor influencing accuracy of product quality forecasting is the uncertainty of original value for CNC machine tool. GM (1, 1) model method can meet the demand of forecasting while with less original data at high accuracy. To counter the fluctuating case of original data, the forecasting precision can be achieved by using the model of GM (1, 1) of grey system theory. The forecast result of high precision was got in forecast of quality prediction of CNC machine tool via GM (1,1) model by means of selecting revision of residual error, which was shown in Fig. 4.

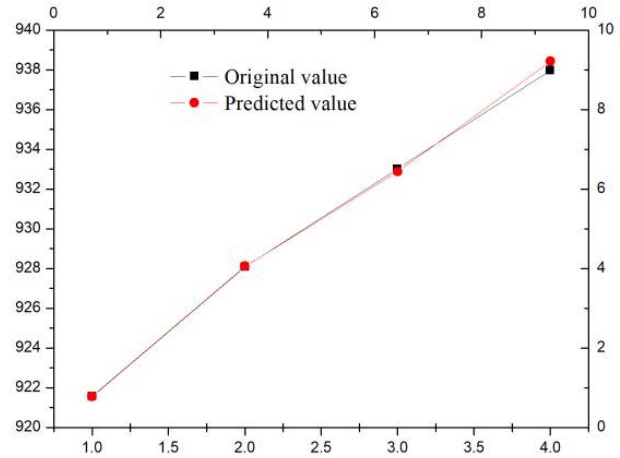

Fig. 4 Comparison chart of original value and predicted value

In addition, the formula for the mean-square deviation is given by:

$$\bar{\varepsilon}^{(0)} = \frac{1}{6}\sum_{i=1}^{6}\varepsilon^{(0)}(i) = 0.0019, S_1 = \sqrt{S_1^2/(6-1)} = 0.3671$$

In the next step, the variance ratio can be given by Eqs. 14 and 15 in the following formula:

$$c = S_1/S_0 = 0.3671/9.7281 = 0.0377,\ \ 0.6475 \times S_0 = 0.6475 \times 9.7281 = 6.2989$$

Then, the small probability of error can be computed through the following:

$$p = |\varepsilon^{(0)}(i) - \bar{\varepsilon}^{(0)}| < 6.2989$$

$$|\varepsilon^{(0)}(1) - \bar{\varepsilon}^{(0)}| = 0.0019 < 6.2989, |\varepsilon^{(0)}(2) - \bar{\varepsilon}^{(0)}| = 0.0365 < 6.2989$$

$$|\varepsilon^{(0)}(3) - \bar{\varepsilon}^{(0)}| = 0.1463 < 6.2989, |\varepsilon^{(0)}(4) - \bar{\varepsilon}^{(0)}| = 0.4547 < 6.2989$$

$$|\varepsilon^{(0)}(5) - \bar{\varepsilon}^{(0)}| = 0.6106 < 6.2989, |\varepsilon^{(0)}(6) - \bar{\varepsilon}^{(0)}| = 0.2675 < 6.2989$$

Based on the variance ratio and the data from Table 1, it can be concluded that these forecasting models are acceptable, $c = 0.0377 < 0.35, p = 1$.

Hence the model precision was found to be very good and can be used for forecast. Thus, the results of the comparison of original data and prediction data are displayed in Fig. 5.

The serial test predictive value of four factors to MTBF was 953.01 hour. And the experiments show that the complex equipment quality prediction system based on more sensors and grey system theory model is efficacious. Although this paper focuses on CNC machine tool, the proposed methods apply to other complex equipment as well.

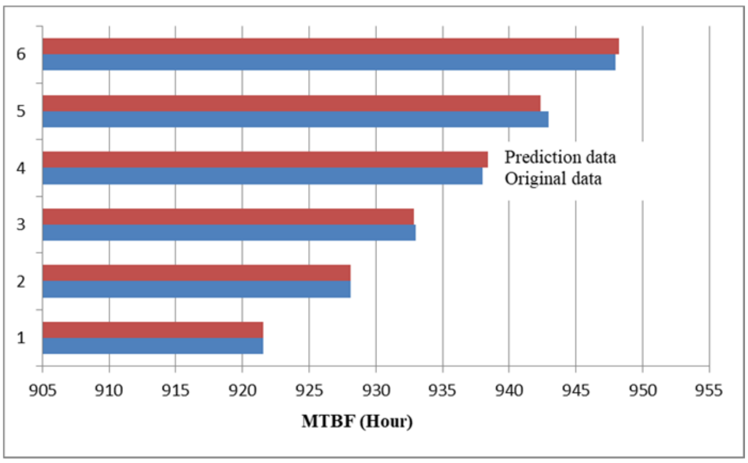

Fig. 5 Contrast relation between original data and prediction data

4. Conclusion

The quality prediction technique and the numerical prediction method were studied in this article. A new algorithm based on grey system theory in the forecasting course is discussed and evaluated. We simulated the prediction process as an intelligence system for complex equipment as well as took quality characteristics prediction factors as input data and the prediction quantities as output data.

This paper also compiled a microcomputer program which deals with the process prediction by using grey system theory. Self-adaptive prediction was implemented to promote accuracy of predicted results by adjusting input parameters of the engineering system. In order to improve the prediction precision, grey system theory model and method were used in these prediction processes. The proposed quality prediction model was used to represent past and current quality characteristics of engineering system and to predict future results of the manufacturing process. It is hoped to elevate the prediction technology and quality of complex equipment to better serve the manufacturing enterprises. This method can also be used in the field of other complex equipment quality prediction and quality target prediction.

In conclusion, this paper presents calculations based on the data of CNC machine tool using grey forecast model. The results of the case study show that the quality level of complex equipment is automated deployment and utility computing. Verification results also showed that the quality prediction model could give satisfactory quality prediction accuracy of complex equipment.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (No. 71671130), and the Provincial Natural Science Foundation, Zhejiang, China (No. LY20G010014).

References

[1] Farahani, A., Tohidi, H., Shoja, A. (2019). An integrated optimization of quality control chart parameters and preventive maintenance using Markov chain, *Advances in Production Engineering & Management,* Vol. 14, No. 1, 5-14, doi: 10.14743/apem2019.1.307.

[2] Bhandari, S.H., Deshpande, S.M. (2011). Analysis of engineered surfaces for product quality monitoring, *International Journal of Computers and Applications,* Vol. 33, No. 4, 284-292, doi: 10.2316/Journal.202.2011.4.202-2670.

[3] Çiflikli, C., Kahya-Özyirmidokuz, E. (2012). Enhancing product quality of a process, *Industrial Management & Data Systems,* Vol. 112, No. 8, 1181-1200, doi: 10.1108/02635571211264618.

[4] Brahmachary, T.K., Ahmed, S., Mia, M.S. (2018). Health, safety and quality management practices in construction sector: A case study, *Journal of System and Management Sciences,* Vol. 8, No. 2, 47-64.

[5] Davrajh, S., Bright, G. (2013). Advanced quality management system for product families in mass customization and reconfigurable manufacturing, *Assembly Automation,* Vol. 33, No. 2, 127-138, doi: 10.1108/01445151311306636.

[6] Brombacher, A., Hopma, E., Ittoo, A., Lu, Y., Luyk, I., Maruster, L., Ribeiro, J., Weijters, T., Wortmann, H. (2012). Improving product quality and reliability with customer experience data, *Quality and Reliability Engineering International,* Vol. 28, No. 8, 873-886, doi: 10.1002/qre.1277.

[7] Amanna, A., Price, M.J., Thamvichai, R. (2011). Grey systems theory applications to wireless communications, *Analog Integrated Circuits and Signal Processing,* Vol. 69, No. 2-3, 259-269, doi: 10.1007/s10470-011-9719-1.

[8] Sosa, M., Mihm, J., Browning, T. (2011). Degree distribution and quality in complex engineered systems, *Journal of Mechanical Design,* Vol. 133, No. 10, Article ID 101008, doi: 10.1115/1.4004973.

[9] Berget, I., Næs, T. (2002). Optimal sorting of raw materials, based on the predicted end-product quality, *Quality Engineering,* Vol. 14, No. 3, 459-478, doi: 10.1081/QEN-120001883.

[10] Pan, Y., Lee, J.H. (2003). Recursive data-based prediction and control of product quality for a PMMA batch process, *Chemical Engineering Science,* Vol. 58, No. 14, 3215-3221, doi: 10.1016/S0009-2509(03)00190-8.

[11] Chetouani, Y. (2009). Model-order reduction based on artificial neural networks for accurate prediction of the product quality in a distillation column, *International Journal of Automation and Control,* Vol. 3, No. 4, 332-351, doi: 10.1504/IJAAC.2009.026780.

[12] Ding, J., Chai, T., Wang, H. (2011). Offline modeling for product quality prediction of mineral processing using modeling error PDF shaping and entropy minimization, *IEEE Transactions on Neural Networks,* Vol. 22, No. 3, 408-419, doi: 10.1109/TNN.2010.2102362.

[13] Ahmed, S., Hossain, M.M., Hoque, M.I. (2017). A brief discussion on augmented reality and virtual reality in construction industry, *Journal of System and Management Sciences,* Vol. 7, No. 3, 1-33.

[14] Ge, Z., Song, Z., Gao, F. (2012). Statistical prediction of product quality in batch processes with limited batch-cycle data, *Industrial & Engineering Chemistry Research,* Vol. 51, No. 35, 11409-11416, doi: 10.1021/ie202554r.

[15] Hou, W., Zhao, L., Zhang, L., Wang, G. (2013). On-line production quality prediction for a commercial naphtha catalytic reforming process, *Information Technology Journal,* Vol. 12, No. 18, 4553-4560, doi: 10.3923/itj.2013.4553.4560.

[16] Zhao, F., Lu, N., Yang, Y. (2013). Product quality prediction method for injection molding process based on operating mode recognition, *Huagong Xuebao/CIESC Journal,* Vol. 64, No. 7, 2526-2534, doi: 10.3969/j.issn.0438-1157.2013.07.030.

[17] Gao, K., Khoshgoftaar, T.M., Wald, R. (2014). The use of under- and oversampling within ensemble feature selection and classification for software quality prediction, *International Journal of Reliability, Quality and Safety Engineering,* Vol. 21, No. 1, doi: 10.1142/S0218539314500041.

[18] Tang, X., Li, Y., Guo, J., Xie, Z. (2014). Final quality prediction for multi-phase batch process based on phase cumulative product quality model, *Transactions of the Institute of Measurement and Control,* Vol. 36, No. 5, 696-708, doi: 10.1177/0142331213501688.

[19] Arsenović, M., Pezo, L., Stanković, S., Radojević, Z. (2015). Factor space differentiation of brick clays according to mineral content: Prediction of final brick product quality, *Applied Clay Science,* Vol. 115, 108-114, doi: 10.1016/j.clay.2015.07.030.

[20] Melhem, M., Ananou, B., Djeziri, M., Ouladsine, M. Pinaton, J. (2015). Prediction of the Wafer quality with respect to the production equipments data, *IFAC-PapersOnLine,* Vol. 48, No. 21, 78-84, doi: 10.1016/j.ifacol.2015.09.508.

[21] Melhem, M., Ananou, B., Ouladsine, M., Pinaton, J. (2016). Regression methods for predicting the product's quality in the semiconductor manufacturing process, *IFAC-PapersOnLine,* Vol. 49, No. 12, 83-88, doi: 10.1016/j.ifacol.2016.07.554.

[22] Ribeiro, C.H.P., Miyoshi, S.C., Secchi, A.R., Bhaya, A. (2016). Model predictive control with quality requirements on petroleum production platforms, *Journal of Petroleum Science and Engineering,* Vol. 137, 10-21, doi: 10.1016/j.petrol.2015.11.004.

[23] Hao, L., Bian, L., Gebraeel, N., Shi, J. (2017). Residual life prediction of multistage manufacturing processes with interaction between tool wear and product quality degradation, *IEEE Transactions on Automation Science and Engineering,* Vol. 14, No. 2, 1211-1224, doi: 10.1109/TASE.2015.2513208.

[24] Zheng, R., Pan, F. (2017). Multi-phase support vector regression soft sensor for online product quality prediction in glutamate fermentation process, *American Journal of Biochemistry and Biotechnology,* Vol. 13, No. 2, 90-98, doi: 10.3844/ajbbsp.2017.90.98.

[25] Yang, Z., Zhu, D., Chen, C., Tian, H., Guo, J., Li, S. (2018). Reliability modelling of CNC machine tools based on the improved maximum likelihood estimation method, *Mathematical Problems in Engineering,* Vol. 2018, Article ID 4260508, doi: 10.1155/2018/4260508.

[26] Bai, Y., Wang, P., Xie, J. (2014). Optimization of urban water supply schemes based on grey system theory, *International Journal of Control and Automation,* Vol. 7, No. 9, 239-246, doi: 10.14257/ijca.2014.7.9.20.

[27] Longstaff, A.P., Fletcher, S., Parkinson, S., Myers, A. (2013). The role of measurement and modelling of machine tools in improving product quality, *International Journal of Metrology and Quality Engineering,* Vol. 4, No. 3, 177-184, doi: 10.1051/ijmqe/2013054.

[28] Nazifa, T.H., Ramachandran, K.K. (2018). Exploring the role of information sharing in supply chain management: A case study, *Journal of System and Management Sciences,* Vol. 8, No. 4, 13-37.

[29] Chuang, T.-F., Chang, Y.-H. (2014). Comparison of physical characteristics between Rana latouchtii and Rana adenopleura using grey system theory and artificial neural network, *Ecological Engineering,* Vol. 68, 223-232, doi: 10.1016/j.ecoleng.2014.03.038.

[30] Bettayeb, B., Bassetto, S.J., Sahnoun, M. (2014). Quality control planning to prevent excessive scrap production, *Journal of Manufacturing Systems,* Vol. 33, No. 3, 400-411, doi: 10.1016/j.jmsy.2014.01.001.

[31] Lee, Y.-C., Wu, C.-H., Tsai, S.-B. (2014). Grey system theory and fuzzy time series forecasting for the growth of green electronic materials, *International Journal of Production Research,* Vol. 52, No. 10, 2931-2945, doi: 10.1080/00207543.2013.857057.

[32] Sang, G., Shi, K., Liu, Z., Gao, L. (2014). Missing data imputation based on grey system theory, *International Journal of Hybrid Information Technology,* Vol. 7, No. 2, 347-356, doi: 10.14257/ijhit.2014.7.2.30.

[33] Zhou, Z., Sang, N. (2012). Image edge detection algorithm based on grey system theory, *International Journal of Digital Content Technology and its Applications,* Vol. 6, No. 23, 782-789.

[34] Shao, Z. (2012). The evaluation on green textile production system based on grey theory, *International Journal of Advancements in Computing Technology,* Vol. 4, No. 2, 65-71.

[35] Tserng, H.P., Ngo, T.L., Chen, P.C., Tran, L.Q. (2015). A grey system theory-based default prediction model for construction firms, *Computer-Aided Civil and Infrastructure Engineering,* Vol. 30, No. 2, 120-134, doi: 10.1111/mice.12074.