GREY THEORY BASED ON LOAD CELL FAILURE PREDICTION IN A WEIGHING SYSTEM

Dr. Zhu Zijian
Mettler-Toledo (Changzhou) Scale & System Ltd.
Changzhou, Jiangsu, China 213014

Abstract:

The reliability of the weighing system is becoming more and more important these years. This paper deals with a new approach to load cell soft failure prediction by the application of Grey theory. Grey theory is a theory which studies poor information and sets up a math model to simulate and predict a system behavior. Collecting the historical data of zero and sensitivity drift to set up a grey model GM (1.1) and with this model, the system can not only simulate the zero and sensitivity drifts but also calculates their possible value in the near future. Therefore, a previous action could be taken before zero and sensitivity running out of the acceptable range.

This method is hoped to be able to improve the reliability of a system and have a potential future in the field of measurement.

Key words:

Grey theory, Prediction, load cell, soft failure

1. BACKGROUND

In the actual weighing application, the system not only requires high precision but also expects to have higher dependability. The load cell plays a central role in the system and its drift will cause the system crash in case some critical values exceed the limit. Sometimes that has been already too late until the last moment. So far, there is no such a method to predict load cell failure in the market. May we know the load cell is getting bad in advance, and then a proper action might be taken to avoid the crash? This paper aims to present a method based on gray theory predicting load cell zero and sensitivity drift to meet the requirement.

2. GRAY THEORY

Gray theory, first proposed by professor Deng Julong in the 80's of 20th century and developed in recent years, has been applied to many prediction fields including some industry application field.

According to Gray theory， the representation of each objective system is extremely complicated, and seems to be disorderly and unsystematic. But there surely has some hiding inherent law within the system., And this system with some known information and some unknown information is called gray system, whose models are called the gray model, abbreviated as GM model

The general procedure to get the initial data is by accumulating or iterative reduceing. The purpose for this is to weaken the randomness information in original data in order to form a strong regular (law) data array. After accumulation for several times, the data array is approximately fitted with a linear continuous differential equation. Solve this differential equation, finally reducing into a primitive array with iteratively reducing the array. By this primitive array, we can calculate the proper output for the next interval; therefore, it can predict the output in a near future. The most typical one is the GM (1.1) model.

In addition, Gray System studies the “lacked data with uncertainty” while Probability & Statistics theory focus**es** on” Tremendous samples with uncertainty” and Fuzzy Sets Theory investigates in "The cognition uncertainty".

*2.0 PROCEDURE **OF** MODELING*

2.1Generating the accumulated array

Assume $x^{(0)} = (x^{(0)}(1), x^{(0)}(2),..., x^{(0)}(n))$

After accumulating, a new array is formed,

that is $x^{(1)}(i) = \sum_{j=1}^{i} x^{(0)}(j)$

2.2building the data matrix and data vector

Let

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1) \quad k = 2,3,\cdots,n$$

Assume B is data matrix while Y is data vector

Then,

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdots & \cdots \\ -z^{(1)}(n) & 1 \end{bmatrix} Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ x^{(0)}(n) \end{bmatrix} U = \begin{bmatrix} a \\ u \end{bmatrix}$$

Solving the linear-equation $Y = BU$ by Least squares method

$$\hat{U} = \begin{bmatrix} \hat{a} \\ \hat{u} \end{bmatrix} = (B^T B)^{-1} B^T Y$$

2.3 set up the time response equation (model)

Introduce the â and û to the time response equation,

$$\hat{x}^{(1)}(k+1) = (x^{(1)}(1) - \frac{\hat{u}}{\hat{a}})e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}}$$

Reverting above algorithm to the following,

$$\hat{x}^{(0)}(i) = \hat{x}^{(1)}(i) - \hat{x}^{(1)}(i-1), \qquad i = 2.3,..., N$$

2.4 Accuracy verification

The absolute error is

$$q\ (k) = \hat{x}^{(0)}(k) - x^{(0)}(k),$$

The relatively error is

$$\varepsilon(k) = q(k) / x^{(0)}(k)$$

3. THE EXAMPLE FOR LOAD CELL FAILURE PREDICTION

3.1 Description：

In our current weighing system, the system crash can be sorted into two kinds, one is called hard crash, which refers to a sudden damage in the system. It is unable to foretell and take the corresponding measure in advance. Another is called soft crash, which means the system breaks down due to some drifts in the system. From the angle of data process, it is possible to use the historic data to find out the rule for the drift. Therefore, it can be known whether the system might malfunction and when that will happen. In this paper, the soft crash for weighing system could be regarded as load cell zero and sensitivity drift. For zero drift, the indicator could read the zero balance once upon a certain period. But it is hard to get the individual load cell sensitivity data in the actual application. Thus, it is assumed that the rate of which one cell's output against the total output of the system could be represented to the sensitivity, so-called distribution rate. In another word, we can chase that rate to predict calculation.

Following are the examples for load cell zero and distribution rate drift mathematics modeling.

3.1 Zero drift prediction

For zero data collection, it can be set to the same situation (needn't to be the zero, can be a certain weight) to acquire the zero data starting from the system setup. Data taken once every two months. With 4 data ready, the prediction could start

For example: for a 3t bulk scale, the zero of 1# load cell:

Initial zero:

Table 1 Initial array

times	1	2	3	4
X(0)	2341	2143	2242	2876

Accumulate the initial data:

Table 2 produced array

Series	1	2	3	4
X(1)	2341	4484	6726	9602

Setup data matrix B,Yn

$$B=\begin{bmatrix}-\frac{1}{2}(x^{(1)}(2)+x^{(1)}(1)) & 1\\ -\frac{1}{2}(x^{(1)}(3)+x^{(1)}(2)) & 1.\\ -\frac{1}{2}(x^{(1)}(4)+x^{(1)}(3)) & 1\end{bmatrix}=$$

$$\begin{bmatrix}-3412.5 & 1\\ -5605 & 1\\ -8164 & 1\end{bmatrix}$$

$$Y=(x^{(0)}(2),x^{(0)}(3),...,x^{(0)}(N))^T$$

$$=(2143,2242,2876)^T$$

Calculate the constant array

$$\hat{U}=\begin{bmatrix}\hat{a}\\ \hat{u}\end{bmatrix}=(B^TB)^{-1}B^TY=\begin{bmatrix}-0.156851\\ 1522.021606\end{bmatrix}$$

Set up differential equation

$$\frac{dx^{(1)}}{dt}-0.156851x^{(1)}=1522.021606$$

Build the exponential function

$$\hat{x}^{(1)}(k+1)=(x^{(1)}(1)-\frac{\hat{u}}{\hat{a}})e^{-\hat{a}k}+\frac{\hat{u}}{\hat{a}}$$

$$=12044.61528e^{-0.156851k}-9703.61528$$

Reverting

$$\hat{x}^{(0)}(i)=\hat{x}^{(1)}(i)-\hat{x}^{(1)}(i-1),\qquad i=2.3,...,N$$

Table 3 model verification

Actual initial data	calculated data after reverting	Absolute error	Relatively error（%）
2341	2341	0	0
2143	2045.43	-97.57	-4.553
2242	2392.79	150.79	6.726
2876	2799.14	-76.86	-2.673
average			4.65038

Conclusion: the error for this response functions less than10％，thus, it meet the accuracy requirement and need not to do absolute error modification.

$$\hat{x}^{(1)}(k+1)$$

$$=12044.61528e^{-0.156851k}-9703.61528$$

According to this model, the zero for the nearly coming every two months is as follows.

X(2)={3274,3830,4481,5242}

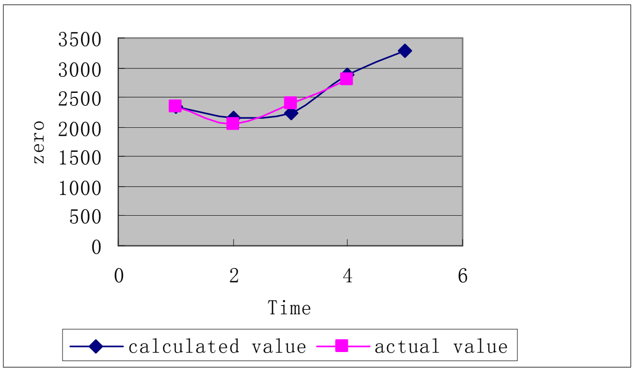

Figure 1　Comparison of calculated zero and actual zero

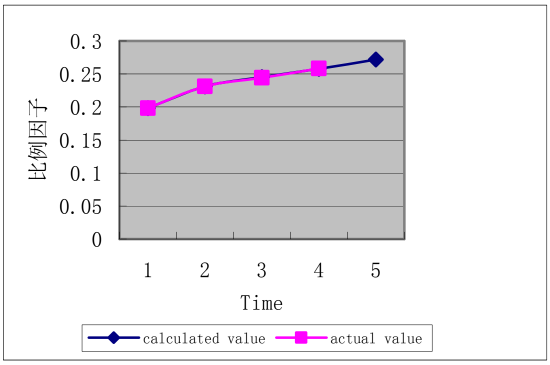

Figure 2　Comparison of calculated value and actual value

If zero is exceeding the preset value stored in terminal, then a warning message will be sent out to notify the user this failure tendency.

3.2 The prediction for distributed rate drift

For a newly installed weighing system, acquire the data in every certain period. The data is the rate of one cell output occupying the total output.

For example, one 6-load cells system, employ the model GM（1.1）to predict the tendency of distributed rate. If the rate changes 35% of the initial value, then a warning message will be sent out.

time	Actual rate	Calculate rate	Absolute error	Relatively error（%）
1	0.198	0.198	0	0
2	0.231	0.23124	0.000247	0.10691
3	0.245	0.24435	-0.000648	-0.26429
4	0.258	0.25820	0.000201	0.07781

$$\hat{x}^{(1)}(k+1) = 4.080352e^{0.055126k} - 3.882352$$

After two month the rate will be：0.272

The change is ：

(0.272-0.198)/0.198=37.4%

Table 4　Model verification

Conclusion: The table -4 shows that the relative error are all less than 0.3%, it means the accuracy of the model is acceptable. According to the calculation of the distributed rate for next two month with this model, it will be 0.272, and changes to 37.4% of initial rate. The changes are exceeding the limit (35%), so a proper method may be taken to prevent the possible failure.

4 CONDLUSION:

A prediction method of load cell soft failure based on gray theory is introduced for the first time. By building up the math model to calculate the future zero and distributed rate for the weigh system (here, the distributed rate is representing the sensitivity of a load cell), a prior notice of a load cell failure plays a role in raising the reliability of a system. (This model uses MATLAB for realization)

5 REFERENCES:

1. Huang Shiuh－Jer .Huang Chien－Lo. Control of an inverted pendulum using grey prediction　mode【J】IEEE Trans on Industrial Application，2000，36（2）：452－458
2. Deng julong，The course on grey Systc theory

【M】huazhong university of science and technology （Wuhan ：HUST Press），1990.

3. Yuan mingyou, Xiao xianyong , gray theory based load for power supply prediction model and application，Journal of sichuan university (Science Edition)，2002, Vol.34 No.4