CHEMICAL ENGINEERING TRANSACTIONS
VOL. 51, 2016

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Tichun Wang, Hongyang Zhang, Lei Tian

ISBN 978-88-95608-43-3; **ISSN** 2283-9216
DOI: 10.3303/CET1651046

Safety Prediction of Soleplate Corrosion State in Petroleum Storage Tank Based on Grey Theory Model

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The corrosion protection of petroleum storage tank is important for safety work in petroleum depot. Precise prediction of soleplate corrosion may reflect the security state of a storage tank, and it can provide scientific references to the anti-corrosion and maintenance in safety management. Grey Model GM (1,1) in the Grey Theory is a good prediction method based on small volume of original data, and it is introduced and applied to predict the soleplate corrosion of No.G-2 petroleum storage tank in Luquan oil depot. In order to improving the calculation speed, the GM (1,1) model is programmed by MATLAB and is further utilized in data processing. Compared with the measurements, the prediction results meet them very well, which shows that this model is practical. Meanwhile, the prediction results also reflect the status and the corrosion rate of a petroleum tank which is of great importance for the future safety management and maintenance works. Meanwhile, the GM (1,1) is suitable for wide applications in other relative fields in oil depots.

1. Introduction

At present, the security status of the petroleum storage tank is an important part of security and risk management in an oil depot. The steel corrosion is important for evaluation of the state and life span of a storage tank. Many factors, such as high detecting costs, small samples, few corrosion data, etc, make it very difficult to predict and evaluate the corrosion trend of the storage tank. Recently, the situation of coat shedding and rusting is taken as the standard to determine whether a tank need maintenance or not, and this kind of judgment is unclear and its anti-corrosion works are labor-consuming and costly (Zhao, 2003; Leygraf and Graedel, 2000). Meanwhile, it also takes an important part in scientific management and investment.

After recent studies on the corrosion of steel surfaces, a scientific method needs to be promoted to predict the corrosion trend and make further prevention (Bhattacharjee et al., 1993; Wang et al., 2010).Compared with other corrosion prediction models such as neural network (Leifer & Mickalonis, 2000; Kenan, 2003), new hygrothermal model (Marra et al., 2015), time prediction model (Hua et al., 2014) and chemical model (Narimani et al., 2015), the Grey Model GM(1,1) in the Grey Theory, which is programmed by MATLAB, is introduced to the prediction of soleplate corrosion in petroleum storage tank based on the interconnected random corrosion data obtained by measuring (Deng, 1989; 2002; Liu et al., 2010). This method can solve such problems that lack of samples and information, and it is used to predict the soleplate corrosion trend to provide scientific references to the anti-corrosion and maintenance in the safety management of oil depot.

2. Grey Model GM(1,1)

2.1 Methodology

The irregular original data $X_{(i)}$ generated through the Accumulated Generating Operation (AGO) in the grey process will be changed to the more regular data $Y_{(t)}$, and the whole process can be obtained from Eq(1).

$$Y(t)=\sum_{i=1}^{t} X_{(i)} \tag{1}$$

$Z_{(t)}$ is the average value of $Y_{(t)}$, and $Z_{(t)}$ can be obtained from Eq(2).

Please cite this article as: Zhao X.G., Zhou Y., Zhao J.Y., Zhan G., Yang P., 2016, Safety prediction of soleplate corrosion state in petroleum storage tank based on grey theory model, Chemical Engineering Transactions, 51, 271-276 DOI:10.3303/CET1651046

$$Z_{(t)} = \frac{1}{2}[Y_{(t)} + Y_{(t-1)}] \tag{2}$$

The first rank linear differential equation of dynamic model is established and it can be expressed in Eq(3).

$$\frac{dY_{(t)}}{dt} + aY_{(t)} = u \tag{3}$$

Where a and u is unknown factors solved from Eq(3), but a and u should satisfy the Eq(4).

$$Y_{(t+1)} = [X_{(1)} - \frac{u}{a}]e^{-at} + \frac{u}{a} \tag{4}$$

The least square method is applied to estimate the parameter vector which is shown in Eq(5).

$$\hat{a} = \begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T Y_N \; ; B^T = \begin{bmatrix} -Z_{(2)} & -Z_{(3)} & \cdots & -Z_{(n)} \\ 1 & 1 & \cdots & 1 \end{bmatrix}; Y_N = (X_{(2)}, X_{(3)}, \cdots, X_{(n)})^T \tag{5}$$

The expression of Eq(5) can be obtained by the matrix operation from Eq(6) to Eq(8)

$$a = \{(n-1)[-\sum_{t=2}^{n} X_{(t)} Z_{(t)}] + [\sum_{t=2}^{n} Z_{(t)}][\sum_{t=2}^{n} X_{(t)}]\}/D \tag{6}$$

$$u = \{[\sum_{t=2}^{n} Z_{(t)}][-\sum_{t=2}^{n} X_{(t)} Z_{(t)}] + [\sum_{t=2}^{n} Z_{(t)}{}^2][\sum_{t=2}^{n} X_{(t)}]\}/D \tag{7}$$

$$D = (n-1)[\sum_{t=2}^{n} Z_{(t)}{}^2] - [\sum_{t=2}^{n} Z_{(t)}]^2 \tag{8}$$

Then a, u is introduced into Eq(4) to get the estimated values of the accumulated data from Eq(9).

$$\hat{Y}_{(t+1)} = (X_{(1)} - \frac{u}{a})e^{-at} + \frac{u}{a} \tag{9}$$

Then the predictions can be obtained through the Inverse Accumulated Generating Operation (IAGO), and the IAGO process is shown in Eq(10).

$$\hat{X}_{(t+1)} = \hat{Y}_{(t+1)} - \hat{Y}_{(t)} \tag{10}$$

Eq(9) and Eq(10) is used to get the predicted values $\hat{X}_{(t)}$ from original data X(i). The prediction precision is not only concerned with the size of original data, but also with the system transmission error. The accuracy is determined by the error transmission mode and error degree in the system. Therefore, the average variance of the predicted values is used to measure the accuracy.
The first order derivative of Eq(9) changes the expression of predictive function to Eq(11):

$$\hat{X}_{(t+1)} = (u - aX_{(1)} - \frac{u}{a})e^{-at} \tag{11}$$

Form the variance propagation theory, the variance is shown in Eq(12).

$$\sigma^2 \hat{X}_{(t+1)} = (\frac{\partial \hat{X}}{\partial a})^2 \sigma_a^2 + (\frac{\partial \hat{X}}{\partial u})^2 \sigma_u^2 + 2(\frac{\partial \hat{X}}{\partial a} * \frac{\partial \hat{X}}{\partial u})^2 \sigma_{au} + (\frac{\partial \hat{X}}{\partial Y_{(1)}})^2 \sigma_0^2 \tag{12}$$

Where the parameters $\sigma_a^2, \sigma_u^2, \sigma_0^2, \sigma_{au}^2, \sigma_a^2$ are elements of the variance or covariance. As a result, the prediction accuracy is calculated as following Eq(12) to Eq(15).

$$\sigma\hat{X}_{(t+1)} = [(aY_{(1)} - Y_{(1)} - tu)^2 * Q_{11} + Q_{22} + 2(aY_{(1)} - Y_{(1)} - tu) * Q_{12}]^{\frac{1}{2}} * e^{-at} * \sigma_0 \tag{13}$$

Where E stands for the column matrix for residuals.

2.2 MATLAB Program for GM(1,1)
According to the requirements of prediction model above, MATLAB is promoted to the design of GM (1,1) (Meng and Li, 2005). Predictions can be calculated from the GM (1,1) equations, and the predictive accuracy between predicted values and actual data is then checked. The main program process is shown in Figure 1:

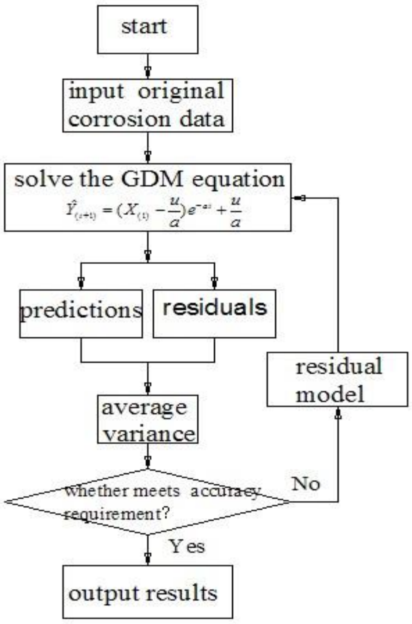

Figure 1: Flow chart of Program

For the following software development, the numerical functions written by *.m files will be translated into DLL files by the COM Builder compiling tools from MATLAB. Then the VS.NET GUI is applied to transfer component generated by MATLAB. VS.NET creates the same name as the original COM component, so the same language can be used by C# to create the reference as well as the COM packaging. The target of comprehensively utilizing the advantages of both VC# and MATLAB software platforms is achieved, so the software development is better modularized.

3. Application

Taking the soleplate corrosion of No.G-2 10000 m^3 storage tank in Luquan oil depot as example, steel corrosion is found when we checked the storage tank soleplate. The soleplate corrosion can be mainly divided into three types, namely cellularity, cloud and pitting, which is both found in the fringe and the inner area of the soleplate (Figure 2).
Therefore, further investigation of the corrosion is carried out by the measuring instruments. The overall soleplate corrosion thickness can be easily obtained by these instruments based on Acoustic Emission (AE) acquisition and data processing system. After the full-scale corrosion investigation, the overall soleplate corrosion is shown in Figure 3.

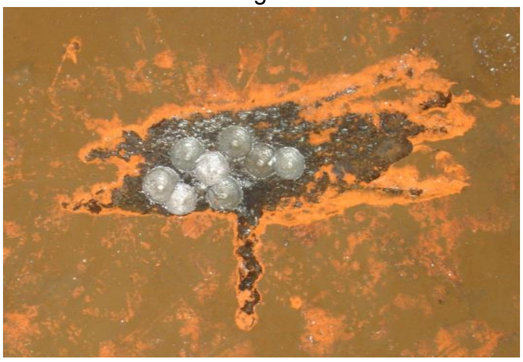

Figure 2: Different types of soleplate corrosion

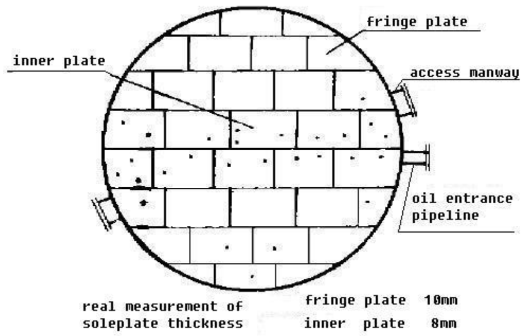

Figure 3: Soleplate corrosion of No.G-2 storage tank

The total area of tank bottom is 651.11 m^2. There are 40 points in all in the measuring of soleplate corrosion thickness, 23 for the fringe and 17 for the inner area. The average thickness is 8 mm. The soleplate corrosion can be divided into three types: cellularity, cloud and pitting, in the proportion of 32.57 %, 25.41 % and 42.02 %, respectively. The corrosion test points accounts for 28.45 % of the total soleplate area, and 269 points is measured, of which 126 for the fringe. To the end of 2010, the deepest corrosion is 3.4 mm, and 4 points over 3 mm are concentrated distributed. Other 124 points, with a maximum depth of 3.34 mm, measure the inner area, but the distribution of the 5 points over 3 mm is not concentrated. The original measuring data is shown in Table 1.

Table 1: Number of casualties

Year	average corrosion thickness (mm)	average corrosion rate (mm/a)	maximum corrosion thickness (mm)	maximum corrosion rate (mm/a)
2006	0.73	—	0.90	—
2007	1.02	0.29	1.23	0.33
2008	1.68	0.66	1.72	0.49
2009	2.32	0.64	2.45	0.73
2010	3.12	0.80	3.40	0.95

The prediction functions calculated by GM(1,1) program are as follows: (1) The average corrosion thickness function: $\hat{Y}_{(t+1)}=2.8182e^{0.338t}-2.0882$, a=-0.3380, u=0.7058; (2) The average corrosion rate function: $\hat{Y}_{(t+1)}=5.7080e^{0.1043t}-5.4180$, a=-0.1043, u=0.7058; (3) The maximum corrosion thickness function: $\hat{Y}_{(t+1)}=3.0476e^{0.3375t}-2.1476$, a=-0.3375, u=0.7248; (4) The maximum corrosion rate function: $\hat{Y}_{(t+1)}=1.3727e^{0.3139t}-1.0427$, a=-0.3139, u=0.3273. The prediction results are shown in Table 2 and the future predictions of corrosion are shown in Table 3.

Table 2: Comparison between predictions (P) and measurements (M)

Year	average corrosion thickness (mm)		average corrosion rate (mm/a)		maximum corrosion thickness (mm)		maximum corrosion rate (mm/a)	
	M	P	M	P	M	P	M	P
2006	0.73	0.7300	—	—	0.90	0.9000	—	—
2007	1.02	1.0333	0.29	0.2900	1.23	1.2202	0.33	0.3300
2008	1.68	1.5891	0.66	0.6275	1.72	1.7069	0.49	0.5062
2009	2.32	2.2281	0.64	0.6965	2.45	2.3878	0.73	0.6928
2010	3.12	3.1241	0.80	0.7731	3.40	3.3401	0.95	0.9483

In order to intuitively observe the corrosion prediction, the predicted results are compared with the measurements and the comparisons are all shown in figures from Matlab program. From these figures, it is found that the average variances of corrosion thickness are no more than ±0.25 and the average variances of corrosion rare are no more than ±0.12. Therefore, the predictions have a high precision.

Table 3: Future predictions of corrosion

Year	average corrosion thickness (mm)	average corrosion rate (mm/a)	maximum corrosion thickness (mm)	maximum corrosion rate (mm/a)
2011	4.3805	0.8581	4.6724	1.2980
2012	6.1420	0.9525	6.5360	1.7766
2013	8.6120	1.0572	9.1429	2.4316
2014	12.0753	1.1735	12.7895	3.3282
2015	16.9313	1.4458	17.8907	4.5555

The average prediction variances are shown in Table 4, while the prediction errors are shown in Table 5. Since the relative errors of the prediction results are fluctuating from 0.13 % to 5.41 %, the predictions meets the measurements very well.

Table 4: Average prediction variance

Year	average corrosion thickness	average corrosion rate	maximum corrosion thickness	maximum corrosion rate
t=0	±0.0846	—	±0.0438	—
t=1	±0.1020	±0.0323	±0.0529	±0.0242
t=2	±0.1262	±0.0301	±0.0652	±0.0264
t=3	±0.1665	±0.0525	±0.0847	±0.0358
t=4	±0.2402	±0.0895	±0.1195	±0.0611

Table 5: Average prediction variance

Year	average corrosion thickness (mm)		maximum corrosion thickness (mm)	
	absolute error	relative error	absolute error	relative error
2006	0	0%	0	0 %
2007	0.0133	1.30 %	0.0098	0.79 %
2008	0.0909	5.41 %	0.0131	0.76 %
2009	0.0919	3.96 %	0.0622	2.54 %
2010	0.0041	0.13 %	0.0599	1.76 %

4. Conclusions

Using GM (1,1) to predict the soleplate corrosion of petroleum storage tank is a new attempt. The practice proves that the innovation not only saves a lot of manpower, financial and material resources, but also has the advantages of methodical, quickness, convenience and practical.

(1) The original corrosion data from 2006 to 2010 is fluctuating and instable. The GM (1,1) is not based on the original data but the AGO data, so the model fits the data better (Table 2-3), and it is feasible and accurate to predict the corrosion of steel surfaces.

(2) The soleplate corrosion is influenced by the temperature, humidity, water content, impurities including H2S and SO2, coating and prevention, etc. However, the predicted values are calculated after considering all these factors. Compared to the corrosion thickness of 2006, the predicted values are steadily increasing, and the average corrosion rate is 0.85mm/a. According to the maximum corrosion rate, there will be perforation before 2013 for the thickness of the tank soleplate is only 8 mm. Anti-corrosion work like lacquering should be carried out in 2012.

(3) Although the corrosion rate of each petroleum storage tank varies in different conditions, the GM (1,1) can still predict it. From the application of GM(1,1) in the corrosion prediction of petroleum storage tanks in Luquan petroleum depot, Tai'an petroleum depot and other depots, the prediction method can not only meet the measurements, but also can stretch from oil tanks to pipelines, equipments, etc.

(4) In some case, the differences between the prediction results of GM(1,1) and the measurements are quite large, then the comprehensive corrosion prediction model can be further developed from the combination of many models, such as neural network, linear regression, Grey Model, etc.

Acknowledgments

Financial supports provided by the National Natural Science Foundation of China (No. 51276195) and Innovation Foundation for Postgraduate of Logistical Engineering University is gratefully acknowledged.

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