Study of the lubrication oil consumption prediction of linear motion guide through the grey theory and the neural network

Y.F. Hsiao[1*] **, Y.S. Tarng**[2]

[1*] Department of Mechanical Engineering
Army Academy R.O.C, Jungli, Taiwan
[2] Mechanical Engineering Department
National Taiwan University of Science and Technology, Taipei 106, Taiwan
C. A: shiao.yf@msa.hinet.net

Abstract: To determine the lubrication oil consumption change of linear motion guide under some mileage, this study designs a test machine to fasten the linear motion guide. The grey prediction model GM(1,1) and neural network are employed for comparison and exploration. Through this study we can understand the differences in prediction of lubrication oil consumption between neural network and grey theory. Experiment results will serve as reference for manufacturers and users for the purpose of quality improvement and selection of better linear motion guides. Based on fewer measurement data, the outcome can be more accurately predicted, and that with a nondestructive test can accurately predict the lubrication oil consumption of the linear motion guide. The outcome indicates that the prediction model of neural network is superior to the grey theory model GM(1,1). The average prediction error of neural network prediction is around 2% - showing a very high accuracy level.

Key-words: neural network；grey theory；linear motion guide；lubrication oil；prediction ；GM(1,1)

1. Introduction

In recent years, due to rapid development of automated machinery and NC tooling machines toward the direction of high precision, high speed and energy conservation, conventional sliding-guided motion have become inadequate for work requirements, and they are gradually replaced by roller-guided linear motion guides. In response to this trend, we conduct the research on type-25 linear motion guides. The experiment process of this section consists of the following steps: preparation of linear motion guides, design and manufacturing of the test machine.

Linear motion guide is a rotating guide. Through cyclic rotation of the balls between the block and the rail, the loading platform can engage in linear motions of high precision along the rail easily. Linear motion guide can be seen as a special bearing. It is not a regular rotation bearing, but an LCD process equipment, semiconductor process equipment, automatic processing equipment, medical apparatus, CNC machine tools, automated robot and

nano-micro-processing device pertinent to linear motion. Any automatic equipment related to linear motion needs to use this important part. So, linear motion guide is a critical part. And the self-lubricating tank on the side of the linear motion guide provides the lubrication oil that the linear motion guide needs for moving. The purpose of this lubrication oil is to reduce friction, save energy and prevent rusting and corrosion. So, it is crucial to the lifespan of a linear motion guide. Correct prediction of lubrication oil consumption and timely refill of lubrication oil will be extremely important. So this paper studies the prediction of the lubrication oil of a linear motion guide.

Studies indicate the grey theory and the neural network have been frequently applied to prediction modeling. Grey theory, developed originally by Deng, is a truly multidisciplinary and generic theory that deals with systems that are characterized by poor information and/or for which information is lacking. The fields covered by grey theory include systems analysis, data processing, molding, prediction, decision making and control. As a result, the grey theory mainly works on systems analysis with poor, incomplete or uncertain messages. The grey theory has been utilized extensively for industrial and economic purposes [1-12]. In recent years, neural networks have become a very useful tool in the modeling of the input-output relationships of complicated systems [13-19]. This is because neural networks have an excellent ability to learn and to generalize (interpolate) the complicated relationships between input and output variables. Both have produced satisfactory results. So, this paper employs both the grey prediction modeling and neural network modeling for prediction of the lubrication oil of linear motion guides. Outcomes of both models are compared. Results of prediction of linear motion guide's lubrication oil consumption will serve as references for linear motion guide manufacturers and user. They can also serve as the basis for tests pertinent to other makes of linear motion guides, with the hope that both testing time and cost can be reduced and profitability can be enhanced.

2. Methodology of grey forecasting

The GM(1,1) is one of the most frequently used grey forecasting model. This model is a time series forecasting model, encompassing a group of differential equations adapted for parameter variance, rather than a first order differential equation. Its difference equation has structures that vary with time rather than being general difference equation. Although it is not necessary to employ all the data from the original series to construct the GM(1,1), the potency of the series must be more than four. In addition, the data must be taken at equal intervals and in consecutive order without bypassing any data [20]. The GM(1,1) model constructing process is described below.

1) Input primitive sequence

Input initial sequence of the model

$$x^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)\right\} \quad (1)$$

2) AGO

Form new sequence out of the primitive sequence through AGO:

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

$$x^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \cdots, x^{(1)}(n)\right\} \quad (2)$$

3) Determine the whitening value $z^{(1)}(k)$

Through AGO the grey background values of the grey derivatives $D(k)$ of sequence $x^{(1)}$ include the hazy set. The whitening value $z^{(1)}(k)$ that contains hazy set can be recorded as

$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1)$

4) Determine B and Yn through least square method

$$Yn = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \quad B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \\ -z^{(1)}(n) & 1 \end{bmatrix},$$

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} \quad (3)$$

5) Solve the equation for a, b

Through $Y_n = B\hat{a}$ and matrix computation rules we can determine

$$\hat{a} = (B^T B)^{-1} B^T Y_n = \begin{bmatrix} a \\ b \end{bmatrix} \quad (4)$$

6) List response equation $x^{(1)}(k+1)$

Through the shadow equation of white differential

$\dfrac{dx^{(1)}}{dt} + ax^{(1)} = b$ we obtain

$$x^{(1)} = ce^{-at} + \frac{b}{a} \quad (5)$$

7) Determine the response equation

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \quad (6)$$

8) Recover the prediction value $\hat{x}^{(0)}(k+1)$

Through 1-IAGO we obtain

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$$

$$= (1-e^{a}) \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} \quad (7)$$

9) Examine the errors of the prediction model：

$$e(k) = \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \times 100\% \quad (8)$$

3. Neural networks

The neural network is a computation system that includes software and hardware. It uses large amount of simple, connected artificial neurons to simulate the function of the neural network of living creatures. An artificial neuron is simple simulation of neurons of living beings. It acquires information from the external environment or other artificial neurons, processes it through very simple computation and outputs the result to the external environment or other artificial neurons. It is well known that modeling the relationships between the input and output variables for non-linear, coupled, multi-variable systems are very difficult. In recent years, neural networks have demonstrated great potential in the modeling of the input-output relationships of complicated systems [21], Consider that $X = \{x_1, x_2, \cdots, x_m\}$ is the input vector of the system where m is the number of input variables and $Y = \{y_1, y_2, \cdots, y_n\}$, is the corresponding output vector of the system where n is the number of output variables. In this section, the use of back-propagation networks to construct the relationships between the input vector X and output vector Y of the system will be explored.

3.1. Back-propagation networks

The back-propagation network is the most frequently utilized model in current development of the neural network. The back-propagation network (Fig. 1) is composed of many interconnected neurons that are often grouped into input, hidden and output layers. The neurons, of the input layer are used to receive the input vector X of the system and the neurons of the output layer are used to generate the corresponding output vector Y of the system. For each neuron (Fig. 2), a summation function for all the weighted inputs is calculated as:

$$net_j^k = \sum_j w_{ji}^k o_i^{k-1} \qquad (9)$$

where net_j^k is the summation function for all the inputs of the j-th neuron in the *k-th* layer, w_{ji}^k is the weight from the i-th neuron to the j-th neuron and o_i^{k-1} is the output of the i-th neuron in the (k-l)-th layer.

As shown in Eq. (9), the neuron evaluates the inputs and determines the strength of each one through its weighting factor, i.e. the larger the weight between two neurons, the stronger is the influence of the connection. The result of the summation function can be treated as an input to an activation function from which the output of the neuron is determined. The output of the neuron is then transmitted along the weighted outgoing connections to serve as an input to subsequent neurons. In the present study, a hyperbolic tangent function with a bias b_j is used as an activation function. The output of the j-th neuron o_j^k for the *k-th* layer can be expressed as:

$$o_j^k = f(net_j^k) = \frac{e^{(net_j^k + b_j)} - e^{-(net_j^k + b_j)}}{e^{(net_j^k + b_j)} + e^{-(net_j^k + b_j)}} \qquad (10)$$

To modify the connection weights; properly, a supervised learning algorithm [22] involving two phases is employed. The first is the forward phase which occurs when an input vector X is presented and propagated forward through the network to compute an output for each neuron. Hence, an error between the desired output y_j and actual output o_j of the neural network is computed. The summation of the square of the error E can be expressed as:

$$E = \frac{1}{2}\sum_{j=1}^{n} (y_j - o_j)^2 \qquad (11)$$

The second is the backward phase which is an iterative error reduction performed in a backward direction. To minimize the error between the desired and actual outputs of the neural network as rapidly as possible, the gradient descent method, adding a momentum term [22], is used. The new incremental change of weight $\Delta w_{ji}^k(n+1)$ can be expressed as:

$$\Delta w_{ji}^k(n+1) = -\eta \frac{\partial E}{\partial w_{ji}^k} + \alpha \Delta w_{ji}^k(n) \qquad (12)$$

Where η is the learning rate, α is the momentum coefficient and *n* is the index of iteration.

With these two phases, all the weights, which are generally randomly set to begin with, can be adjusted appropriately so as to minimize the error between the desired and the actual outputs of the neural network. After the learning process is finished, the neural network memorizes all the adjusted weights and is ready to recognize new input data based on the knowledge obtained from the learning process. Through this learning process, the network memorizes the relationships between input vector X and output vector Y of the system through the connection weights. Implementation steps are shown in Figure below (Fig. 3).

4. Setup of Experiment Equipment and Experiment Condition

For this experiment we design and produce a testing machine, which is shown in (Fig. 4). The overview is shown in (Fig. 5). The linear motion guide is manufactured by ABBA Linear Technology

Company (Model: BRH25A). The width of the rail is 23mm, and the length 3m. Fixed on one side is a self-lubricating oil tank, which uses Type-460 lubrication oil to automatically lubricate the linear motion guide during motions. The structure of linear motion guide and oil tank is illustrated in (Fig.6). Installed on a 3m-long track, the linear motion guide moves back and forth on the track, and mileage is recorded. The carriage of this testing machine is for fastening three block sets of the same model. CNC Controller HUST3 is employed to control the server motor. This control device can be used to set up the travel and the speed, which through a timing belt causes the carriage to make left-right movement at the speed of 1.2m/s. Following every 200km the hidden oil tank of the linear motion guide is removed for weight measurement. This oil tank weighs 11.9g without oil and 25.85g when it is full. In this experiment it is filled up to 90％ or 23.76g. The linear motion guide is conditioned to move left and right at a pace of 1.2m/sec automatically. Due to the fact that this motion guide is used mainly by light-load automatic industrial entities, a load cell is installed on the linear motion guide. This load cell is capable of adjusting the load as shown in (Fig. 7). Its rated load is set at 420kg, or about 20% of the basic static load rating of the linear motion guide. The load can be adjusted through the rotation socket screw on the load cell, and the size of the load can be transmitted to the control panel through the sensor under the rotation socket screw. The load only affects the linear motion guide in the middle. It does not affect linear motion guides on either side. The purpose of linear motion guides on either side is to guide the left-right movement.

5. Experiment Outcome

Left side of (Table.1) shows actual lubrication oil consumption obtained for 200-1400km. This paper employs 200-1000km as the sequence for grey prediction modeling and neural network modeling, and uses it to predict 1200-1400km lubrication oil consumption. The predicted results obtained by the GM(1,1) model and Neural Network model are shown in (Table.1) and (Fig. 8).

Grey prediction is shown below.

a. Steps for grey prediction modeling under tension are shown as:

1) Model's primitive sequence

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(5)\}$$

$$= \{23.76, 21.4, 18.75, \cdots, 17.75\}$$

2) AGO

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \cdots, x^{(1)}(5)\}$$

$$= \{23.76, 45.16, 63.91, \cdots, 99.76\}$$

3) Determine B and Yn through least square method

$$Yn = \begin{bmatrix} 21.4 \\ 18.75 \\ \vdots \\ 17.75 \end{bmatrix}, \quad B = \begin{bmatrix} -34.46 & 1 \\ -54.54 & 1 \\ \vdots & \\ -90.89 & 1 \end{bmatrix}$$

$$\hat{a} = (B^T B)^{-1} B^T Y_n$$

$$= \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} 0.0625 \\ 22.9512 \end{bmatrix}$$

4) List the response equation

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a}$$

5) Solve $\hat{x}^{(1)}(k)$ for 1-IAGO

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$$

$$= (1 - e^{a}) \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak}$$

$$= \{20.81, 19.55, 18.36, \cdots, 15.22\}$$

6) Error Examination

$$e(k) = \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \times 100\%$$

$$= \{2.77, -4.25, -1.45, \cdots, 9.11\}$$

The mean absolute percentage error (MAPE) of the GM(1,1) model and neural network model from 1200 to 1400 are 7.44% and 2.15%, respectively. The outcome indicates that the prediction model established through neural network is superior to the prediction model established through the grey theory, in that the error of the neural network model is less significant.

6. Conclusions

From this study we understand that both grey modeling and neural network modeling can help us obtain reasonable prediction outcomes based on small amount of data. But the prediction of neural network modeling is better. (Table. 1) shows the MAPE of the prediction outcome of neural network modeling is 2.15%, and that of grey modeling is 7.44%. That indicates the prediction outcome of neural network modeling is superior to that of grey modeling. Results of this study also demonstrate the fact that application of neural network prediction modeling to single-input and single-output prediction has attained excellent results. It is proved to be an effective model for predicting lubrication oil consumption of linear motion guides. We also learn that the prediction outcome of grey modeling is not as good as that of neural network modeling. So it says much about the fact that neural network prediction modeling is very effective for prediction of lubrication oil consumption of linear motion guides. The grey theory has been a very powerful prediction model, especially when available data are inadequate. But its prediction of lubrication oil consumption of linear motion guides is not as accurate as that of neural network prediction modeling. In summary, neural network prediction modeling is suitable for prediction of lubrication oil consumption of linear motion guides. It accuracy is superior to that of grey theory modeling GM (1,1). Outcomes of this study will be provided for linear motion guide manufacturers for testing of linear motion guides of different specifications, in hopes that the testing time may be reduced, the production cost may be lowered and profitability of the company may be enhanced, so the linear motion guide industry of Taiwan, like the electronic industry, will become a major player in the world and surpass other major players like Europe, America and Japan.

Acknowledgements

The authors wish to express their gratitude to all members of the Design Department and Production Department of ABBA Linear Technology Company, Taipei, Taiwan, ROC, for their invaluable participation and assistance.

References

[1] Y. F. Hsiao, Y. S. Tarng and W.J. Huang, Optimization of plasma arc welding parameters by using the Taguchi method with the grey relational analysis, *Materials and Manufacturing Process*, Vol. 23, 2008, pp. 51-58.

[2] Y. F. Hsiao, Y. S. Tarng and K.Y. Kung, Process parameter determine of linear motion guide with multiple performance characteristic by grey-based Taguchi methods, *WSEAS Transactions on Mathematics*, Vol.6, 2007, pp. 778-785.

[3] Y. F. Hsiao, Y. S. Tarng, K. Y. Kung, Study of prediction of linear motion guide rigidity through grey modeling of linear differential and linear

difference equations, *WSEAS Transactions on Mathematics*, Vol. 5, 2006, pp. 932-938.

[4] L. C. Hsu, Applying the Grey prediction model to the global integrated circuit industry, *Technological Forecasting and Social Change*, Vol. 70, 2003, pp. 563-574.

[5] Y. Jiang, Y. Yao, S. Deng, Z. Ma, Applying grey forecasting to Predicting the operating energy performance of air cooled water chillers, *International Journal of Refrigeration*, Vol. 27, 2004, pp. 385-392.

[6] C. H. Hsu, S. Y. Wang, L.T Lin, Applying data mining and Grey theory in quality function development to mine sequence decisions for requirements, *WSEAS Transactions on Information Science and Applications*, Vol. 4 (6), 2007, pp. 1269-1274.

[7] C. H. Li, M. J. Tsai, Multi-objective optimization of laser cutting for flash memory modules with special shapes using grey relational analysis, *Optics and Laser Technology*, Vol. 41 (5), 2009, pp. 634-642.

[8] H. H. Liang, M. J. Hung, K. F. R. Liu, The application of evaluation model using fuzzy grey decision system for the safety of hillside residence area in Taiwan, *WSEAS Transactions on Information Science and Applications*, Vol. 4 (5), 2007, pp. 916-923.

[9] C. S. Chang, The growth forecasting of major telecom services, *WSEAS Transactions on Information Science and Applications*, Vol. 4 (5) , 2007, pp. 996-1001.

[10] C. C. Cheng, K. L. Hsieh, Incorporating fuzzy aggregation operator and grey relationship analysis into constructing a MCDM model, *WSEAS Transactions on Information Science and Applications* , Vol. 3 (11), 2006, pp. 2100-2106.

[11] Y. S. Tarng, S. C. Juang, C.H. Chang, The use of grey-based Taguchi methods to determine submerged arc welding process parameters in hardfacing, *Journal of Materials Processing Technology*, Vol. 128 (1-3), 2002, pp. 1-6.

[12] C. C. Hsu, C. Y. Chen, Application of improved grey prediction model for power demand forecasting, *Energy Conversion & Management*, Vol. 44, 2003, pp. 2241-2249.

[13] E. O. Ezugwu, S. J. Arthur, E. L. Hines, Tool-wear prediction using artificial neural networks, *Journal of Materials Processing Technology*, Vol. 49 ,1995, pp. 255-264.

[14] J. Y. Kao, Y. S. Tarng, A neural-network approach for the on-line monitoring of the electrical discharge machining process, *Journal of Materials Processing Technology*, Vol. 69, 1997, pp. 112-119.

[15] S. C. Juang, Y. S. Tarng, H. R. Lii, A comparision between the back-propagation and counter-propagation networks in the modeling of TIG welding process, *Journal of Materials Processing Technology*, Vol. 75, 1998, pp. 54-62.

[16] Y. S. Tarng, S. T. Hwang, Y. W. Hsieh, Tool failure diagnosis in milling using a neural network, *Mechanical Systems and Signal Processing*, Vol. 8(1) , 1994, pp. 21-29.

[17] Y. S. Tarng, Y. W.Hsieh, S. T. Hwang, Sensing tool Breakage in face milling with a neural network, *International Journal of Machine Tools Manufacture*, Vol. 34(3), 1994, pp. 341-350.

[18] Y. S. Tarng, T. C. Li, M. C. Chen, On-line drilling chatter recognition and avoidance using an ART2-A neural network, *International Journal of Machine Tools Manufacture*, Vol. 34(7) ,1994, pp. 949-957.

[19] J. C. Su, J. Y. Kao, Y.S. Tarng, Optimisation of the electrical discharge machining process using a GA-based neural network, *International Journal of Advanced Manufacturing Technology*, Vol. 24 (1-2) , 2004, pp. 81-90.

[20] J. L. Deng, *Grey prediction and decision*, Huazhong University of Science and Technology, Wuhan, China, 1986.
[21] J. A. Freeman, D. M. Skapura, *Neural Networks: Algorithms, Application and Programming Techniques*, Addison -Wesley, New York, 1991.
[22] J. McClelland, D. Rumelhart, *Parallel Distributed Processing*, vol. 1. MIT Press, Cambridge, MA, 1986.

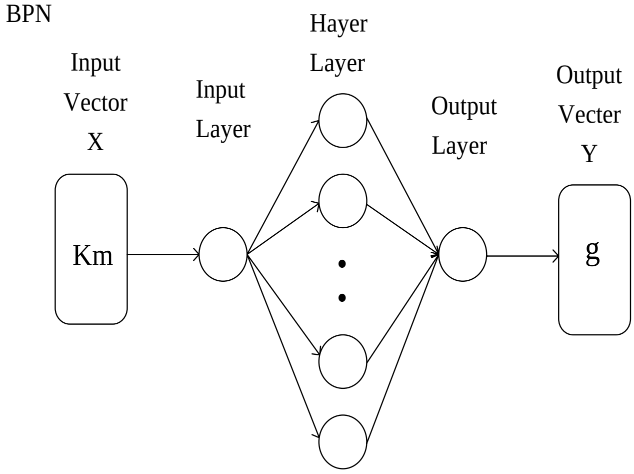

Fig.1.Configuration of the back-propagation network for the modeling of the linear motion guide lubrication oil test

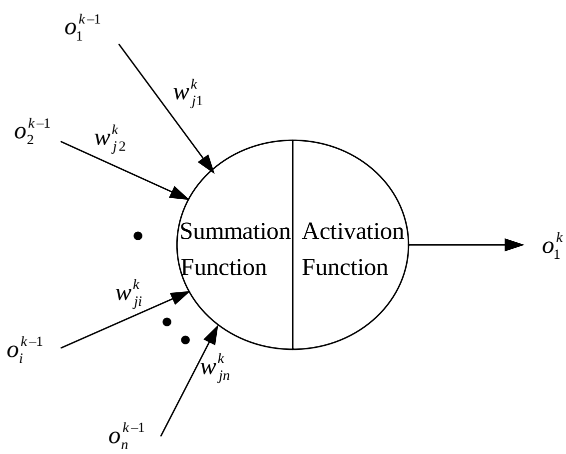

Fig. 2. Artificial neuron with an activation function.

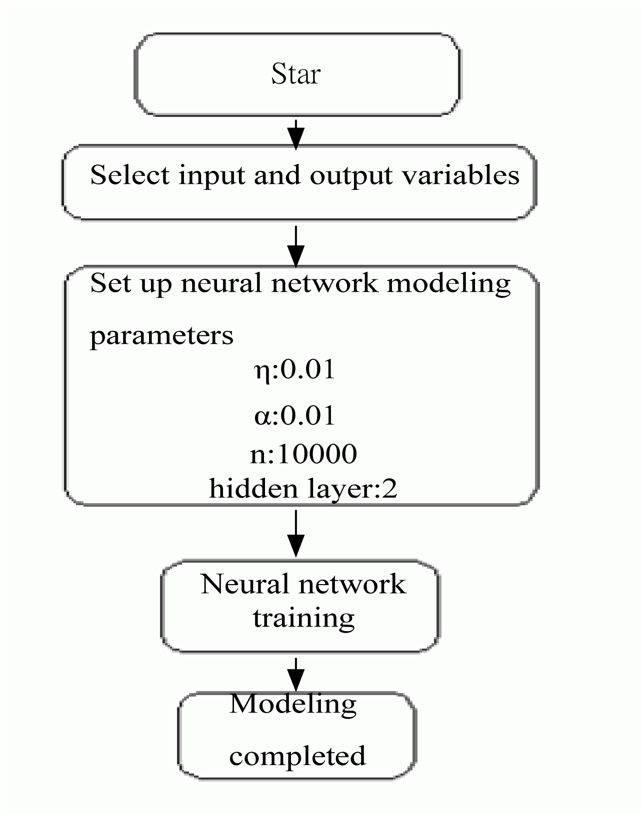

Fig.3. Neural network implementation steps

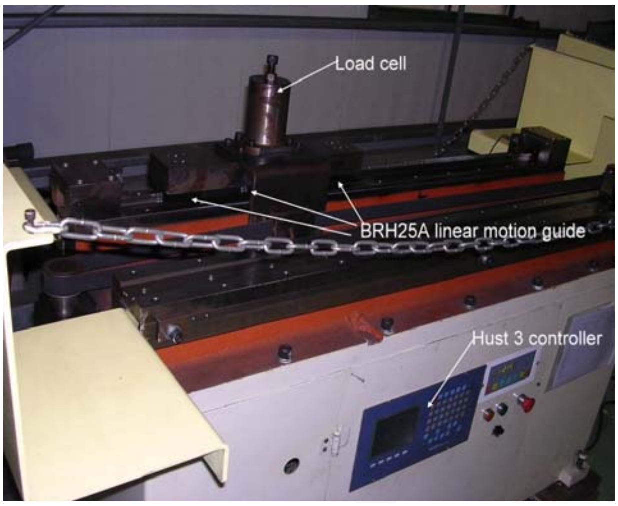

Fig.4. Lubrication oil consumption testing device

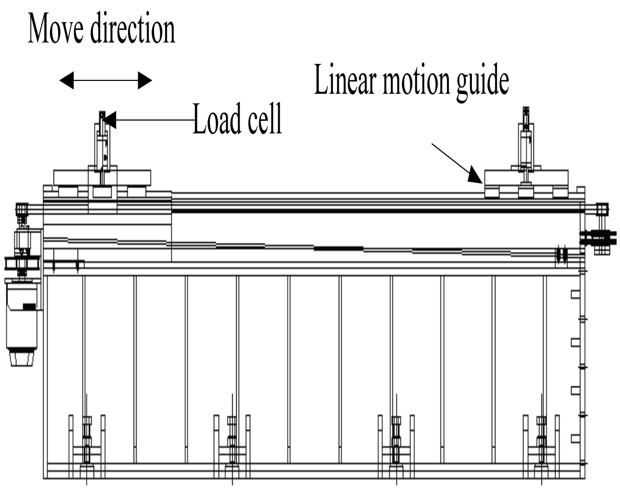

Fig.5. Lubrication oil consumption testing device overview

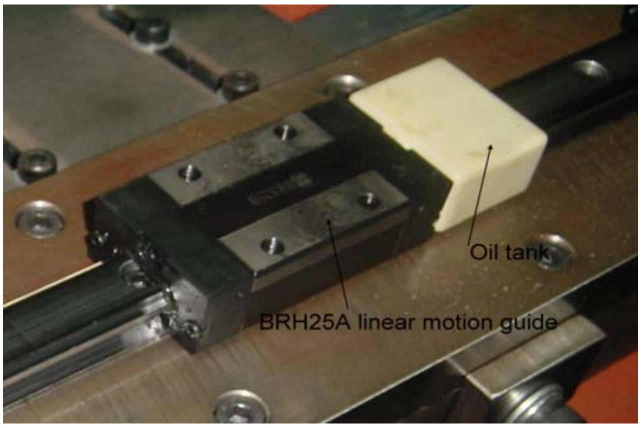

Fig. 6. BRH25A linear motion guide and lubrication oil tank

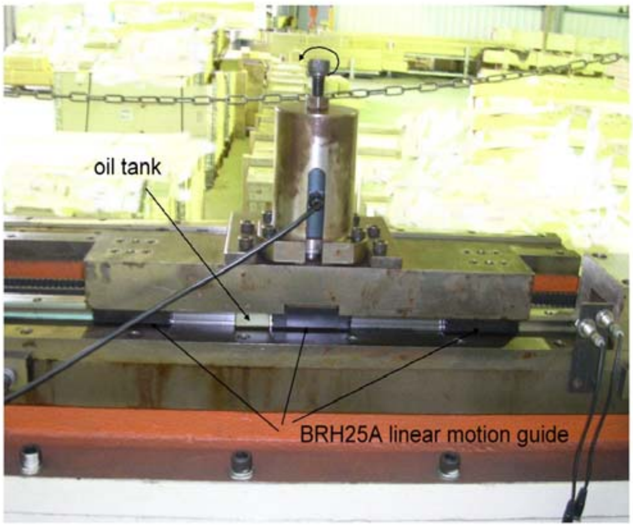

Fig.7. Load cell

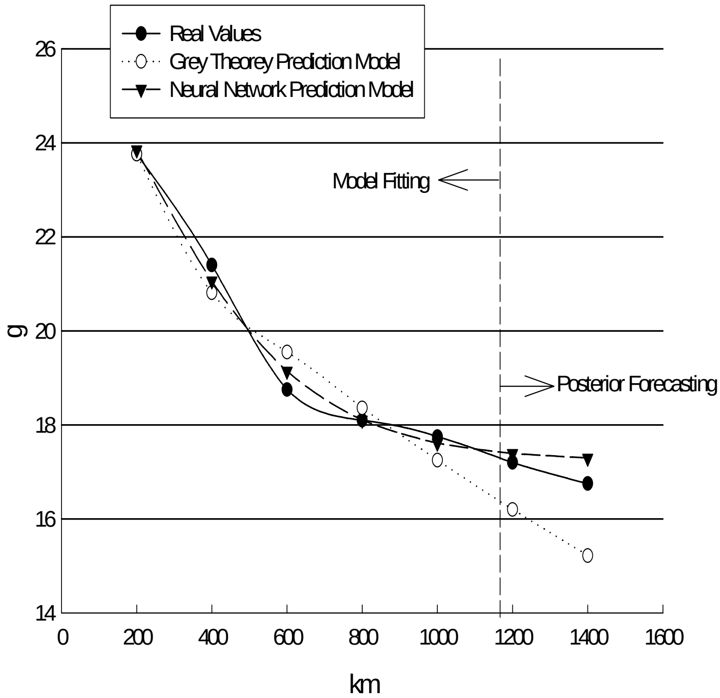

Fig.8. Real values and model values for lubricant of linear motion guide from 200km to 1600km

Table. 1. Model values and forcast errors(unit:g)

km	Real value	GM(1,1)		Neural network	
		Model value	Error (%)	Model value	Error (%)
200	23.76	23.76	-	23.85	-0.4
400	21.4	20.81	2.77	21.06	1.6
600	18.75	19.55	-4.25	19.14	-2.1
800	18.1	18.36	-1.45	18.1	0
1000	17.75	17.25	2.81	17.61	0.8
MAPE			2.82		0.98
1.4	17.2	16.2	5.77	17.39	-1.1
1.6	16.75	15.22	9.11	17.291	-3.2
MAPE			7.44		2.15