Design of Magnetic Levitation System Based on Inverse Control Techniqueusing Adaptive Neuro-Fuzzy Inference System

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Abstract

The design of ANFIS network based inverse control technique is proposed in this paperfor this system. Simulation is implemented in MATLAB after the ANFIS is trained and it is shown that results are applicable in process industry and acceptable for reference control applications. The effectiveness of the proposed ANFIS in inverse controller it has been tested by entering random selected points which represent the values of input voltage from the system under control as a reference input to inverse modelling, after that entering the results of inverse modelling to the modelling of magnet levitation system to form the desired output. The result is acceptable with small errors about 0.0011.

Keywords: - ANFIS, Inverse control, Direct Inverse Control, Magnetic levitation system.

الخلاصـــــــــة

في هذا العمل، تم اقتراح السيطرة المعكوسة المعتمدة على العصبي _ الضبابي وذلك لتصميم مسيطر بسيط ومباشر النظام التحليق المغناطيسي. في هذه الطريقة يستم تدريب شبكة مسيطر النظام التكيفي العصبي الضبابي الاستدلالي الهجين (ANFIS) لتكوين المسيطر والذي يعطي الفعالية المعكوسة للنظام. وتم تنفيذ المحاكاة في برنامج الماتلاب، وتبين نتائج المحاكاة انه قابلة للتطبيق في المجالات الصناعية ومقبولة لتطبيقات التحكم المرجعية. تم اختبار فعالية النظام المقترح في السيطرة العكسية وذلك بادخال مجموعة من القيم العشوائية التي تمثل قيمة فرق الجهد الى النموذج العكسي للنظام، بعد ذلك تم ادخال نتائج النموذج العكسي للنظام الى نموذج النظام لاستخراج القيمة المطوبة . والنتائج الاختبار كانت مقبولة وبقيم الخطأ الجذري للمعدل التربيعي(RMSE) وهي 0.0011.

كلمات مفتاحية: مسيطر النظام التكيفي العصبي الضبابي الاستدلالي الهجين(ANFIS)، السيطرة المعكوسة ، السيطرة المعكوسة المباشرة ، نظام التحليق المغناطيسي

List of Abbreviations

ANFIS	Adaptive Neuro-Fuzzy Inference System.
FLS	Fuzzy Logic Systems.
NN	Neural Network.
MF	Membership Function
NF	Neuro-Fuzzy
FALCON	Fuzzy Adaptive Learning Control Network.
NEFCON	Neuro-Fuzzy Control.
RMSE	Root Mean Square Error

I- Introduction

In the industrial field, implemented the magnetic levitation system successfully for many application, and exhibit many advantages such as the capability to operate in high vacuum environments, low noise, frictionless and so on. Magnetic levitation systems are inherently nonlinear systems, uncertainly and open loop unstable. Consequently, controlling Magnetic levitation system is very difficult by using the classical approach such as PID controller.In identification and control processes the most applied methods of the nonlinear systems are the artificial models such as Fuzzy Logic Systems (FLSs) and Neural Networks (NNs). The known supports of FLSsand

NNsmethods are their capability to learn and perfect performance for the nonlinear functionsapproximation(Ahmed El Hajjaji , M Ouladsine, August 2001).

Magnetic levitation has been successfully implemented for many applications, such asvibration isolation systems, high-speed suspension train in Germany and Japan, rocket-guiding projects, photolithography steppers,supraconductor rotor suspension of gyroscopes and magnetic bearings (Ahmed and Ouladsine 2001; Nataraj and Mukesh, 2008).

Recently, the magnetic levitation systems used in space missions since the Magnetic Levitation setup technology used as the zeroth stage of the launch is seen as a reliable, safe, and inexpensive launch support for payloads launching into space(Nataraj and Mukesh, 2008).The advantage of magnetic levitation systems are frictionless, the capability to work in high vacuum environments, low noise and so on (Nataraj and Mukesh, 2008).Despite the fact that magnetic levitation systems are described by highly nonlinear differential equations and have unsteady manner, most approaches design are based on the linearized model on a nominal operating point (Ahmed and Ouladsine 2001). The magnetic levitation systemsschematic diagram shown in Fig.1.

Generally using PID current correction as a controller to electromagnetic levitation systems to lift the magnet by the air gap active monitoring.The FLSs and NNs are the newer controller introduced to conventional state-based control.In this paper ANFIS as one of hybrid neural-fuzzy system is used to predict the vertical position of a levitated magnet from past values of its position and a control current through an electromagnet over which the levitated magnet is suspendedto take advantages of these complementary intelligent methods. Section II and section IIIshows the inverse control and ANFIS fundamental respectively. In Section IV, Simulations results and discussionare presented. Finally, conclusions are given in Section V.

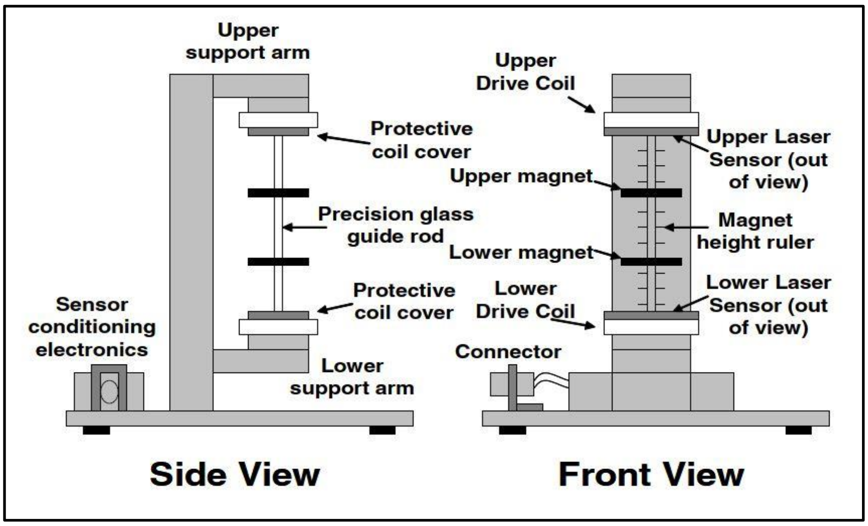

Figure 1:Schematic diagram of magnetic levitation systems

II- Inverse Control

The Inverse Control Design significant challenge is to get the inversion of a plant. Obtaining the inverse of a plant for nonlinear systems using analytical methods has a lot of difficulties, plus it could unlikely be successful. However, inverse control could use intelligent systems methods with its nonlinear approximation ability to perform the task(Muhammad *et.al.,* 2014).

Generally, identification process and controller design are two main stages in inverse control development using intelligent networks such as neural and fuzzy networks for unknown nonlinear dynamic discrete systems(Yu Tang *et.al.*, 2015). In the identification process steps the first intelligent network is used to approximate the considered system under the control. In the controller design step, another intelligent network is trained to determine the desired control signals in terms of the measured inputs and outputs as well as the given reference (Hua Deng *et.al.*, 2005).

The inverse model for system with time dependent dynamics can be incorporated as controller in two methods: Inverse control with online adaptive learning and direct inverse control (Pushpak *et.al.*, 2015) .

A- Direct inverse control

Direct inverse control, shown in Fig.2 uses the inverse model to control directly the system. Inverse model of a system, whose dynamics is given by equation (1), will take the dynamics given by equation (2)(Akarsh Sinha and Jaganatha 2015):

$$y(j+1) = f\left[y(j), y(j-1), y(j-2), \ldots, x(j), x(j-1), x(j-2), \ldots\right] \quad (1)$$

$$\hat{x}(j) = \hat{f}^{-1}\left[y(j), y(j-1), y(j-2), \ldots, x(j), x(j-1), x(j-2), \ldots\right] \quad (2)$$

Where $y(j-i)$ is the value of output at ith state (time) and $x(j-i)$ is the value of input at ith state (time).

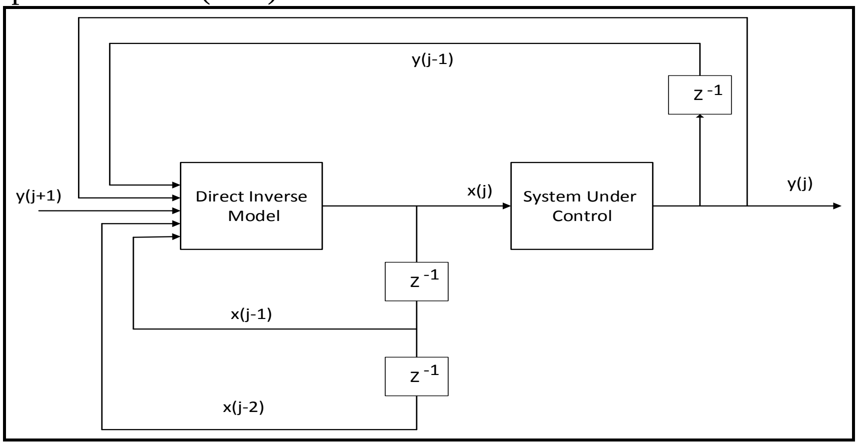

Figure 2: Direct inverse control schematic

B-Inverse control with online adaptive learning

Fig.3 shows the structure of adaptive inverse control system. There are two kinds of adaptive inverse control: (1) restrain of plant noise (2) control of plant dynamic response

Adaptive inverse control main idea is using signals coming from a controller for driving an object while the model of the controller is the inverse model of the object. The object output follows the controller input which leads to realizing the anticipate control effects(Yulin Gong and Yongyin Qu, 2011).

The transfer function of adaptive inverse control system from disturbance input to the output of plant is as follows:

$$W(s) = \frac{1 - G_{pm}(s).G_{INV}(s)}{1 + G_p(s)G_{INV}(s) - G_{pm}(s)G_{INV}(s)} \quad (3)$$

Where $G_p(s)$ is plant, $G_{INV}(s)$ is plant inverse model, $G_{pm}(s)$ is plant model.

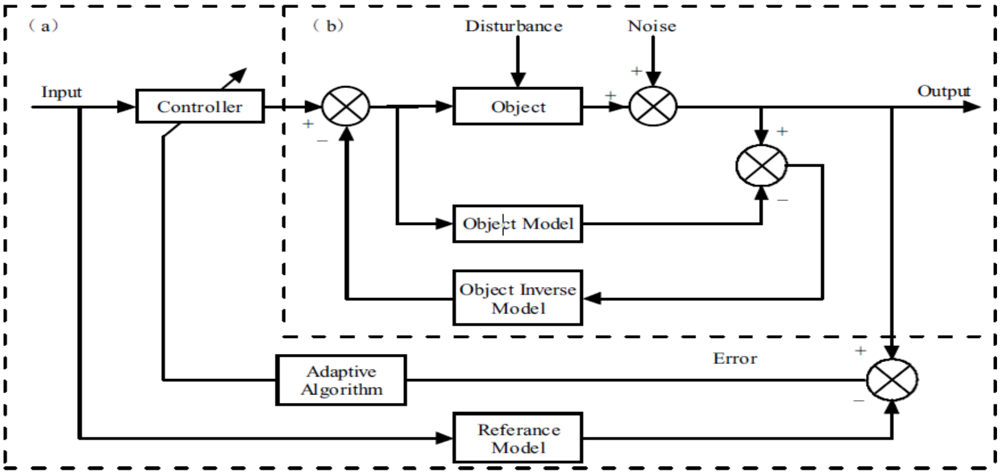

Figure 3: structure of adaptive inverse control system

III-ANFIS

The combination between the two intelligent system NN and FLS are forms the ANFIS. This combination of FLS and NN gives the advantages of both technologies, this combination categorized into three models; concurrent, cooperative and fully fused (sumathi and surekha 2010). In the concurrent model the NN continuously aid the FLS to provide all required parameters particularly when it is cannot measure the controller input variables directly. In the cooperative model the NN determines the Membership Functions (MFs) from its training data; the rules formed using fuzzy clustering (sumathi and surekha 2010). Finally, fused Neuro-Fuzzy (NF) shares the structures information and the knowledge representations, the learning algorithm applied to the fuzzy system through interpreting this fuzzy system into NN architecture. This model have many types like ANFIS, Fuzzy Adaptive Learning Control Network (FALCON), Neuro-Fuzzy Control (NEFCON) and others(sumathi and surekha 2010).

Typically, the ANFIS mechanism has two inputs and one output based on the common IF-THEN Sugeno rule(Yulin Gong and Yongyin Qu 2011).

$$IF\ x_a\ is\ A_i\ AND\ x_b\ is\ B_i\ THEN\ R_j = k_{0j} + k_{1j}x_a + k_{2j}x_b \tag{4}$$

Where: A_i and B_i are fuzzy sets, x_a and x_b are input variables, R_j is the output, j is the rules number and k is consequent parameter. The ANFIS architecture has five basic layers function as shown in Fig.4:

Layer 1 (Fuzzification layer): This layer generates the MFs, Equation (5)represents the Gaussian MF (used as example),

$$O_i^1 = \mu A_i(x) = exp\left(-\frac{(x - d_i)^2}{\sigma_i^2}\right) \tag{5}$$

Where $O_i$the layer1 output, x is the input to the ith node, μ the membership function, A_i is a linguistic label associated with this node and the$\sigma_i$and $d_i$denote the width and the center of the Gaussian function respectively.

Layer 2 (Rules layer): the product of all inputs of layer 2, knownas the firing strengths

$$O_i^2 = w_i = \mu A_i(x) \times \mu A_i(y) \tag{6}$$

Where w_i is the output rules of layer2.

Layer 3 (Normalization layer): This layer normalizes MFs:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad (7)$$

Layer 4 (Defuzzification layer): calculates the rules weighted consequent parameters:

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}\left(a_i x + b_i y + c_i\right) \quad (8)$$

Where $\overline{w_i}$ comes from the output of layer 3 and $\{a_i, b_i, c_i\}$ is the parameter of MFs.

Layer 5 (Summation layer): calculates the overall output of the ANFIS:

$$O_i^5 = f = \sum_i \overline{w_i} f_i = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \quad (9)$$

Where f is the output of layer 5

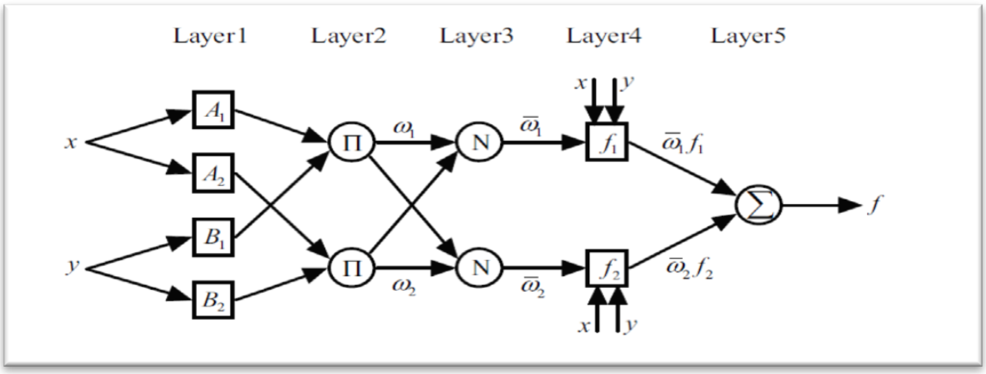

Figure 4: ANFIS Architecture

IV- Simulations Results and Discussion

The magnet levitation performance system is evaluated by Matlab 2014a through simulation, and using ANFIS to predict a levitated magnet vertical position from past values of its position and a control current through an electromagnet over which suspended of the levitated magnet.First step is loading the two values oflevitated magnet each with 1x4001 cell array, the first value represent electromagnet current while the second value represent the levitated magnet position.

The first step to use ANFIS for system identification in this work is to select the input signals for training and determine the argument variable which should be as an input to an ANFIS model. There are many methods to select these inputs, such as the sequential forward method in which all inputs is chosen sequentially to optimize the overall squared error. And another more computationally intensive method is to do an itemized search on all potential combinations of the candidates input.

We assume that in order to predict the output value at time u(j), y(j), that there are an enough number of input candidates, 10 for example and there are values are formed from the input data and the output data of the system as in the following sets:

Output=

$$Y = \{y(j-1), y(j-2), y(j-3), y(j-4)\} \quad (10)$$

Input=

$$U = \{u(j-1), u(j-2), u(j-3), u(j-4), u(j-5), u(j-6)\} \quad (11)$$

Then by using the second exhaustive search on the input candidates available in equations (10) and (11). The final result for this search yield select three input: two of them from the output data, and the third comes from the input data, as shown following:

$y(j-1)$, $y(j-2)$ and $u(j-2)$ are the selected input to ANFIS.

Fig.5 shows the proposed system of magnetic levitation. Depending on above selection process, the ANFIS consist of three inputs with one output, Takagi-Sugeno method of fuzzy inference with 8 rules as shown in Fig.6.

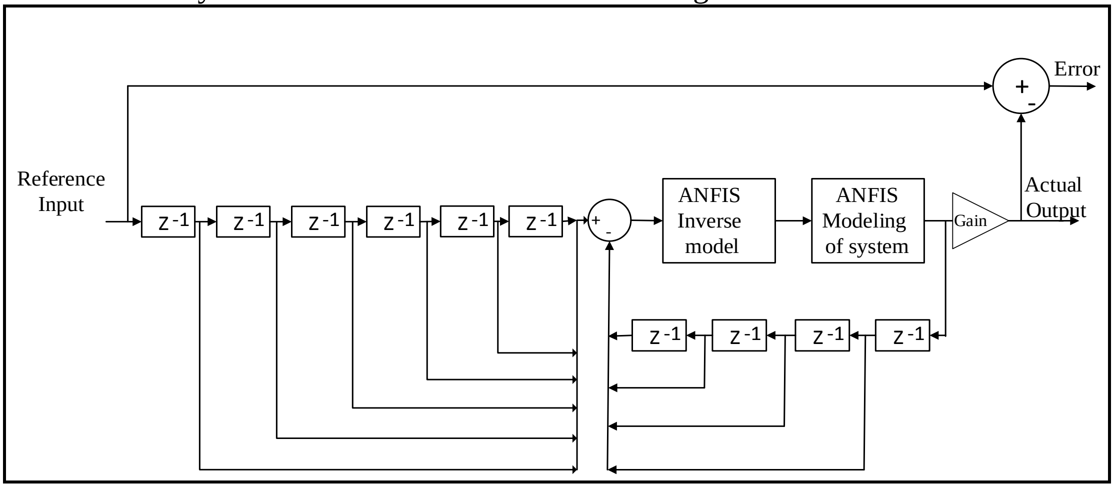

Figure5:Proposed system of magnetic levitation

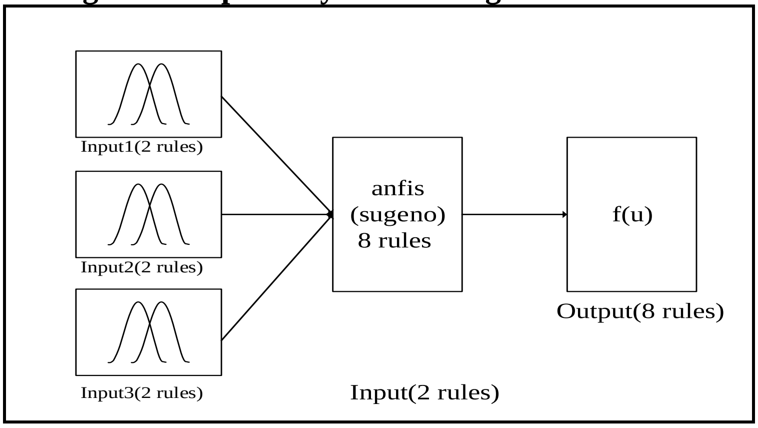

Figure 5: System diagram of ANFIS

The total data that used in thiswork is 600 data points divided into 400 used for train the identification structuresand other 200 used for testing phase. Fig.7 shows the input and output data of magnet levitation dynamical system under simulation test.

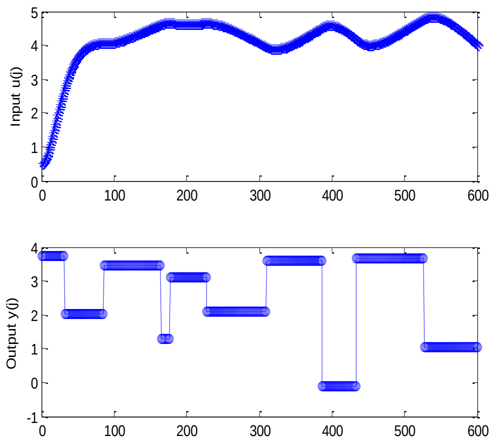

Figure 6: input and output data of magnet levitation dynamical system.

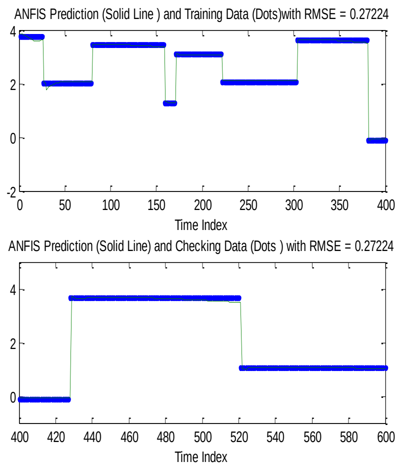

Figure 7: training and checking data with ANFIS prediction of inverse modeling

To find the inverse model first exchange the input with output data, thentrain the ANFIS to find the inverse modeling of the system. Fig.8 shows the training and checking results of ANFIS with Root Mean Square Error (RMSE) is equal to 0.27224.

The next step is to put back the original input-output data to find the modeling of the original system, Fig.9 show these input and output data.The results of ANFIS to modeling system shown in Fig.10, that show the ability of ANFIS network to prediction the system in training and checking process with very low RMSE (0.00011014).

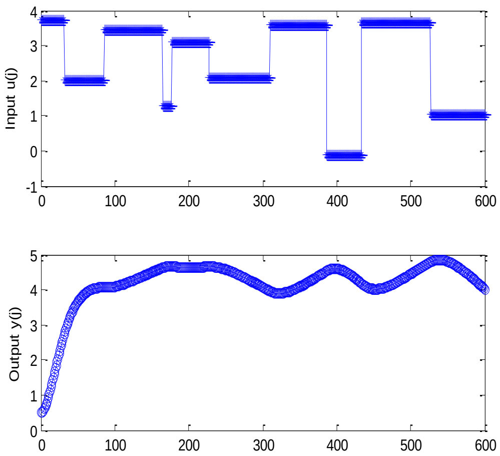

Figure 8:the original input and output data of the system

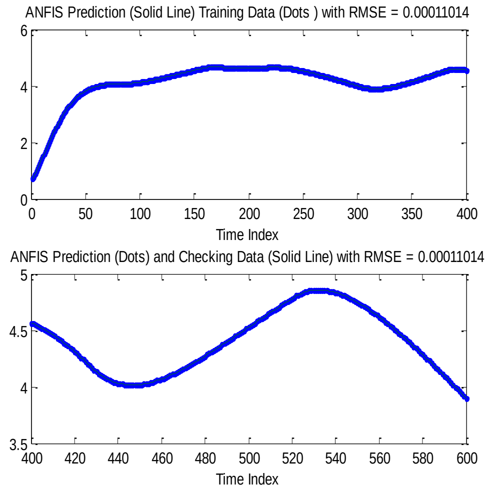

Figure 9:Simulation result using ANFIS training data checking

From Fig.8 and Fig.10 the simulation results show that the ANFIS modeling hasfast position tracking ability, good performance and strong robustness with low error. Fig.11show the flowchart of the ANFIS training and checking processes for the identification stage of this work.

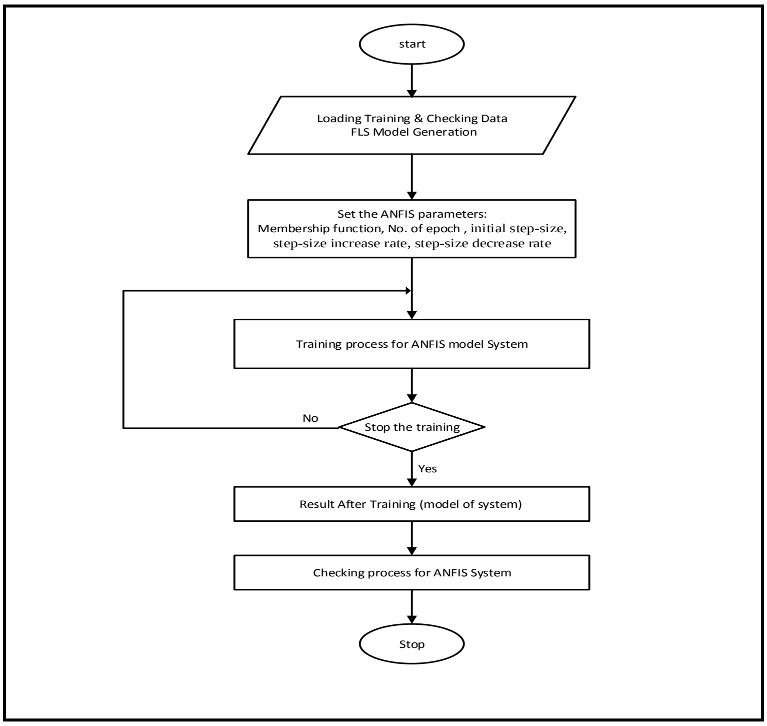

Figure 10: ANFIS training and checking flowchart for identification process

Fig.12 shows the overall structure of the proposed system control based on an inverse modeling designed for magnetic levitation systems. Fig.13show the testing results with random selected points from the system under control.

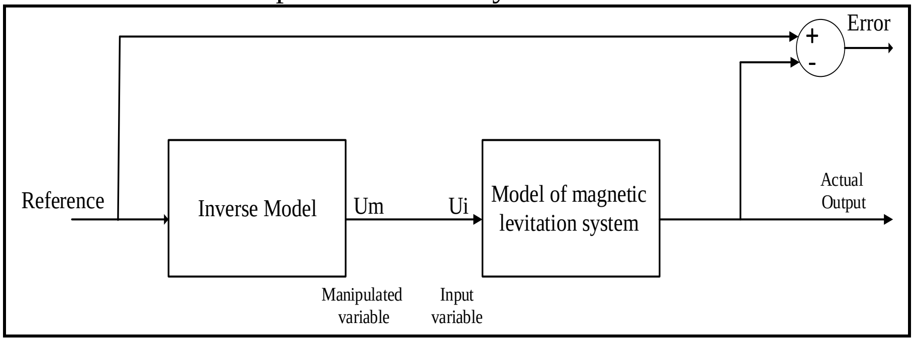

Figure 11Proposed system of magnetic based on inverse modeling design

In Fig.13 it can be seen that the actual values are fit to the desired value most of the times except small intervals.

Fig.14 shows the error curve after sorting the difference between the actual and desired output, the highest value of error is 3.1×10^{-3} and most of the time the error is very low approximately zero.

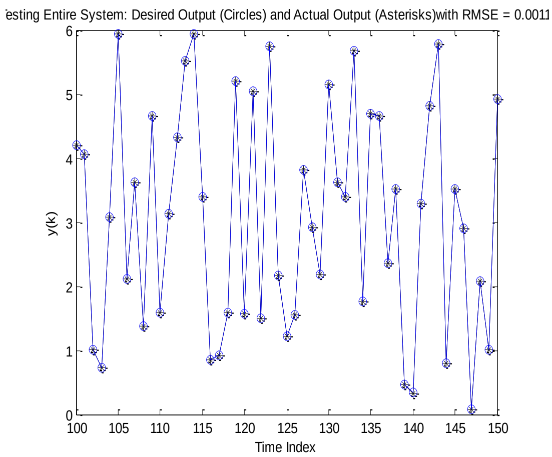

Figure 12 show the desired and actual output

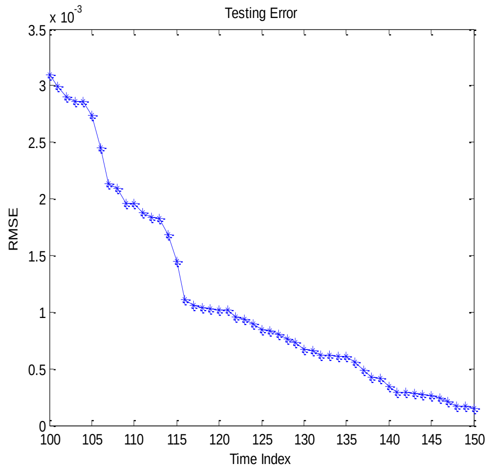

Figure 13 show the maximum and minimum error

V- Conclusions

In this paper, the effective design and training process of ANFIS controller based on inverse controller model is proposed to estimate magnetic levitation system.The magnetic levitation has been successfully controlled by using an ANFIS network based inverse control technique.The model and inverse model of a magnetic levitation system design by ANFIS. Inverse modelling of system can be used alone as a controller directly before its modelling and that gives a simplicity in the design compared with other methods control. The simulation results show that the output of system follows the input reference signalwith the ANFIS controlwith acceptable results in terms of time delay factor.The simulation study demonstrates validity of the proposed design methodology.From Figure 8 and Figure 10 the simulation results show that the ANFIS modeling hasfast position tracking ability, good performance and strong robustness with low error.

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