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Sun Tracking System Based On Neural Network

Lecturer Dr. Fouad Shaker Tahir
Applied of Science Dept.
University of Technology
Iraq-Baghdad

Lecturer Dr. Jabbar Khalaf Mohammed
Energy and Renewable Energies
Technology Center
University of Technology

Abstract

The design and simulation of compatible controller depend on neural network was discussed in this paper . A new model of neural network and a new type of neural controller will proposed aiming to reduce the complexity without sacrificing efficiency of traditional type. More complex neural-based solar tracker. The proposed technique reduces the disadvantages which appear in the traditional systems. In addition the goal of this paper based on solar plant system for testing purposes and to develop a useable technology for the ever growing demand for green power.

Key words: photovoltaic tracking system , artificial neural network application , intelligent system design.

نظام المتتبع الشمسي باعتماد الشبكات العصبية

م.د. فؤاد شاكر طاهر
الجامعة التكنولوجية

م.د. جبار خلف محمد
الجامعة التكنولوجية

الخلاصة :

تم في هذا البحث مناقشة تصميم ومحاكاة مسيطر متوافق يعتمد على الشبكة العصبية في عمله. لقد تم اقتراح نموذج جديد من الشبكات العصبية إضافة إلى نوع جديد من وحدة التحكم العصبية، ويهدف إلى الحد من التعقيد من دون التضحية بكفاءة النوع التقليدي. ان الاسلوب المقترح يسهم في تقليل العيوب التي تظهر في النظم التقليدية ،إضافة إلى ذلك فان هذه الورقة تهدف إلى الاعتماد على وحدة النظام الشمسي لغرض أجراء الاختبارات وتطوير تقنية قادرة على مواكبة الطلب المتزايد جدا على الطاقة الخضراء.

1. Introduction

Solar energy systems have emerged as a viable source of renewable energy over the past two or three decades, and are now widely used for a variety of industrial and domestic applications. Such systems are based on a solar collector, designed to collect the sun's energy and to convert it into either electrical power or thermal energy [1].

There are three ways to increase the efficiency of photovoltaic (PV) system. The first is to increase the efficiency of the solar cell. The second is to maximize the energy conversion from the solar panel. The third method to increase the efficiency of a PV system is to employ a solar panel tracking system [2].

The position of the sun with respect to that of the earth changes in a cyclic manner during the course of a calendar year. Tracking the position of the sun in order to expose a solar panel to maximum radiation at any given time is the main purpose of a solar tracking PV system.[3] **Figure(1)** show Sun Path During Winter and Summer Solstices [4].

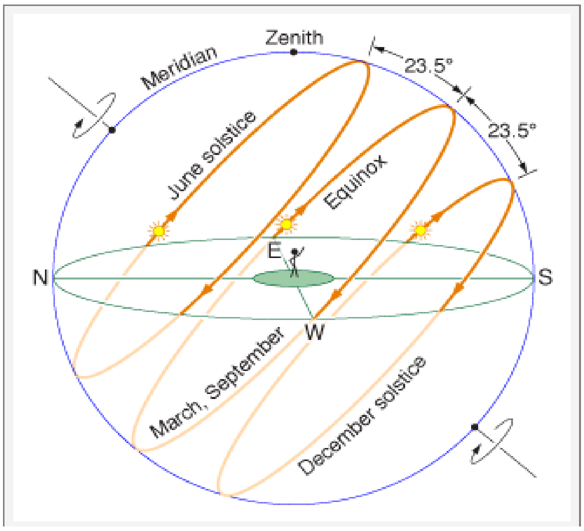

Fig. (1): illustration of the summer and winter solstices.[4]

The Trackers are used to keep PV-panels directly facing the sun, thereby increasing the output from the panels. Trackers can nearly double the output of an array. Careful analysis is required to determine whether the increased cost and mechanical complexity of using a tracker is cost effective in particular circumstances.

For many years, several energy companies and research institutions have been performing solar tracking for improving the efficiency of solar energy production. A variety of techniques of solar energy production used have proven that up to 30% more solar energy can be collected with a solar tracker than with a fixed PV system [5].

2. Solar Plant

The main element in a solar electric power plant is the solar panel. Physically it consists of a flat surface on which numerous p-n junctions are placed, being connected together through electrically conducting strips. As technology evolved, the efficiency of the conversion in solar panels increased steadily, but still it does not exceed 12% for the most advanced, spherical cell designs. To further complicate matters, the solar panels also exhibit a strongly non-linear I-V characteristic and a power output that is also non-linearly dependant on the surface insulation. The temperature of the panel is also crucial to its normal operation, the silicon junction needing a steady and not too high temperature (80 ^oC) degrees Celsius being the maximum recommended operating temperature. The optimal performance is attained around 30 degrees Celsius. The dependence of the solar panel performance on the direct insulation is one of the main reasons for a sun tracking system. Compared to a fixed panel, the mobile panel on a tracker is kept under the best possible insulation for all positions of the Sun, as the light falls close to the geometric normal incidence angle. Solar trackers have been associated with neural networks since the beginning of the study, because as we have seen, the solar panels are strongly non-linear devices and the problem of their output maximization is also a nonlinear problem, the neural networks being well – known for their ability to extract solutions to non-linear problems with variable parameters [5,6].

3. Solar Tracking and Efficiency

Solar tracking, like all optimization measures, has some inherent limitations and some parameters to be considered before a final solution is applied. Although beneficial as a method of maximizing solar panel output, tracking is to be made using motors or actuators, and a controller that will add to the "internal service quota" of the solar plant. This has to be carefully balanced to the gains of the system, in each case, if we want to design a completely self-sustaining plant. Still, there are quite a number of research plants implementing several types of solar trackers to compare various solutions and their efficiency [7].

Present work consists of a neural control application on a non linear plant, based on the model reference technique. Firstly, a neural network is designed to identify the plant, i.e., the neural network 'learns' the plant behavior through some kind of training, and this knowledge is then used to generate an output signal which is compared with the actual plant output. This comparison is fed back and inputted to another neural network which will act as the controller. This neural controller is designed in such a way that makes the plant output to follow the output of a model reference, which dynamics be well known.

4. MRNN controller (Model Reference Neural Network controller)

As shown in **Figure (2),** the basic control scheme consists of a feed forward MRNN controller and a fixed gain feedback controller. The MRNN is first used as an identifier to emulate the inverse dynamics of the dc servo system, and this network is called Model Reference Neural network Identification (MRNNI), it is trained off-line and on-line. When MRNNI is trained, it is used as a feed forward controller called Model Reference Neural Network Control (MRNNC). The system control voltage U is composed of the feed forward controller output voltage Un and the feedback controller U_P. If the MRNNI has learned the inverse model of the system, the MRNNC alone provides all the necessary voltage for the system to track the desired trajectory and output of the feedback controller will tend to zero [8,9,10].

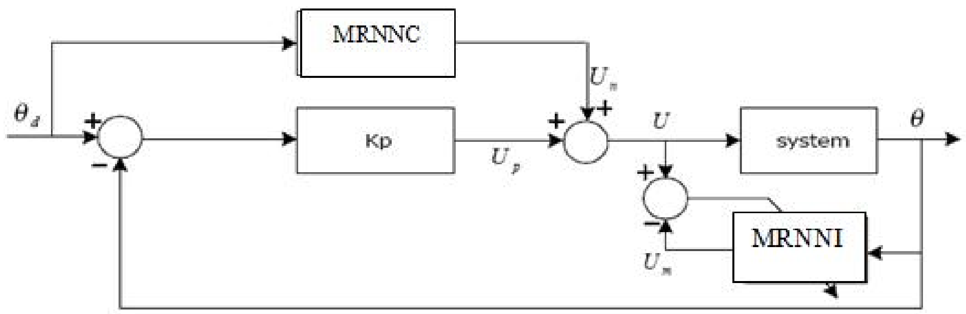

Fig.(2) MRNN control for the sun-tracking system.

5. System Design.

In this paper we used a three-layered neural networks . it consists of an input layer that contains two neuron and a bias, the output layer contains one neuron with liner activation function while the hidden layer contain 13 hidden neuron which can approximate any nonlinear function to any desired accuracy. MRNN networks superior to multiplayer feed forward static neural networks to deal with dynamic problems. The structure of three layers MRNN is shown in **Figure (3).** It Consists of an input layer, an output layer and one recursive hidden layer. Where I_i(k),w_j, w_{ij} , s_j and O(k) are the ith input to the MRNN, the connecting weight between jth recursive neuron and the output of networks, connecting weight between ith input to network and the jth hidden neuron, the output of jth hidden neuron and the output of the MRNN. The mathematical model of MRNN is shown below:

Where $x_j(k)$ is the output of jth recursive neuron, w_j is the recursive weight of jth hidden neuron, f (•) is sigmoid function. When MRNN is used as MRNNI, output of networks $O(k)= U_m (k)$. When MRNN is used as MRNNC, $O(k)= U_n (k)$.

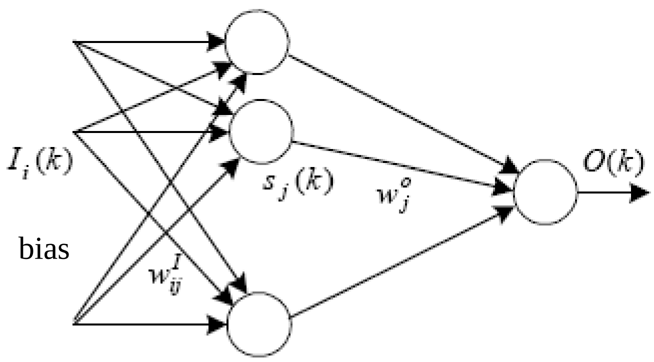

Fig. (3): MRNN three layer neural network.

$$s_j(k) = w_j^D x_j(k-1) + \sum_i w_{ij}^I I_i(k) \tag{1}$$

The cost function to train MRNNI is defined as:

$$J = \frac{1}{2}(U - U_m)^2 = \frac{1}{2} e_m^2 \tag{2}$$

The objective of the learning process is to adjust the network parameters (weights) so as to minimize the cost function *J* over the entire train set. The back propagation algorithm is given below [10].

$$\Delta w(k) = -h \frac{\partial J}{\partial w} \tag{3}$$

$$= h e_m(k) \frac{\partial U_m}{\partial w} \tag{4}$$

$$= h e_m \frac{\partial O(k)}{\partial w} \tag{5}$$

Where *w*(*k*) is any weight of MRNNI, *h* is the learning rate of this weight. Define the output gradients with respect to output, recurrent, and input weight, respectively as below

$$\frac{\partial O(k)}{\partial w_j^o} = x_j(k) \tag{6}$$

$$\frac{\partial O(k)}{\partial w_j^D} = w_j^o P_j(k) \tag{7}$$

$$\frac{\partial O(k)}{\partial w_{ij}^I} = w_j^o Qu(k) \tag{8}$$

$$P_g(k) = \frac{\partial x_j(k)}{\partial w_j^D} = f'(s_j) x_j(k-1) \tag{9}$$

$$Q_{ij}(k) = \frac{\partial x_j(k)}{\partial w_{ij}^I} = f'(s_j) I_i(k) \tag{10}$$

From above equations, learning algorithm of weight w_{ij} , D_j *w* and O_{jw} can be got. The learning rate can be chosen properly [11,12].

6. Identification and Control

For the dc system position tracking, the MRNNI is used to identify the unknown system dynamics (DC motor, amplifier, and the mechanical friction) that mapping the control voltage *U* to the motor position. Because the MRNNI is used to identify the inverse model of the DC servo system, the inputs to feed forward controller MRNNC is a desired position trajectory and the output of MRNNC is control voltage for system to tack the desired trajectory. The relation between control voltage and the motor position can be written as a difference equation as shown below [13,14].

$$U(k) = d_1 q(k-3) + d_2 q(k-2) + d_3 q(k-1) \qquad (11)$$

If the aim is to track the desired speed, similarly can get the difference relationship between control voltage and the speed of dc motor as below

$$U(k) = e_1 w(k) + e_2 w(k-1) + e_3 w(k-2) \qquad (12)$$

Where d_1 , d_2 , d_3 and e_1 , e_2 , e_3 are system parameters . Equations (11) and (12) can be written in this form

$$U(k) = h(q(k-1), q(k-2), q(k-3)) \qquad (13)$$
$$U(k) = g(w(k), w(k-1), w(k-2)) \qquad (14)$$

The MRNNI is trained to emulate the unknown function $h(\bullet)$ or $g(\bullet)$. For position tracking, the inputs to the MRNNI are θ (k-1), θ (k-2) and θ (k-3) for speed tracking, the inputs to the MRNNI are $w(k)$,$w(k-1)$ and $w(k-2)$. When the MRNNI is trained, it is used as a feed forward controller MRNNC. For position tracking, the inputs to MRNNC are desired trajectory $\theta_d(k-1)$, $\theta_d(k-2)$ and $\theta_d(k-3)$. For speed tracking, the inputs to MRNNC are desired speed $\omega_d(k)$, $\omega_d(k-1)$ and $\omega_d(k-2)$. Control voltage U, is the sum of the MRNNC, U_n , and the feedback controller, U_p .

$$U = U_n + U_p \qquad (15)$$

7. Experimental Results .

The ANN based identification architecture was implemented in MATLAB using neural network toolbox software.

firstly, it trains of the neural network with the input data. Secondly, it tests the consistency of the results, using random data, to assure it is different from the known data used before. Performance of the plant behavior is measured through the Mean Square Error (MSE) which is calculate by:

$$MSE = \frac{1}{Q}\sum_{i=1}^{Q} e^2(t) = \frac{1}{Q}\sum_{k=1}^{Q} (t(k) - a(k))^2 \qquad (16)$$

where Q is the number of input/output pairs used for training purposes.

$$\{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_Q, t_Q\} \tag{17}$$

t(k) is the *k-th* plant output value for a given input value *p(k)*, and *a(k)* is the *k-th* output expected value. After the *MSE* is calculate, it is used to adjust weights and biases of the neural network associated with the controller. A MSE performance value of $6.2715e^{-008}$ was attained for training algorithm at the maximum number of epochs (200) as shown in **Figure (4)**

For training the model reference control system it use a random reference input. The neural network response after successful completion of the training is shown in **Figure (5).** It is clear from the plot that the actual neural network output tracks the reference model output, which is the same as the desired position track plot.

Figures (6), (7) and **(8)** show the results reported for the plant behavior after be submitted to the controller action, during controller training phase.

Testing and validation data and respective output of the plant are shown in these figures. Note that, although the general behavior of the reference model is followed by the plant operating under control of the neural controller, some 'chattering' appears on the ridges of the response signal. It will also appear on the 'real' plant response.

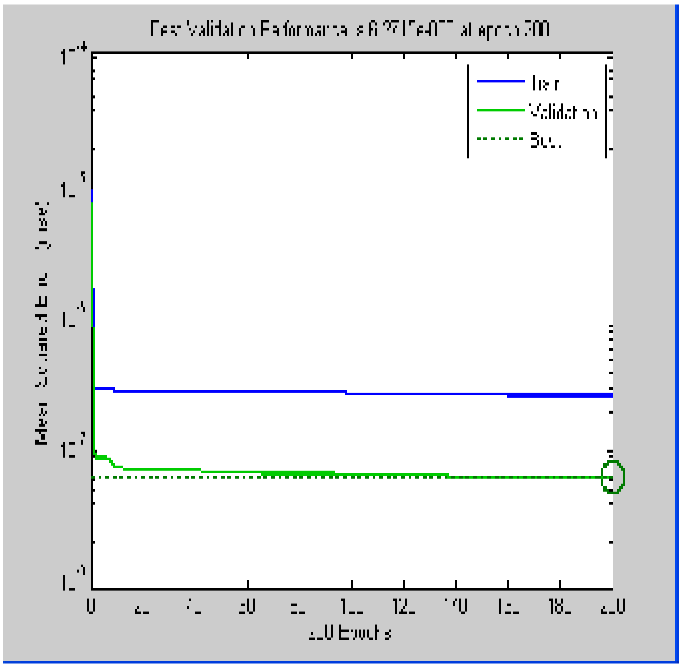

Fig. (4) performance for neural network control

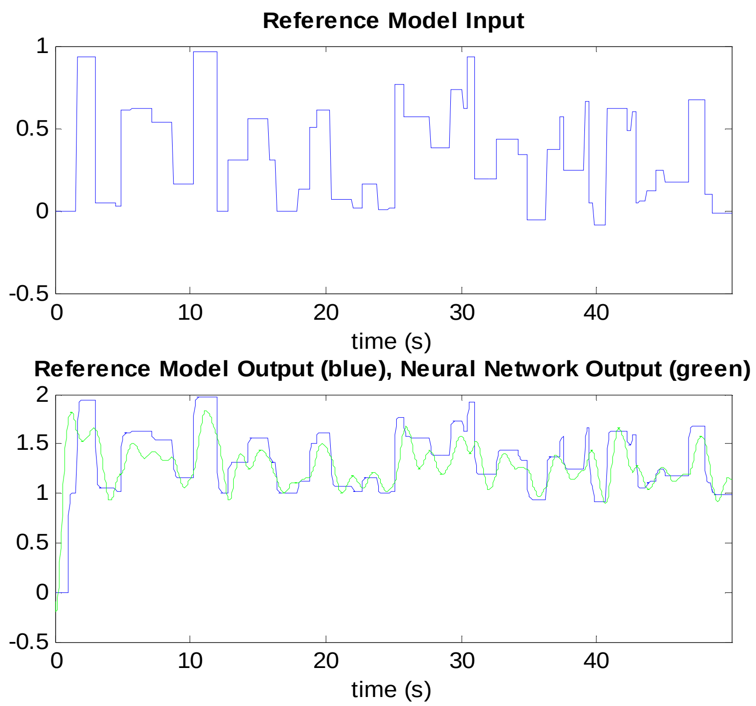

Fig. (5): Plant response for NN model Reference control.

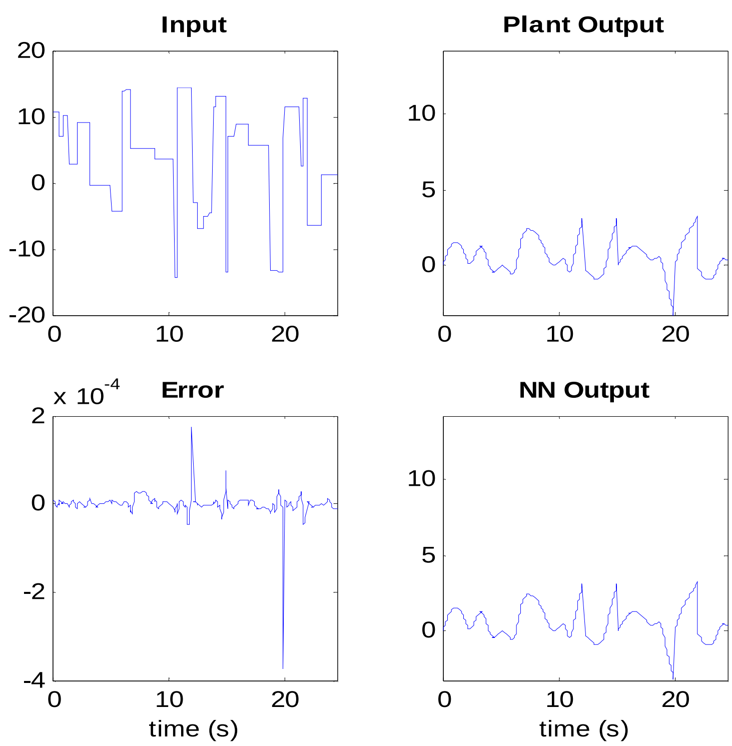

Fig. (6): Training data for NN model reference control.

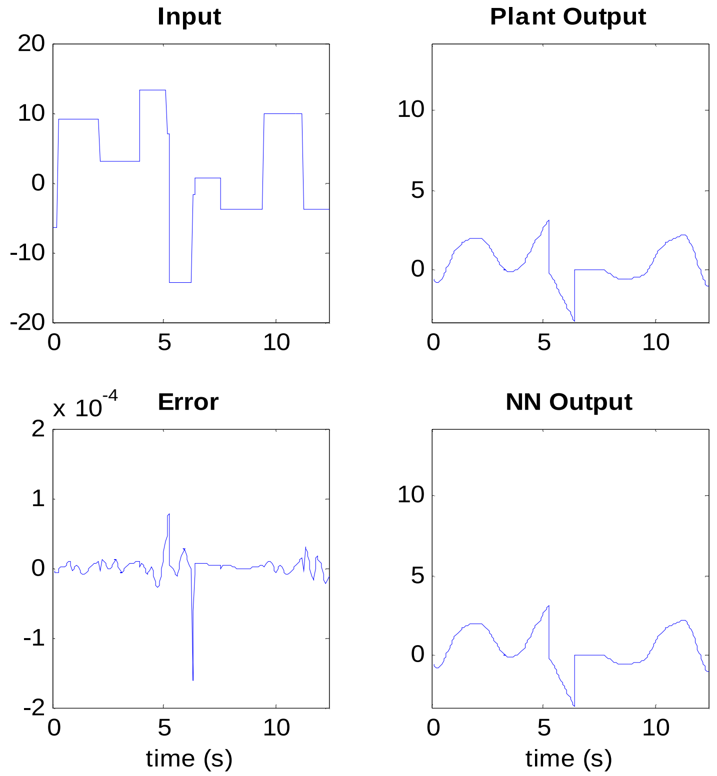

Fig. (7) : Testing data for NN model reference control.

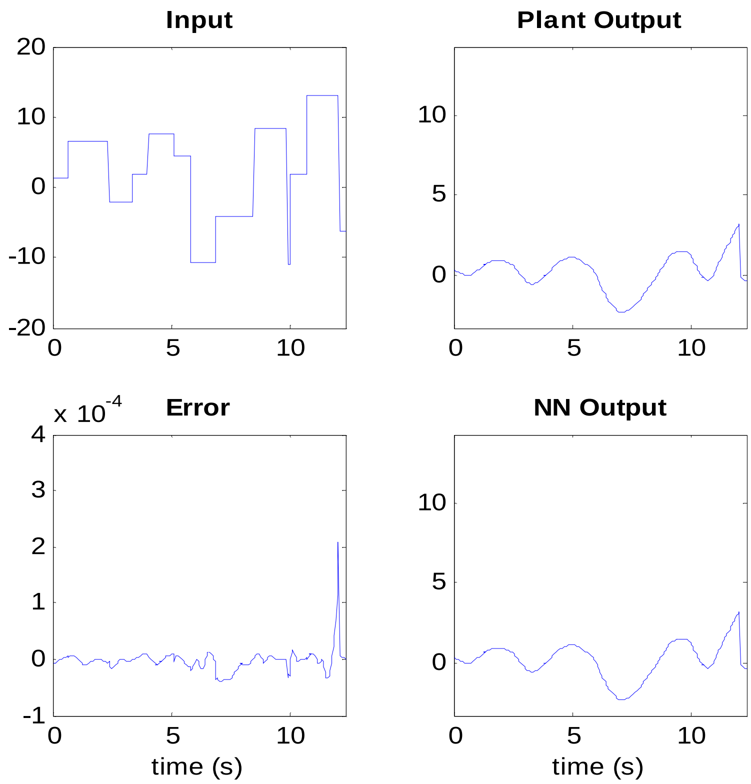

Fig. (8) : Validation data for NN model reference control.

8. Conclusions

The paper presents a real-time control of a low speed sun tracking system. It is shown that, MRCNN is efficient for system identification and control. The system through this proposed method can track any selected trajectories with high performance under strong mechanical friction and other nonlinear factors.

This control method can be applied to complex and nonlinear system and consolidate the idea that it may have better performances over other control scheme.

The proposed method reduces the disadvantages which appear in the traditional systems.

References

1. **Svein Erik " Fundamentals of Grid Connected Photovoltaic Power Electronic Converter Design" University of Science and Technology, 2007.**
2. **Aldo V.Darosa, "Fundamental of Renewable Energy Processes", Elsevier INC, 2005.**
3. **Robert Weissbach, "A Microcontroller-based Solar Panel Tracking system", Pennsylvania Stat University, 2007.**
4. **Understanding Astronomy of The Sun and the Seasons"http://physics.weber .edu/schroeder/ur/Sun and Seasone.html.2011**
5. **Terry R. Galloway "Solar House : A Guide for the Solar Designer", Elsevier INC, 2004.**
6. **Stan Gibilsco, "Alternative Energy Demystified", McGraw-Hill companies, 2007.**
7. **Douglas C. MacCourt," Renewable Energy Development in Indian Country". Alliance for Sustainable Energy, LLC, 2010**
8. **Ahmed. M. Kassem," Modeling, Analysis and Neural MPPT Control Design of a PV Generator Powered DC Motor-Pump System", Wseas Transactions on Systems, Issue 12,Volume 10, December 2011**
9. **Fredric, M. "Principlples of Neuro Computing for Science and Engineering", Mc. Graw-Hill, 2001.**
10. **Juan R. Rabunal . Julian Dorado, "Artificial Neural Network in Real-life Application", Idea Group Inc, 2006**
11. **Roland S. Burns ,"Advanced Control Engineering", Butterworth-Heinemann,2001.**

12. Imre Benyo, "Cascade Generalized Predictive Control Applications , in Power Plant Control ," Oulu University Press. 2006

13. Vladimir Zakian “Control System Design”, Springer-Verlag London Limited, 2005.

14. Ioannis Douratsos and J. Barry Gomm," Neural Network Based Model Reference Adaptive Control for Processes with Time Delay "International Journal of Information and Systems Sciences, Volume 3, Number 1, Pages 161{179, 2007