

January 2012

Neural Network System Identification and Controlling of Multivariable System

H. M. Reshma Begum

Department of Control And Instrumentation Engineering, Kalasalingam University, Tamilnadu, India,
reshmabegum24@gmail.com

P Revathi

Department of Control And Instrumentation Engineering, Kalasalingam University, Tamilnadu, India,
msgtorevathi@gmail.com

Babiyola D.

Department of Control And Instrumentation Engineering, Kalasalingam University, Tamilnadu, India,
babiyola.d@gmail.com

Follow this and additional works at: <https://www.interscience.in/ijess>



Part of the [Electrical and Electronics Commons](#)

Recommended Citation

Reshma Begum, H. M.; Revathi, P; and D., Babiyola (2012) "Neural Network System Identification and Controlling of Multivariable System," *International Journal of Electronics Signals and Systems*: Vol. 1 : Iss. 3 , Article 2.

DOI: 10.47893/IJESS.2012.1030

Available at: <https://www.interscience.in/ijess/vol1/iss3/2>

This Article is brought to you for free and open access by the Interscience Journals at Interscience Research Network. It has been accepted for inclusion in International Journal of Electronics Signals and Systems by an authorized editor of Interscience Research Network. For more information, please contact sritampatnaik@gmail.com.



Neural Network System Identification and Controlling of Multivariable System



H.M.Reshma Begum, Revathi.P, Babiyola. D

Department of Control And Instrumentation Engineering, Kalasalingam University, Tamilnadu, India
E-mail : reshmabegum24@gmail.com, msgstorevathi@gmail.com, babiyola.d@gmail.com

Abstract— Most of the industrial processes are multivariable in nature. Here Greenhouse system is considered which is the important application in agricultural process. Greenhouse is to improve the environmental conditions in which plants are grown. In this paper we have proposed identification of greenhouse system using input and output data sets to estimate the best model and validate the model. For MIMO systems, Neural Network System identification provides a better alternative to find their system transfer function. The results were analyzed and the model is obtained. From this obtained model, the system is controlled by conventional method. By these method we can identify the model and control the complicated systems like Greenhouse.

Keywords - GreenHouse, Neuralnetwork system identification, conventional controller.

I. INTRODUCTION

The main purpose of a greenhouse is to improve the environmental conditions in which plants are grown. In greenhouses provided with the appropriate equipment these conditions can be further improved by means of climate control. Modern greenhouse and computerized climate control modules have become inseparable nowadays. Computerized climate control is an intrinsic part of present day modern greenhouse. The functions of the computerized climate control can be summarized as follows:

- (a) It takes care of maintaining a protected environment despite fluctuations of external climate.
- (b) It acts as a program memory, which can be operated by the growers as a tool to control their crops.

The main advantages of using computerized climate control are as follows:

- (1)Energy conservation;
- (2)Better productivity of plants;
- (3)Reduced human intervention.

The main environmental factors affecting the greenhouse climate control are as follows:

- Temperature
- Relative Humidity of the inside air
- Vapor pressure Deficit
- Transpiration Sunlight

- CO₂ Generation
- Wind speed
- Lighting
- Actuators responsible for the climate variations are:
 - Heating System
 - Cooling System
 - Mechanical fan Fog cooling Lighting System.

2. MATERIALS AND METHODS

Fig. 1 depicts the block diagram of the controller embedded in the system model. As can be seen, the Controller is operated in five interrelated stages.

- 1- Set points: This block shows the set points of greenhouse climate that plant can grow up properly.
- 2- The input variables of greenhouse model: In this stage some variables represent influence on the greenhouse climate such as: inside Temperature, inside air humidity, outside temperature, outside air humidity, radiation.
- 3- The greenhouse model: This converts the output of actuators and some parameters like temperature, air humidity and outside radiation of greenhouse to the actual temperature and air humidity of greenhouse.

- 4- The actuator model: These blocks simulate the performances of actuators and receive the output of the controllers as the situation of actuators and then give the affections of them in green house
- 5- The control stage: In this stage the set points are compared with the measured parameters following the comparison, a dynamic decision is made regarding the situation of the actuators.

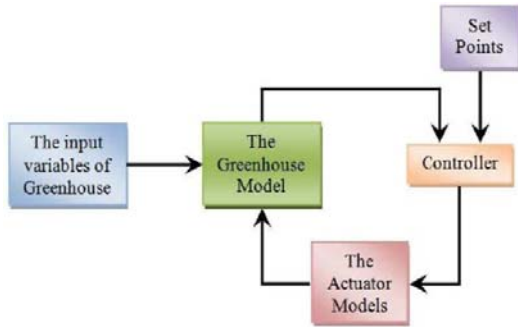


Fig 1. Block Diagram of controller in system

3. GREEN HOUSE CLIMATE MODEL

The greenhouse climate model describes the dynamic behavior of the stated variables by use of differential Equations of the air temperature, humidity, CO₂ concentration etc, this differential equation are results of combination of the various physical processes involving heat and mass transfer taking place in the greenhouse and from the greenhouse to the outside air Fig.2.a

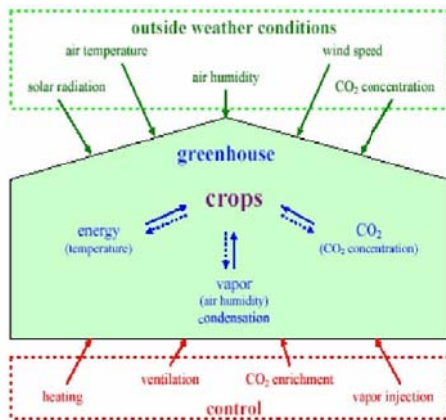


Fig 2a: Scheme of greenhouse climate model

The important variables are (references, perturbations and commands) the complexity of

phenomena (biologic, weather, evolution of the plants...), make that we have a system multivariable, nonlinear and non-stationary. Moreover, the perturbations, as the wind velocity and the global radiation, can sometimes have a power more raised than the command such the heating. For these reasons, we thus preferred to apply a multimodal based on fuzzy logic and taken into account all the variables of which we dispose Fig.2.b

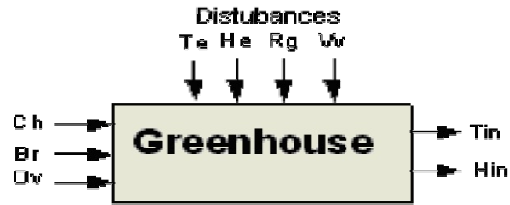


Fig.2.b input/output diagram of greenhouse system where, Ti and Hi are respectively temperature and relative humidity of the internal air, the perturbation variables are Te (external temperature), He (external humidity), Rg (solar radiation), Vr (wind velocity) and the input variable are Ch (heating), Br (moistening) and Ov (roofing).

4. NEURALNETWORK SYSTEMIDENTIFICATION

The science of artificial neural networks is based on the neuron. In order to understand the structure of artificial networks, the basic elements of the neuron should be understood. Neurons are the fundamental elements in the central nervous system.

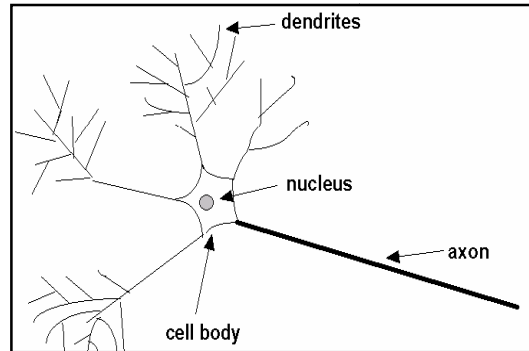


Fig.3.The diagram shows the basic elements of a neuron

A neuron is made up of 3 main parts -dendrites, cell body and axon. The dendrites receive signals coming from the neighboring neurons. The dendrites send their signals to the body of the cell. The cell body contains the nucleus of the neuron. If the sum of the received signals is greater than a threshold value, the neuron fires by sending an electrical pulse along the axon to the next

neuron. The following model is based on the components of the biological neuron (Fig. 3). The inputs X_0 - X_3 represent the dendrites. Each input is multiplied by weights W_0 - W_3 . The output of the neuron model, Y is a function, F of the summation of the input signals.

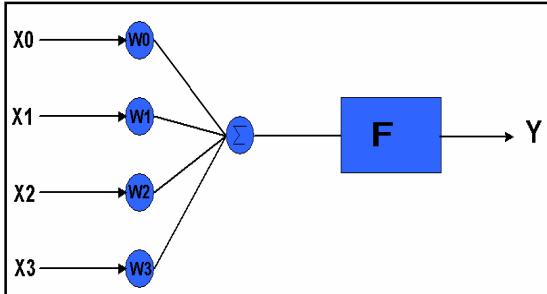


Fig.4.Diagram of neuron model

Advantages of ANN's

1. The main advantage of neural networks is that it is possible to train a neural network to perform a particular function by adjusting the values of connections (weights) between elements. For example, if we wanted to train a neuron model to approximate a specific function, the weights that multiply each input signal will be updated until the output from the neuron is similar to the function.
2. Neural networks are composed of elements operating in parallel. Parallel processing allows increased speed of calculation compared to slower sequential processing.
3. Artificial neural networks (ANN) have memory. The memory in neural networks corresponds to the weights in the neurons. Neural networks can be trained offline and then transferred into a process where adaptive learning takes place.

Types of Learning:

Neural networks have 3 main modes of operation supervised, Reinforced unsupervised learning. In supervised learning the output from the neural network is compared with a set of targets, the error signal is used to update the weights in the neural network. Reinforced learning is similar to supervised learning however there are no targets given, the algorithm is given a grade of the ANN performance. Unsupervised learning updates the weights based on the input data only.

Neural network structures:

There are 3 main types of ANN structures -single layer feed forward network, multi-layer feed forward network and recurrent networks. The most common type of single layer feed forward network is the perceptron.

Other types of single layer networks are based on the perceptron model.

Back propagation Algorithm:

Purelin is a neural transfer function. Transfer functions calculate a layer's output from its net input.

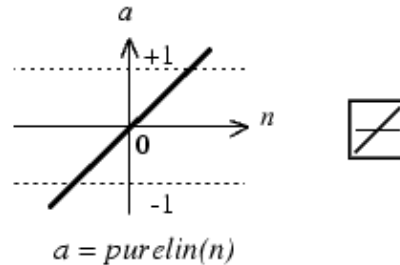


Fig.5.purelin transfer function

Tansig is a neural transfer function. Transfer functions calculate a layer's output from its net input.

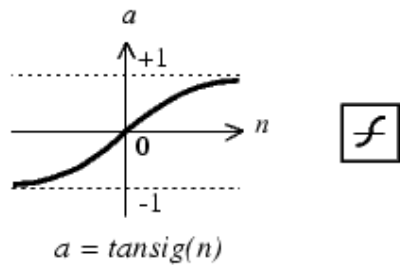


Fig.6. Tansig Transfer function

5. RESULTS

Using Neural Network Tool, the performance plot, the training state, the regression plot were obtained which are shown in Fig.7, 8, 9.

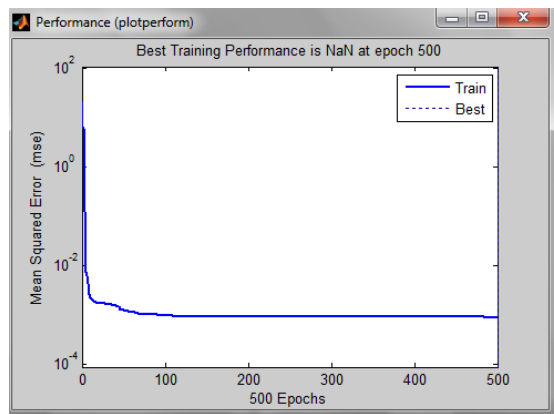


Fig.7.Performance Plot for neural network

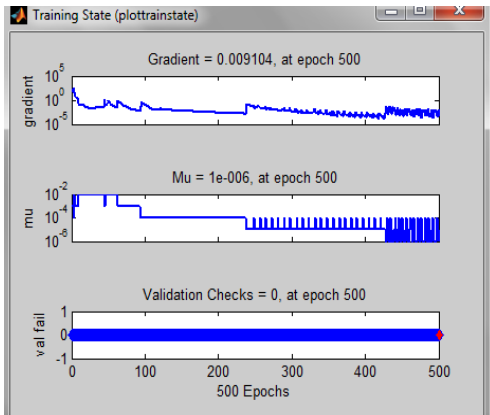


Fig.8.Training state for neural network

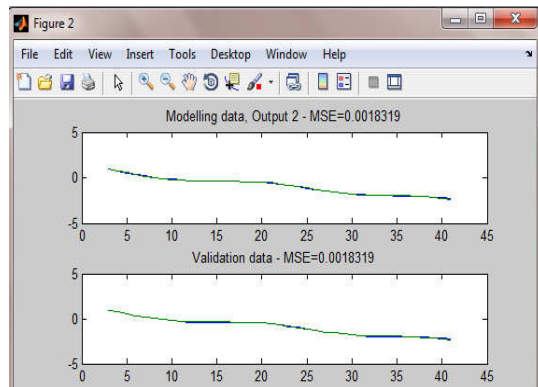


Fig.11.validated output

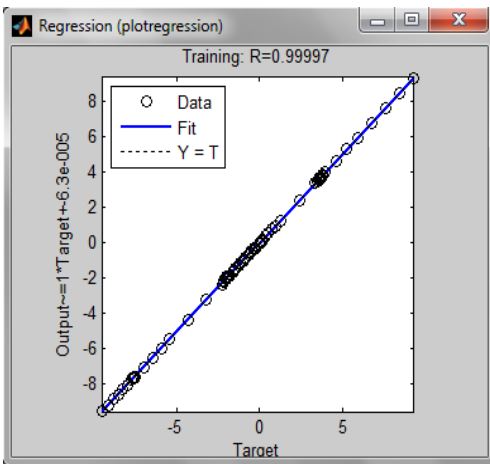


Fig.9.Regression Plot for neural network

The Neural Network Mean square error for the testing data is shown in Fig.10, and the Mean square error for the validation is shown in Fig.11. The validation obtained shows very less error i.e. 0.0018 for which best Transfer function is obtained.

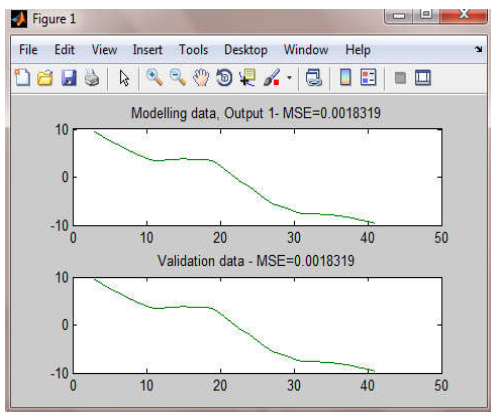


Fig.10.Testing data output

5. CONVENTIONAL CONTROLLER

Consider the generalized process shown in Fig. 12. It has an output y , a potential disturbance d , and an available manipulated variable m .

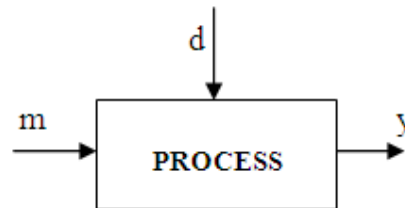


Fig.12.Process

The disturbance d (also known as load or process load) change in an unpredictable manner and our control objective is to keep the value of the output y at desired levels. A feedback control action takes the following steps:

1. Measures the value of the output (flow, pressure, liquid level, temperature, composition) using the appropriate measuring device. Let y_m be the value indicated by the measuring sensor.
2. Compares the indicated value y_m to the desired value y_{sp} (set point) of the output. Let the deviation (error) be $\varepsilon = y_{sp} - y_m$.
3. The value of the deviation ε is supplied to the main controller. The controller in turn changes the value of the manipulated variable m in such a way as to reduce the magnitude of the deviation ε . Usually, the controller does not affect the manipulated variable directly but through another device (usually control valve), known as the final control element.

Figure 12, shows the summaries pictorially the foregoing three steps.

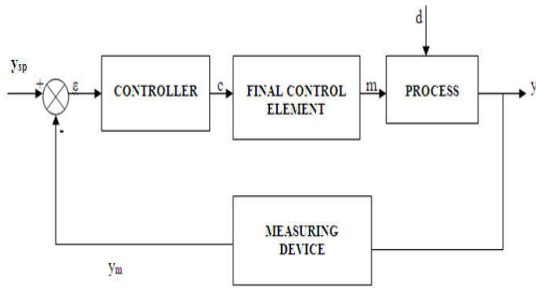


Fig.13.Feedback loop

The system in fig.12 is known as open loop, in contrast to the feedback-controlled system of fig.13, which is called closed loop. Also, when the value of d or m changes, the response of the first is called open-loop response, while that of the second is the closed-loop response. The basic hardware components of a feedback control loop are the following:

- Process model: The first item on the agenda is “process identification.” We either derive the transfer functions of the process based on scientific or engineering principles, or we simply do a step input experiment and fit the data to a model. Either way, we need to find the controlled variable and also the measured variable. We then need to decide which should be the manipulated variable. All remaining variables are delegated to become disturbances.
- Measuring instrument or sensors: For example, thermocouples (for temperature), bellows, or diaphragms (for pressure or liquid level), orifice plates (for flow) and so on.
- Transmission lines: It is used to carry the measurement signal from sensor to the controller and the control signal from the controller to the final control element. These lines can be either pneumatic or electrical.
- Controller: The amplified signal from the transmitter is sent to the controller, which can be a computer or a little black box. There is not much we can say about the controller function now, except that it is likely a PID controller, or a software application with a similar interface.
- Final control element: Usually, a control valve or a variable-speed metering pump. This is the device that receives the control signal from the controller and implements it by physically adjusting the value of the manipulated variable.

Each of the elements above should be viewed as a physical system with an input and an output.

Consequently, their behavior can be described by a differential equation or equivalently by a transfer function.

6. TYPES OF CONVENTIONAL CONTROLLERS:

There are three basic types of conventional controllers:

1. Proportional controller
2. Proportional-integral controller
3. Proportional-integral-derivative controller

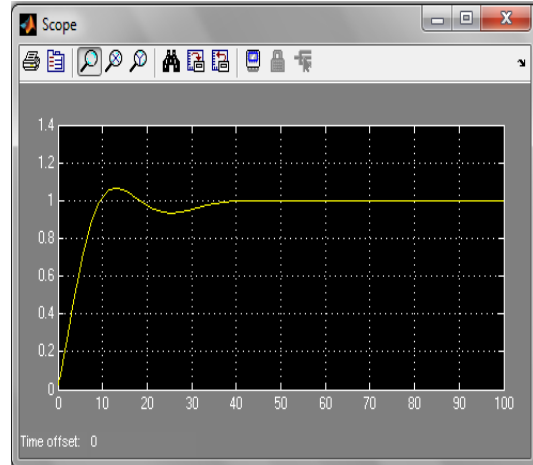


Fig.14. Conventional controller output for Multivariable system

7. CONCLUSION

Here input and output data for green house system was collected. For multiple inputs and multiple output system, neural network system identification is better to identify a model. From the model, it was able to control any complicate systems like Greenhouse. Further to improve the performance we can use intelligent controllers.

REFERENCES

[69] Hybrid fuzzy-logic and neural-network controller for MIMO systems Jeen Lin a, Ruey-Jing Lian b,* a Department of Mechanical Engineering, National Taipei University of Technology, No. 1, Sec. 3, Zhongxiao E. Rd., Taipei City 10608, Taiwan b Department of Industrial Management, Vanung University, No. 1, Wanneng Rd., Zhongli City, Taoyuan County 32061, Taiwan

[70] Greenhouse Model Identification based on Fuzzy Clustering Approach A. Erra Greenhouse Model Identification based on Fuzzy Clustering Approach A. Errahmani*, M. Benyahlef** and I. Boumhidi* * LESSI,

- [71] Department de physique, Faculté des Sciences Dhâr El Mehraz BP, 1796. [3] I. Laribi Maatoug, R.Mhiri, An Explicit Solution for the Optimal Control of Greenhouse Temperature relying on Embedded System, ICGST-ACSE, Volume 8, Issue I, ISSN: 1687-4811, 2004
- [72] J-F Balmat, F. Lafont, Multi-model architecture supervised by kohonen map, International Conference on Electronic Sciences, Information Technology and Telecommunication (SETIT), Mahdia, Tunisia, 6:17-21, 2003.
- [73] A. Fink, M. Fischer, O. Nelles, Supervision of Nonlinear Adaptive controllers Based on Fuzzy Models, Control Engineering, 8: 1093-1105, 2000.
- [74] O. Nelles, A. Fink, R. Isermann, Local Linear Model Trees (LOLIMOT) Toolbox for Nonlinear System Identification, 12th FAC Symposium on System Identification (SYSID), Santa Barbara, USA, 2000.
- [75] J.S.R. Jang, ANFIS: Adaptive-network based fuzzy inference system, IEEE Transactions on Systems, Man and Cybernetics, 23(3): 665-685, 1993.
- [76] L. Ljung, System identification-theory for the user Englewood cliffs, NJ: Prentice-Hall, 1987.
- [77] M. Sugeno, G.T. Kang Structure identification of fuzzy model, Fuzzy Sets and Systems, 28: 15-33, 1987.
- [78] Emara H, Elshafei AL. Robust robot control enhanced by a hierarchical adaptive.
- [79] Fuzzy algorithm. Eng Appl Artif Intell 2004;17(2):187-98.
- [80] Kim E. Output feedback tracking control of robot manipulators with model uncertainty via adaptive fuzzy logic. IEEE Trans Fuzzy Syst 2004; 12(3): 368-78.
- [81] Lin J, Lian RJ. DSP-based self-organising fuzzy controller for active suspension systems. Vehicle Syst Dyn 2008;46(12):1123-39.
- [82] Mollov S, Babuška R. Analysis of interactions and multivariable decoupling fuzzy control for a binary distillation column. Int J Fuzzy Syst 2004; 6(2):53-62.
- [83] El-Hawwary MI, Elshafei AL. Robust adaptive fuzzy control of a two-link robot arm. Int J Robot Autom 2006;21(4):266-72.
- [84] Chen B, Tong S, Liu X. Fuzzy approximate disturbance decoupling of MIMO nonlinear systems by back stepping approach. Fuzzy Sets Syst 2007;158(10): 1097-125