



Development of System Identification Fault in Gas Turbine Using Neural Network

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ABSTRACT: System identification is an important way of investigating and understanding the world around. Identification is a process of deriving a mathematical model of a predefined part of the world, using observations. There are several different approaches of system identification, and these approaches utilize different forms of knowledge about the system

In this research, a SIMULINK based Neural Tool has been developed for analysis and design of multivariable neural based control systems. This tool has been applied to the control of a high purity distillation column of a gas plant. The proposed control scheme offers an optimal response for both theoretical and practical challenges posed in process control task, in particular when both, the quality improvement of gas products and the operation efficiency in economical terms are considered.

The code consisted of various training functions, different number of neurons as well as a variety of transfer (activation) functions for hidden and output layers of the network. It was shown that the optimal model for a two-layer network with MLP structure, consisted of 25 neurons in its hidden layer and used *trainlm* as its training function, as well as *tansigand logsigas* its transfer functions for the hidden and output layers. It was also observed that *trainlm* has a superior performance in terms of minimum MSE, compared with each of the other training functions. The resulting model could predict performance of the system with high accuracy.

KEYWORDS: Gas turbine, system identification, modelling, simulation, optimization, neural network.

I. INTRODUCTION

System identification is the process of deriving a mathematical model of a system using observed data. Modeling is an essentially important way of exploring, studying and understanding the world around. A model is a formal description of a system, which is a separated part of the world. A model describes certain essential aspects of a system. In system modeling three main principles have to be considered. These are separation, selection and parsimony. The world around is a collection of objects, which are in interactions with each other: the operation of one object may have influence on the behavior of others. In modeling we have to separate one part of the world from all the rest [1].

GAS turbines have been used widely in industrial plants all over the world, and specifically in places such as offshore plants and oil fields which are far away from urban areas. GTs are the main source of power generation. Their key role in this developing industry has motivated researchers to explore new methods to predict dynamic behavior of these complex systems as accurately as possible. A variety of analytical and experimental techniques has been developed so far to approach an optimal model of gas turbines. Artificial neural network is one of the techniques that has been playing a significant role in system identification and modelling of industrial systems during recent decades. Although using artificial neural network for industrial applications is still a controversial issue, its capability to capture dynamics of the systems without any prior knowledge about them and their complicated dynamical equations, is an important advantage. There are considerable research activities in the field of ANN-based system identification and modelling of gas turbines. In spite of considerable research activities that have been carried out so far in system identification and modelling of gas turbines using artificial neural networks, system optimization is still a challenging and controversial issue [2]. Because of sophisticated and nonlinear dynamic behaviour of GTs, significant effort and attention still needs to be paid to the dynamics of these systems. These efforts aim to unfold unknowns behind undesirable events such as unpredictable shutdowns, over-heating and over-speed during gas turbine operation. Fortunately, using black-box system identification and modelling techniques such as ANN, can effectively assist researchers who work in this area.



International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 9, September 2016

The study in this area can be categorised into aero gas turbine models and stationary (mainly power plant) gas turbine models

II. REVIEW OF RELATED WORKS

It was considered that the full load situation for ANN-based system identification and modelling single-shaft gas turbines [3]. In some GT models, the nonlinear terms in the model were restricted to the second order. Besides, most of the ANN based models of gas turbines were built on the basis of a specific training function ('trainlm') and transfer functions ('tansig' or 'logsig' type in the hidden layer, and 'purelin' type in the output layer). According to the methodology used in this study, various back propagation training functions, different number of neurons and a variety of transfer functions were employed to train the network in order to explore an optimal ANN model using MLP structure. To increase the level of generalization for the model, the data sets were partitioned randomly for training, validation and test purposes.

In this study, firstly a brief description of gas turbine performance is presented. Then, a rebuilt SIMULINK model of a low power gas turbine based on a previous research by [4]. Is briefly presented. This paper describes ANN based system identification processes including generating the required data sets for training of the network using the SIMULINK model, writing the computer code and training the network. Finally, the results of the study are presented and concluding remarks are discussed.

The FLANN is basically a flat net and the need of the hidden layer is removed and hence, the Back Propagation learning algorithm used in used in this network becomes very simple. The functional expansion effectively increases the dimensionality of the input vector and hence the hyper-planes generated by the FLANN provide greater discrimination capability in the input pattern space. Pao have reported identification and control of nonlinear systems using FLANN [13]. Chen and Billings [5] have reported nonlinear system modeling and identification using ANN structures. They have studied this problem using an MLP structure and a radial basis function network and have obtained satisfactory results with networks.

Chen and Billings [6] have utilized a FLANN structure with polynomial expansion in terms of outer product of the elements of the input vector for this purpose, and the output node has linear characteristics. In this thesis, the performance of the FLANN structure with trigonometric polynomials for function expansion has been compared with that of an MLP structure with simulation by taking system model examples

III. METHODOLOGY

3.1 Development with Neural networks Algorithm

Neural networks are distributed information processing systems made up of a great number of highly interconnected identical or similar simple processing units, which are doing local processing, and are arranged in ordered topology. An important feature of these networks is their adaptive nature, which means that its knowledge is acquired from its environment through an adaptive process called learning. The construction of neural networks uses this iterative process instead of applying the conventional construction steps (e.g., programming) of a computing device. The roots of neural networks are in neurobiology; most of the neural network architectures mimic biological neural networks, however in engineering applications this neurobiological origin has only a limited importance and limited effects.

In the system identification stage, it is developed a neural network model of the gas plant under control using the modeling error. In the control design stage, the neural network controller is coupled with the neural network model, so as to adjust the network controller weights using the

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 9, September 2016

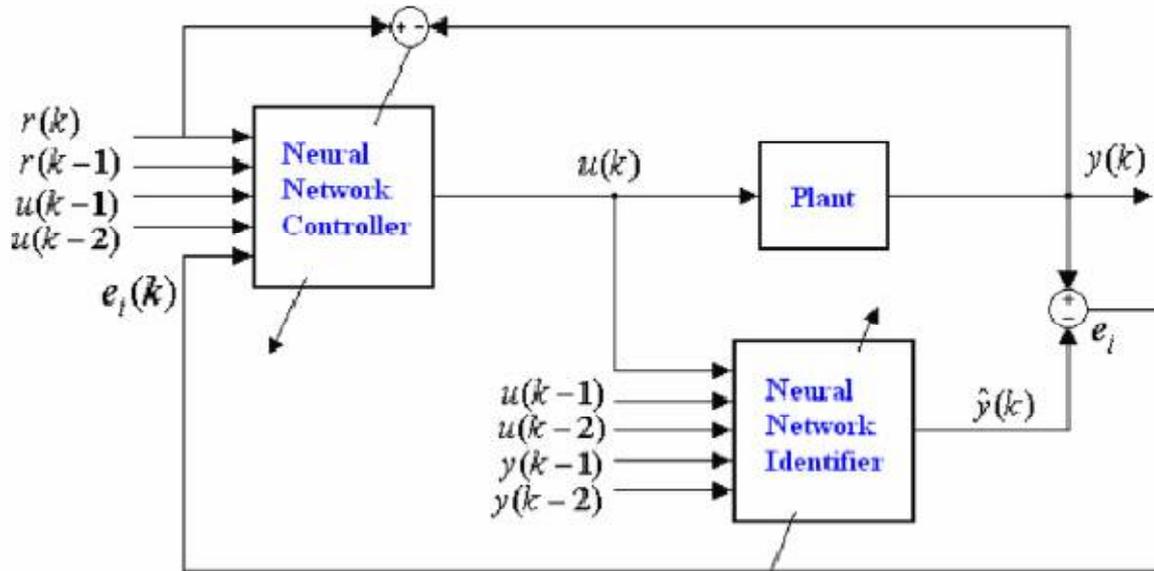


Fig. 3.1 Structure for neural network modeling and control

It is desired to demonstrate the neural network design tool applied both to the modelling and control of a high purity gas plant (Fig. 3.2).

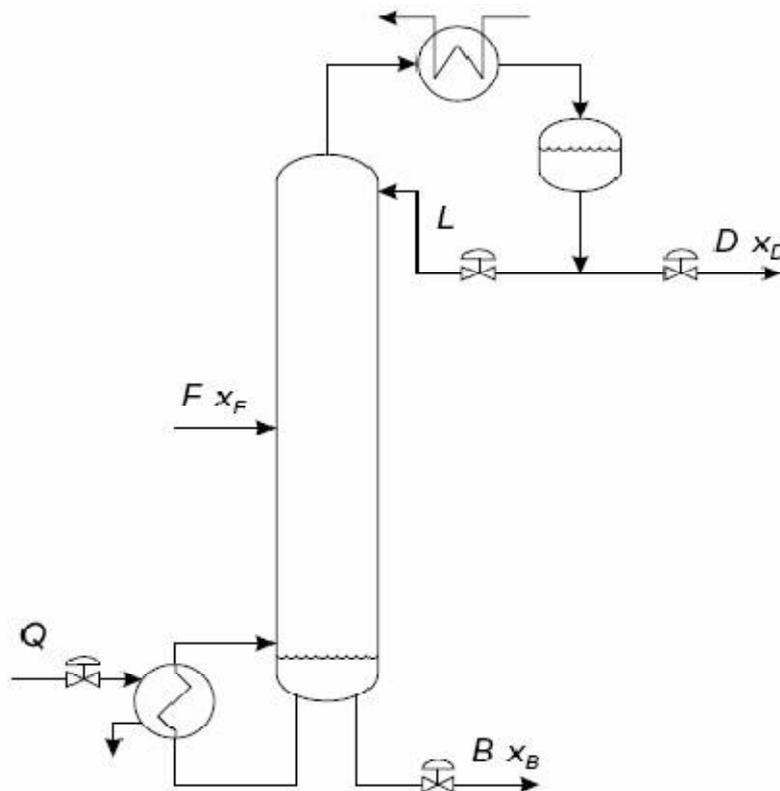


Fig. 3.2 Gas Pipe

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 9, September 2016

The binary mixture enters as a feed stream with flow rate F , composition XF and enthalpy q between two sections (a rectifying section and a stripping section). Mass transfer occurs between the vapour flowing up and the gas flowing down the column. The vapour exiting at the top of the column is condensed, and part of the resulting gas flow is returned at the column at the top (reflux L), while the remainder is taken as the distillate product D with composition XD . Part of the gas flow out of the bottom of the column is vaporized in a reboiler and sent back to the bottom of the column, while the remainder is taken as the bottom product B with composition XB . The column consists of a 9 bubble cap trays. The overhead vapour is totally condensed in a vapour cooled condenser which is open at atmospheric pressure. The reboiler is heated electrically, and the preheated feed stream enters the column at the feed tray as saturated gas. The process inputs that are available for control purposes are the heat input to the reboiler Q and the reflux flowrate L . The reflux rate L and heat flow Q were used as inputs to the neural network model being top and bottom compositions XD and XB considered as targets, while feed variables (F, XF, q) have been treated as process disturbances. The neural controller is obtained with top and bottom composition errors as inputs and reflux rate and heat flow as outputs

IV. RESULTS AND DISCUSSIONS

This results show a system identification of gas plant using feedforward Neural-network models with tapped delay lines

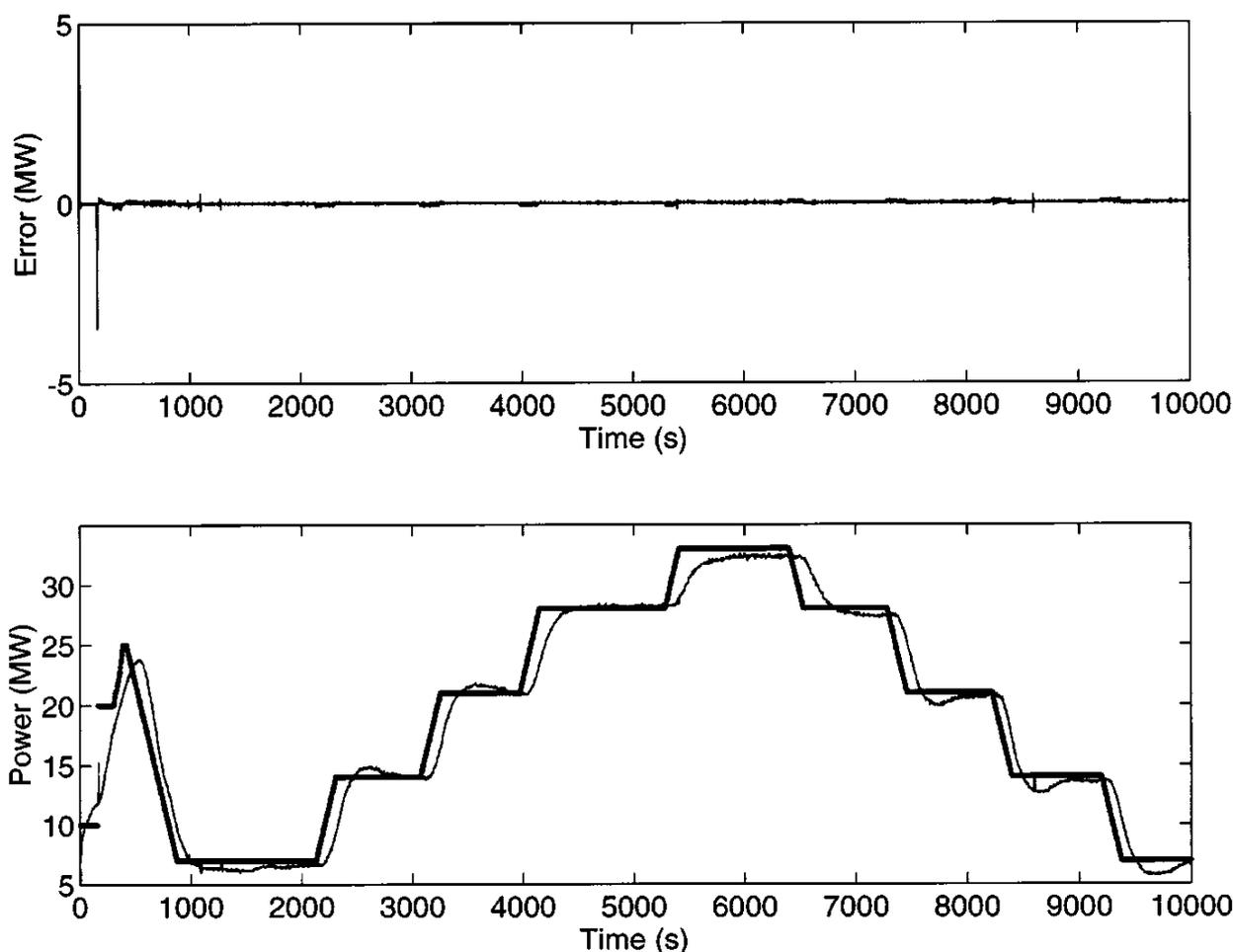


Fig. 4.1. Identification error (top) and reference (thick), output and model output (thin) (bottom) for the real gas power plant data set. Gradient parameter adaptation based on sensitivity analysis



International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

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Vol. 5, Issue 9, September 2016

The real data set consists of two time series corresponding to the electrical power desired from the plant, and the real power production. Fig 4.1 shows the identification error and the real and model output for an experiment with a five-node ADC model with gradient parameter adaptation based on sensitivity analysis and $\ell = 0.1$. At time $t = 100$ the adaptation mechanism has stopped and the model performs its prediction task quite well, which implies that the underlying dynamics of the plant have been acquired by the ADC model.

V. CONCLUSION AND RECOMMENDATION

Artificial neural network was used as a robust and reliable technique for system identification and modeling of complex systems with nonlinear dynamics such as gas turbines. It provides outstanding solutions to the problems that cannot be solved by conventional mathematical methods. However, ANN-based techniques were applied to the systems through a variety of approaches which include different structures and training methods. In this study, a new ANN-based algorithm was developed for offline system identification of a low-power gas turbine. A comprehensive computer program code was developed and run in MATLAB environment using the obtained data from a re-simulated model of a gas turbine in SIMULINK. Code generation was on the basis of combinations of various training functions, number of neurons and transfer functions for ANN with two-layer MLP structure. The resulting model shows that the ANN-based method can be applied reliably for system identification of gas turbines. It was precisely predicted that dependent parameters of the gas turbine based on the changes in the independent inputs of the system.

REFERENCES

1. Bergen, and D. Hill. A structure preserving model for power system stability analysis. IEEE Trans on Power App. Syst., vol. PAS-100, no. 1, pp. 25–35, 2010.
2. A.P.Vaidya and Rohit V. Patil (2012), " Comparison of Different Types of Voltage Stability Assessments During Congestion ", IEEE-International Conference On Advances In Engineering, Science And Management (ICAESM -2012) March 30, 31, 2012.
3. Ademoye, T., & Feliachi, A. (2011). Decentralized synergetic control of distribution systems. IEEE Power Systems and Exposition.
4. Ademoye, T., Feliachi, A. & Karimi, A. (2011). Coordination of synergetic excitation controller and SVC-damping controller using particular swarm optimization. IEEE Power System and Energy Society General Meeting.
5. Ademoye, T., & Feliachi, A. (2012). Reinforcement learning tuned decentralized synergetic control of power systems. Electric Power Systems Research, 86, 3440.
6. APPRAEZ (2012), " Etude Comparative De Méthodes De Simulation De La Stabilité Transitoire ", école de technologies supérieures, Université du Québec, Avril 2012.

BIOGRAPHY



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