MODELLING AND FUZZY CONTROL OF BIOMASS STEAM BOILER SYSTEM

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Abstract

Use of biomass in industrial boilers requires more efficient control systems. In order to keep constant and undisturbed technological steam production for large changes in the operating conditions more process knowledge must be incorporated into the system. Control of the biomass steam boiler system often needs an experience operator intervention. In the particular case the operator based on presented process data manually controls the supply of the biomass and change primary air temperature and flow in to the combustion chamber. Local control loops increase the degree of automation and assure safety technological steam production. In order to minimize operator intervention and to stabilize technological steam production a Fuzzy controller seems to be ideal solution.

The paper shows an implementation of the Fuzzy control system that improves and optimizes a technological steam production of the biomass steam boiler system. The analysis and identification of real process data give promising mathematical model that was used for the development of an appropriate control algorithm in simulations. Recurrent auto-associative neural network model improves state space model in wider range of measured data. After small adjustments a Fuzzy controller was successfully implemented on real Biomass Steam Boiler System.

Keywords: Fuzzy Control, Neural Network, Biomass Steam Boiler System.

Presenting Author's biography

Nenad Muškinja. Graduate in electrical eng. in 1988 from the Techical Faculty of the University of Maribor (UM), in 1992 received M.Sc. degree from the Technical Faculty, UM, in 1997 received D.Sc. degree from the UM, FERI, in 1998, 2008 assistant professor, associate professor. For the present Prof. Nenad Muškinja is employed at the University of Maribor, FERI, Institute of Automation in the Laboratory of process automation. He has participated as a researcher in over 35 scientific research and R&D projects. Bibliography of Nenad Muškinja consists of more than 200 units, 12 in scientific journals and books, more than 50 presented on conferences, and number of project reports, diploma works, etc.

1 Introduction

Use of biomass in industrial boilers requires more efficient control systems. In order to keep constant and undisturbed technological steam production for large changes in the operating conditions more process knowledge must be incorporated into the system. Control of the biomass steam boiler system often needs an experience operator intervention [1]. In the particular case the operator based on presented process data manually controls the supply of the biomass and change primary air temperature and flow in to the combustion chamber. Local control loops increase the degree of automation and assure safety technological steam production. In order to minimize operator intervention and to stabilize technological steam production a Fuzzy controller seems to be ideal solution [2].

The development and adaptation of an appropriate fuzzy control algorithm can't be done directly while production is running. For this purpose the mathematical model of technological steam production is needed. Based on measurement data and appropriate system identification techniques black box models may describe the system well in specific operating conditions.

2 Steam Boiler System

A steam boiler system basic data:

Steam:

- power ~ 15MW,
- production ~ 20t/h,
- pressure ~ 450 kPa and
- temperature ~ 435 °C.

Fuel:

- wood lignin,
- wood biomass,
- sawdust and
- polymer.

Fig. 1 shows SCADA snapshot as it appears in real technological steam production. Operator manually controls speed of fuel supply CV1 [Hz], desired temperature of primary air CV2 [°C] and primary air flow speed CV3 [Hz] while monitoring combustion chamber temperatures Tu1, Tu2, Td1, Td2 [°C] and technological steam production flow Qs [t/h]. The automatic control of the secondary air flow is needed to control the combustion chamber wall temperature. There is also automatic control of steam pressure and negative air pressure inside the chamber.

3 System Identification

The system identification is based on real process measured data. We made small step changes of all control values in the process and also closed loop measurements.

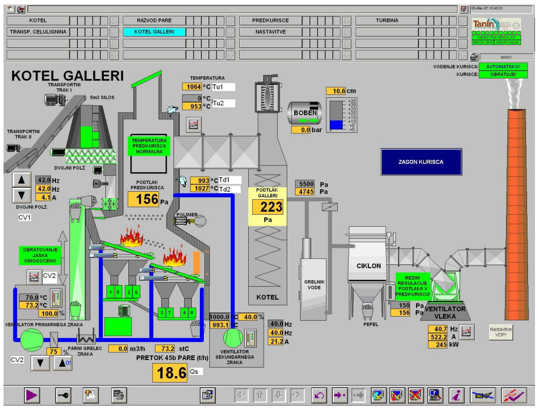

Fig. 1 SCADA snapshot of fuel feed system, combustion chamber and steam boiler system.

3.1 Real time measurements

All needed measurement data has been imported and normalized from SCADA Historian. Fig. 2 , Fig. 3 and Fig. 4 shows imported normalized combustion chamber temperature and normalized steam production changes during manual and automatic control of steam boiler system.

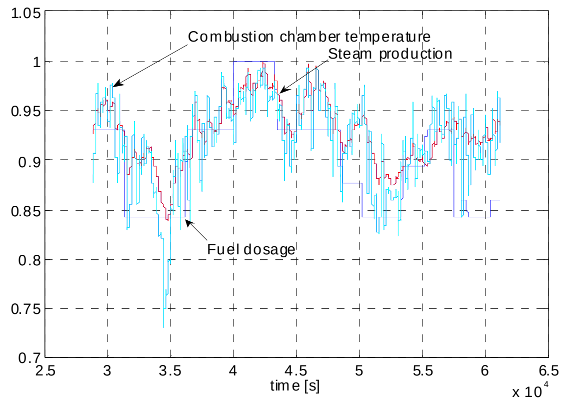

Fig. 2 Normalized combustion chamber temperature and steam output based on fuel dosage step changes.

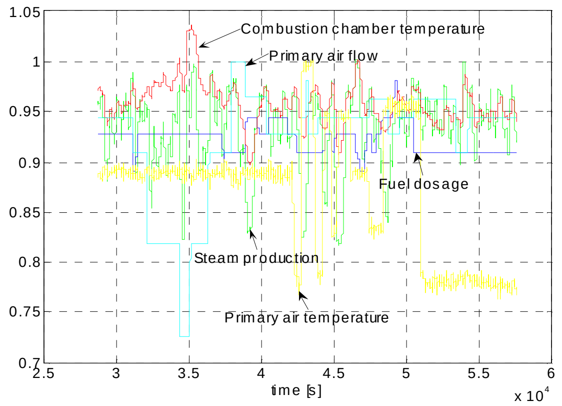

Fig. 3 Normalized combustion chamber temperature and steam production output based on step fuel dosage changes, step primary air flow changes and primary air temperature changes.

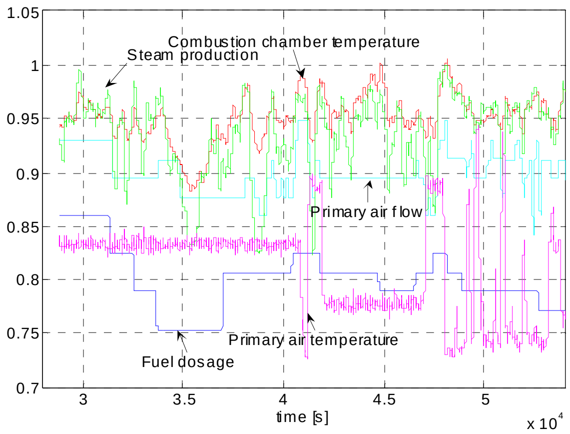

Fig. 4 Normalized combustion chamber temperature and normalized steam production in normal operation.

All measurement data obtained by Historian has been analyzed and passed through the identification procedure to obtain a model.

3.2 Identification of state space linear model

The linear mathematical model of a steam boiler system has four input and two output variables as depicted in Fig. 5.

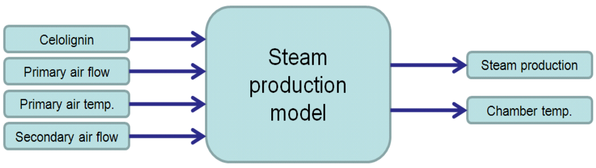

Fig. 5 Steam production model with corresponding inputs and outputs,

Input variables:

- Frequency of the fuel dosage motor Fd [Hz],
- Primary air temperature Tp [°C],
- Primary air flow Qp [m3/h] and
- Frequency of the motor for the secondary air flow supply Fs [Hz].

Output variables:

- Combustion chamber temperature Td2 [°C] and
- Steam production Qs [t/h].

The Matlab identification procedure pem.m as prediction error estimate was used for the state space model estimation. Best identification result was achieved with measured data shown in Fig. 4 where normal operation of steam production was considered.

Fig. 6 and Fig. 7 show step responses of an identified state space model simulation. Fig. 8 shows validation of identified state space model on measured data. The steam production model does not precisely match measured data but it has good dynamic behavior and precise static values according to a measured ones.

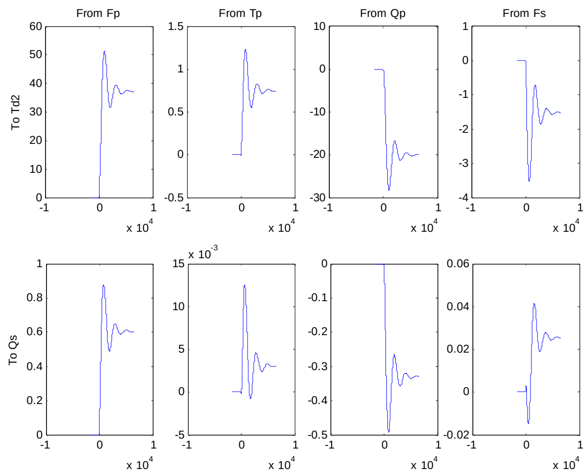

Fig. 6 Step responses of identified state space model.

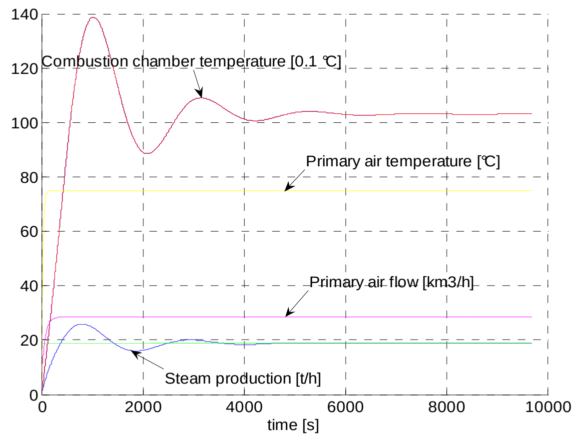

Fig. 7 Simulation of combustion chamber temperature and steam production based on identified model of steam boiler system.

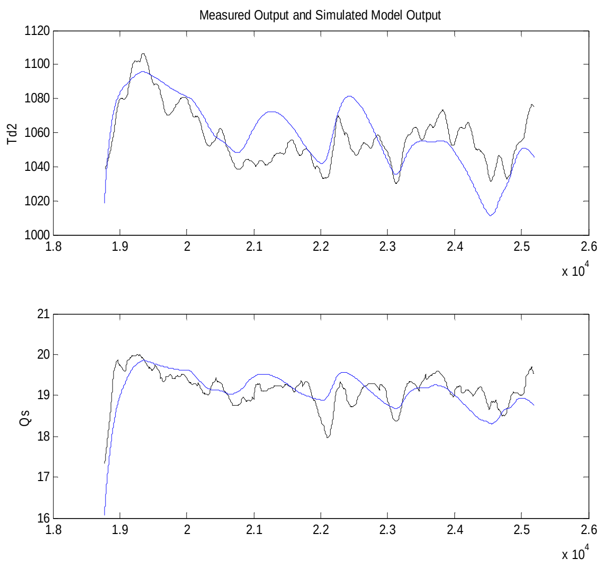

Fig. 8 Comparison of combustion chamber temperature and steam production based on identified model and measured data.

3.3 Recurrent auto-associative neural network model

In order to obtain a better dynamical model of the process neural networks were addressed. A special type of neural network can be used called an auto-associative neural network (AANN) which is a feed-forward neural network that performs identity mappings; network inputs are reproduced at the output layer. To obtain model of the process according to measured values a classic AANN can be used. However we wish to observe dynamic behavior of the process, therefore a use of recurrent AANN was suggested latter [3].

The AANN normally consists of an input layer, three hidden layers, and an output layer. The input/output layers can have an identical number of neurons, but not necessarily. The first/third hidden layer is called mapping/demapping layer, respectively, and usually contains more neurons than input/output layer. The middle hidden layer is called the bottleneck layer with strictly less neurons than input/output layer. The transfer functions for the mappings/de-mappings are non-linear whereas the transfer function for the bottleneck and output layers can be linear or non-linear. The number of hidden neurons in all three hidden layers of the network is very important as the compression role of the network reduces network's accuracy and increases output error.

The key feature of the AANN is its data compression/regeneration by the bottleneck layer. The input, mapping, and bottleneck layers compress the input information to a lower dimension, after which the de-mapping and output layers recover the main underlying features of the original information. The bottleneck layer can be used to extract generalized characteristics of the process, and can be treated as a method for extraction of nonlinear principal components. The main task is to select the proper number of neurons in the bottleneck layer, which represent the system behavior, and to observe model correlations between variables by using extracted nonlinear principal components. The AANN also has to be properly trained to produce desired outputs. In network training both input and target vectors are identical, where the objective function, mean squared error between the network outputs and inputs, is minimized.

Several training procedures and neural network parameters settings were tested to obtain desired results. The sampling time used was 5s, due to reduced computational complexity of training and a large number of data samples from process measurements (fairly slow process changes). Network training was conducted upon different data pre-processing methods. First case was the usual pre-processing where output data is normalized to fit output range interval between -1 and 1. In the second case pre-processing was realized according to mean values and standard deviation, where values were defined upon input data specifics. After successful training, the AANN was defined by 15 neurons in mapping and de-mapping layer, bottleneck layer had 5 neurons, and input/output layers were measured values of the process. 70% of measured data samples were used for modeling and 30% were used for validation.

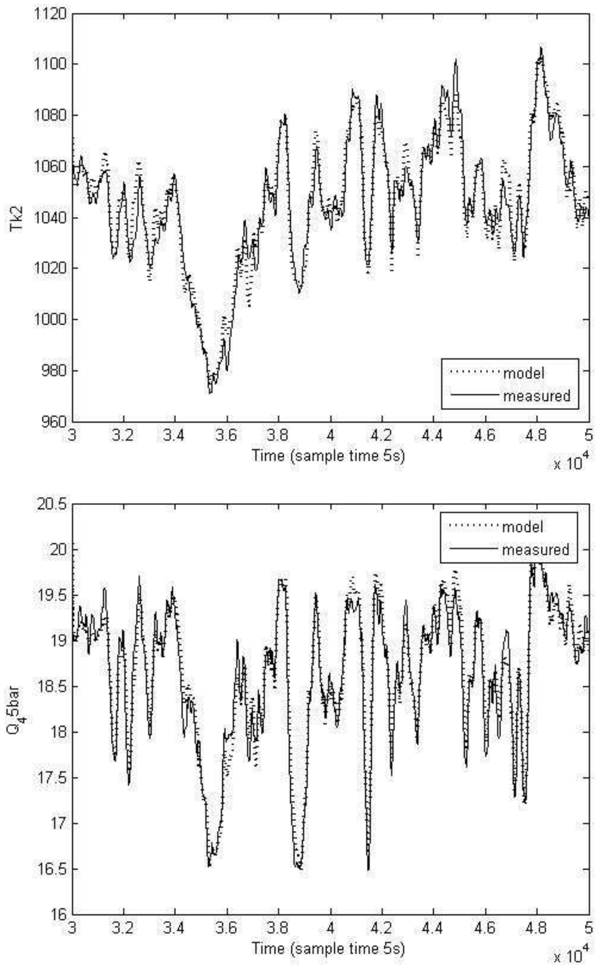

Fig. 9 Comparison of combustion chamber temperature and steam production based on identified model and measured data.

Steady state model (Fig. 9) obtained by AANN structure is very accurate for a wide range of data, however it doesn't describe dynamics of the process adequately as variables has changeable delays, sampling times, dynamics, etc. To incorporate dynamics into developed model of the process a recurrent AANN structure was suggested where outputs are taken back to the input layer. This has for the consequence that the neural network is not fully auto-associative because additional past inputs of the process are required and that vector of inputs is not necessary identical to the vector of outputs. However, the neural network is auto-associative with respect to the output variables. The number of neurons in the input and output layers is determined by the structure of the process model.

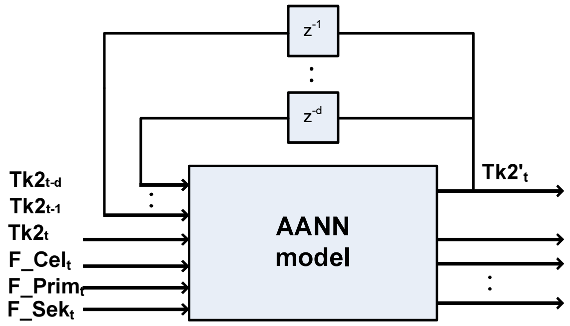

Fig. 10 A recurrent AANN with delayed input into the model to form dynamic behavior of the temperature Tk2. Similar goes for steam production output Q_45bar.

The architecture of the dynamic AANN is modified as presented in Fig. 10. The output of the network, delayed a number of times, is fed back to the input layer so that both process temporal and spatial patterns are incorporated in the structure of the recurrent AANN. For this case, the neural network is auto-associative only for the current output variables, and obviously only the current measurements are processed at each sampling time. The recurrent AANN model structure was reduced to 10 neurons in mapping/demapping layer and in bottleneck layer were 5 neurons and due to the complexity and number of neurons the training procedure had to be repeated several times to achieve best results. For training algorithm a Levenberg-Marquardt back-propagation was used. Neurons of input and hidden layers were nonlinear “tansig” activation functions, while output layer had linear output.

Properly trained AANN produced a fairly good dynamic model of the process. Comparison between final recurrent AANN model output and measurements is shown in Fig. 11. Dynamic properties are shown in Fig 12 where several input step changes were simulated and tested.

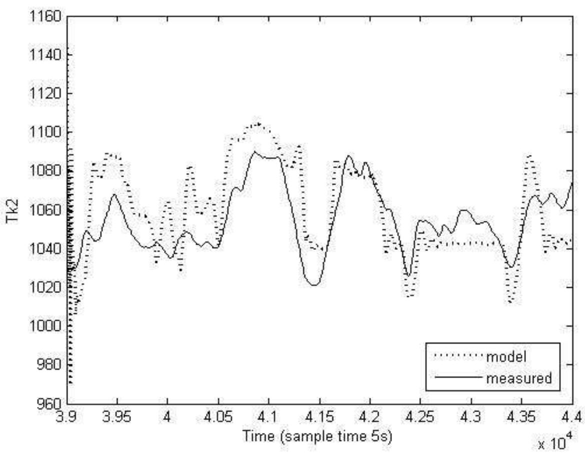

Fig. 11 Comparison between recurrent AANN model output and measured combustion chamber temperature.

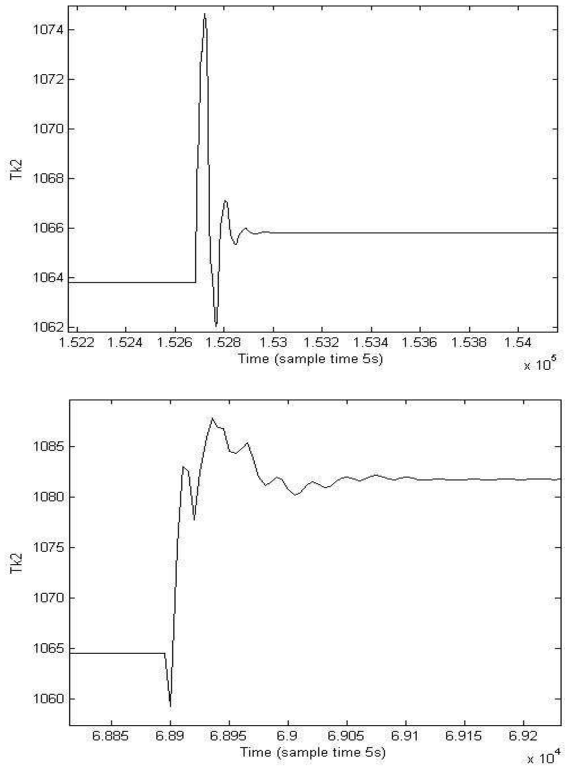

Fig. 12 The top figure presents dynamic response of the model combustion chamber temperature upon the input step change where temperature of the primary air was raised for 10 °C. The lower figure presents dynamic response of the same variable upon step change of fuel injection (motor speed) into the furnace for 1 Hz.

4 Fuzzy controller design

Based on observations during normal operation and operator assistance the Fuzzy controller has been designed for both combustion chamber temperature control and steam production control. The Fuzzy control system has four input and three output variables.

Input variables:

- Combustion chamber temperature error ETd2 [°C],
- Combustion chamber temperature trend dTd2 [°C/s],
- Steam production deviation eQs[t/h] and
- Steam production deviation dQs[t/hs].

Output variables:

- Deviation of a fuel dosage motor frequency
- dFd [Hz/s],
- Deviation of the primary air flow motor frequency dFp [Hz/s] and
- Deviation of the primary air temperature dTp [°C/s].

All input and output variables have three membership functions equally distributed. A Fuzzy inference engine consists of 21 rules that completely describe all operator assistance needed for successful control of steam production and temperature control (Fig. 13).

1. If (eT2 is N) and (dT2 is N) then (dTp is N)(dFp is ZE) (1)
2. If (eT2 is N) and (dT2 is ZE) then (dTp is N)(dFp is P) (1)
3. If (eT2 is N) and (dT2 is P) then (dTp is N)(dFp is P) (1)
4. If (eT2 is ZE) and (dT2 is N) then (dTp is P)(dFp is N) (1)
5. If (eT2 is ZE) and (dT2 is ZE) then (dTp is ZE)(dFp is ZE) (1)
6. If (eT2 is ZE) and (dT2 is P) then (dTp is N)(dFp is P) (1)
7. If (eT2 is P) and (dT2 is N) then (dTp is P)(dFp is N) (1)
8. If (eT2 is P) and (dT2 is ZE) then (dTp is P)(dFp is N) (1)
9. If (eT2 is P) and (dT2 is P) then (dTp is P)(dFp is ZE) (1)
10. If (eQ45 is N) and (dQ45 is N) then (dFc is ZE) (1)
11. If (eQ45 is N) and (dQ45 is ZE) then (dFc is N) (1)
12. If (eQ45 is N) and (dQ45 is P) then (dFc is N) (1)
13. If (eQ45 is ZE) and (dQ45 is N) then (dFc is ZE) (1)
14. If (eQ45 is ZE) and (dQ45 is ZE) then (dFc is ZE) (1)
15. If (eQ45 is ZE) and (dQ45 is P) then (dFc is ZE) (1)
16. If (eQ45 is P) and (dQ45 is N) then (dFc is P) (1)
17. If (eQ45 is P) and (dQ45 is ZE) then (dFc is P) (1)
18. If (eQ45 is P) and (dQ45 is P) then (dFc is ZE) (1)
19. If (eQ45 is P) and (eT2 is ZE) and (dT2 is ZE) then (dTp is P) (1)
20. If (eQ45 is N) and (eT2 is ZE) and (dT2 is ZE) then (dTp is N) (1)
21. If (Podtlak is Nizek) then (dFp is N) (1)

Fig. 13 Fuzzy rules of steam production Fuzzy controller.

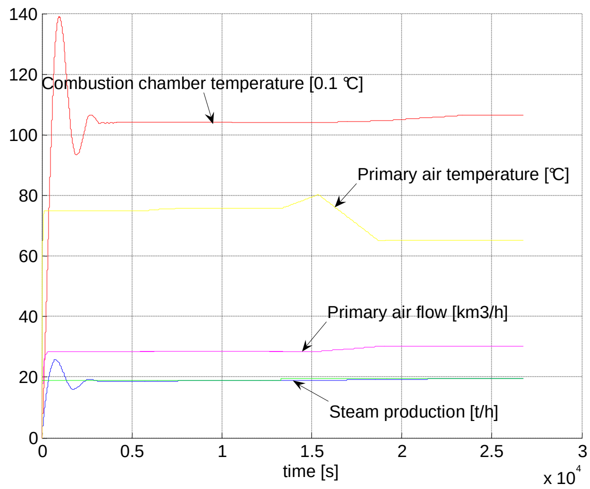

Fig. 14 Simulation of combustion chamber temperature and steam production using Fuzzy steam production controller.

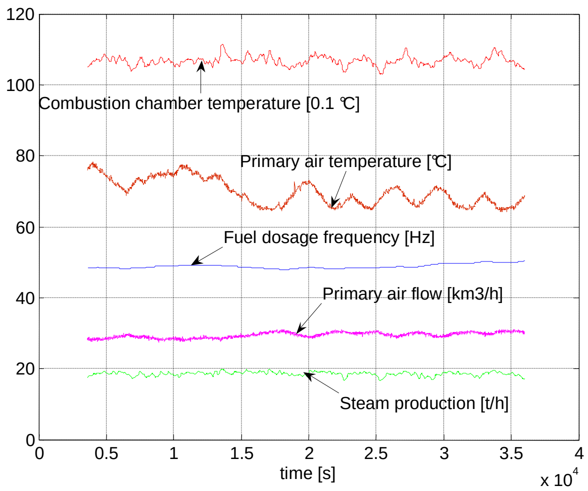

Fig. 15 Real time results while using implemented Fuzzy steam production controller.

Fig. 14 shows simulation results while using designed Fuzzy steam production controller. Simulation results show that designed Fuzzy steam controller may be implemented on real steam production system. For this purpose some fine adjustments of Fuzzy controller input and output gains have been done. Fig. 15 shows real time results while using implemented Fuzzy steam production controller. Steam production has been automated and operator assistance has been minimized.

5 Conclusions

An implementation of Fuzzy control systems is very convenient for the industry where expert knowledge of the operator is needed. In order to avoid unnecessary interference during the production the design of the appropriate controller must be made in simulations. Therefore the identification of the mathematical model of an industrial process has to be done. This is sometime very difficult because of varying and non-linear behavior of the observed industrial process. The identification method used for the steam production system modeling gives good approximation of real steam production system only for specific operating conditions. Recurrent auto-associative neural network model improves state space model in wider range of measured data. It has been shown that the design of a Fuzzy steam production controller do not need precise mathematical model of non-linear process. It is only important that dynamic changes shows right direction and static values mach measured ones. Input and output variables of the Fuzzy controller must be carefully selected and Fuzzy rules must imitate expert knowledge of the operator in order to achieve a desired control performance.

6 References

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