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Black-Box Modeling of A Process Simulator Using Wireless Temperature Measurements

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Abstract—The development of two black-box (ARX and ARMAX) models for a process simulator has been carried out in this work. Wireless input/output data obtained from The Cussons P3005 type process control simulator which temperature measurements can be made at four different points which are first tank (T1), heater output (T2), second tank input (T3) and second tank output (T4) temperatures. Wireless temperature experiments were achieved by using MATLAB/Simulink program and wireless data transfer during the experiments were carried out with radio waves at a frequency of 2.4 GHz. The wireless data used for the models development were generated using a unit step change between % 10-70 values on the heater capacity of the process simulator. The model orders used for the estimation of the model polynomial coefficients were determined by optimizing the Rissanen's Minimum Description Length with the aid MATLAB. The comparison between the experimental, ARX and ARMAX simulated temperatures of three different points on the process simulator have revealed that the ARMAX models can be used to represent the process succesfully. Furthermore, ARMAX models were discovered to be better in performance because of faster than ARX models in getting to the steady-state and without any oscillations when a step input was applied to both models.

Keywords—Black-Box modeling, ARX, ARMAX, Rissanen's Minimum Description Length, MATLAB/Simulink, wireless measurement and control

I. INTRODUCTION

Various measurable chemical, physical and biological properties may be collected by a network of spatially distributed devices, available during the industrial production or experimental studies in the laboratory. Actually, the use of wireless monitoring, acquisition and storage of various measured parameters. The stored data may be used for developing control and optimization strategies of chemical processes. Also, the collected data may be used for studying the modeling, identification or optimization. Real time monitoring by implementation of wireless networks contributes to minimization of potential production risks and energy requires, emerging mainly from environmental influences and human actions with easy installation and lower maintanence cost according to cable measurement and control.

Advanced controllers such as classical PID control [1-2], nonlinear control [3-4], robust control [5-6], optimal control [7-8], model predictive control [9-10], fuzzy logic control [11-12], neural network control [13-14], adaptive fuzzy control [15] and fuzzy PID control [16-17] can also be implemented to predict the energy consumption and take appropriate actions to reduce energy consumption. The performance of the controllers depends largely on the accuracy of the system models and the processes being controlled. Therefore the development of accurate models is necessary which perform well under the wide range of operating conditions and are able to cope with the nonlinear behavior of the system. The researchers have developed several methods such as white-box models [18], black-box models [19-24] and grey-box models [25-26] to model the behavior of the various processes.

The black-box models are developed by measuring the data of the process input and output and fitting a mathematical function to the data. The development of rigorous theoretical models may not

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be practical for a complex process like this where the models require a large number of equations with a significant number of process variables and unknown parameters. But the development of black-box models does not require the understanding of the system physics and they have high accuracy compared to the physics-based models though they suffer from the poor generalization capabilities. The statistical black-box models consist of single and multivariate linear and polynomial regression techniques, autoregressive (AR), ARX, autoregressive moving average (ARMA), finite impulse response (FIR), autoregressive moving average exogenous (ARMAX), output error (OE) and Box–Jenkins (BJ) models. The mathematical expression for the generalized structure of statistical black box models in a simple input/output relationship is applied to various systems.
In this study, two black-box models, (ARX and ARMAX), are developed and compared for process simulator which wireless temperature experiments achieved in this work using the System Identification Toolbox of MATLAB (MathWorks 2011). Wireless temperature experiments were achieved by using MATLAB/Simulink program and wireless data transfer during the experiments were carried out using radio waves at a frequency of 2.4 GHz. ARX and ARMAX model performances are compared with the simulation results of three different points on the process simulator.

II. EXPERIMENTAL SYSTEM AND PROCEDURE

1) Process Description

The process control simulator consists of two main units, an instrument console and a framework carrying the process equipment which is shown in Figure 1. The instrument console contains the electronic flow, level, temperature controllers and electrical switchgear. It is connected to the process equipment by several cable assemblies. The process equipment consists of a water tank, water circulating pump, electrical water heater, two vessels, two electrically positioned control valves and a heat exchanger. In process control simulator, twelve manual valves are available for different process experiment loops. In the process simulator, temperature measurement and control can be made at four different points which are first tank (T1), heater output (T2), second tank input (T3) and second tank output (T4).
The wireless system developed for transferring data between the computer and the control panel. To achieve the data transfer between computer in Process Control Laboratory and the process simulator in Unit Operations Laboratory, by using the two antennas are found in the laboratory connected to the computer and outside connected to the process simulator. Control valves outputs are connected to the modules, the necessary calibrations are made. The water is pumped via the electrical heater into the reactor up to a certain level. The water then flows back to the sump tank via the cooler. Heat is fed to the water by the heater and residual heat removed by the cooler so as to return the sump tank water temperature to a suitable base level. Heater which is connected on-line to the computer is used as a manipulated variable [27].
Wireless temperature experiments were achieved by using MATLAB/Simulink program and wireless data transfer during the experiments were carried out using radio waves at a frequency of 2.4 GHz. MATLAB/Simulink block diagram was used for the on-line wireless temperature experiments with a computer in the office. There have four moduls, wireless on/off block for the wire or wireless experiments, numerical or graphical display blocks of process parameters, blocks of giving numerical values of valve openness, blocks of stored errors on the MATLAB/Simulink block diagram shown in Figure 2.

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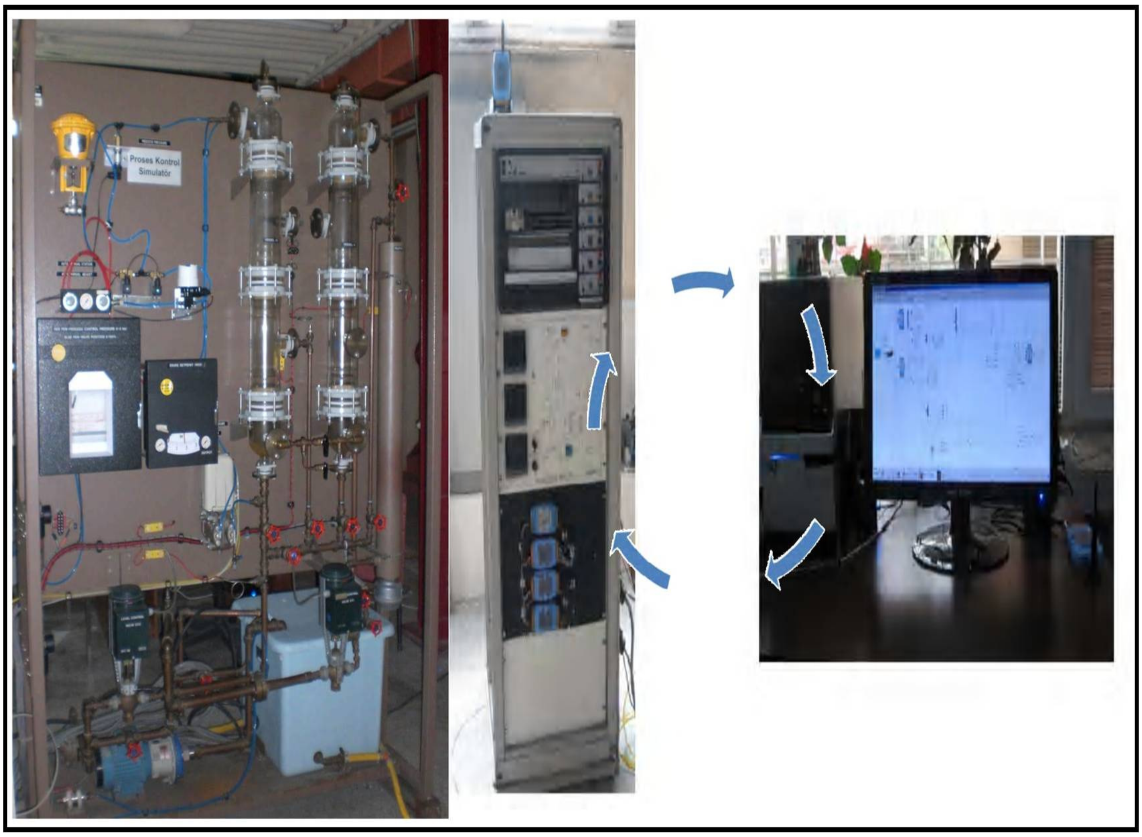

Figure 1. Experimental system: Process simulator, control panel and computer on-line connected to the process simulator with wireless technology

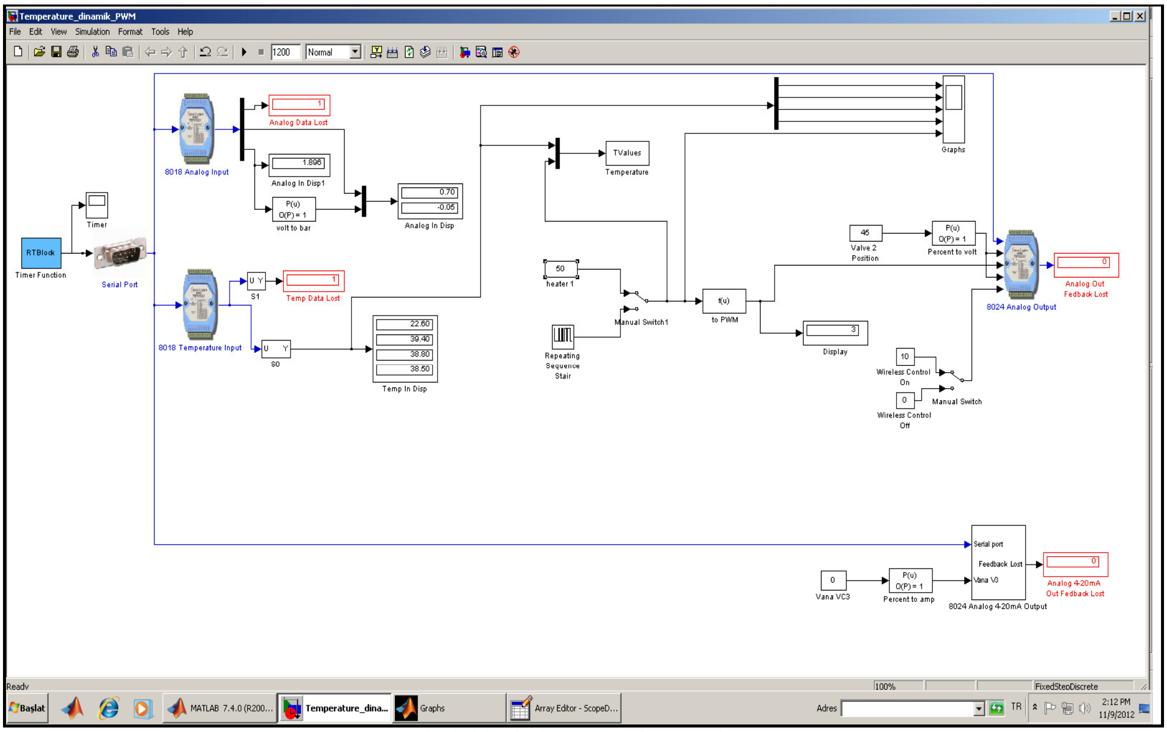

Figure 2. MATLAB/Simulink block diyagram for wireless temperature experiments

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2) Wireless Data Generation

The wireless data generated by operating the process simulator described above and shown in Figure 1. Wireless data were used for the development of the ARX and ARMAX models of the three temperatures at different points on the process simulator using Process Identification Technique. The ARX and ARMAX model parameters were estimated with the aid of System Identification Toolbox of MATLAB program. Wireless temperature experiments were carried out on process simulator during the 1500s time period. First 300s the heater operated % 10 heating capacity for the temperature is expected to become at steady-state. The fluid flow was obtained by running the pump when the level control valve was % 35 opening. The cooling water was opened after liquid level was fixed value. The heater output temperature was expected to become at steady-state while % heating capacity was on. A step change effect was performed as input signal which apply the heater capacity between % 10-70 values and the heater output, second tank input and output temperature changes with time as output signal which selected as the controlled variables while the heater capacity was chosen as the manipulated variable. These effects were given to the heater and output temperatures taken with MATLAB/Simulink during the experiments shown in Figure 2.

3) Black-Box Modeling

Given the process simulator, which has, apart from the disturbance e, the capacity of heater (R) input variable and the three temperature (T2-T3-T4) as the output variables respectively, that is represented as shown in Figure 3, its general black-box model structure can be formulated as depicted in Figure 4.

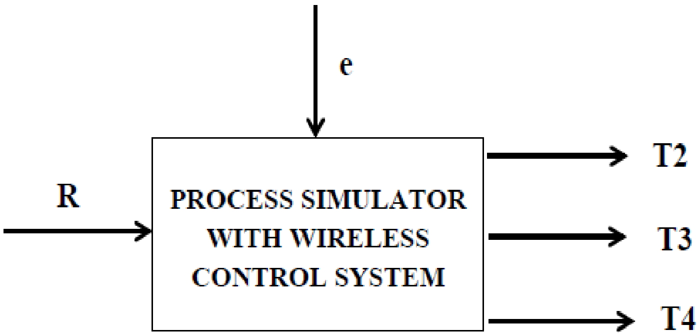

Figure 3. Process simulator diyagram for input (R) and output variables (T2-T3-T4)

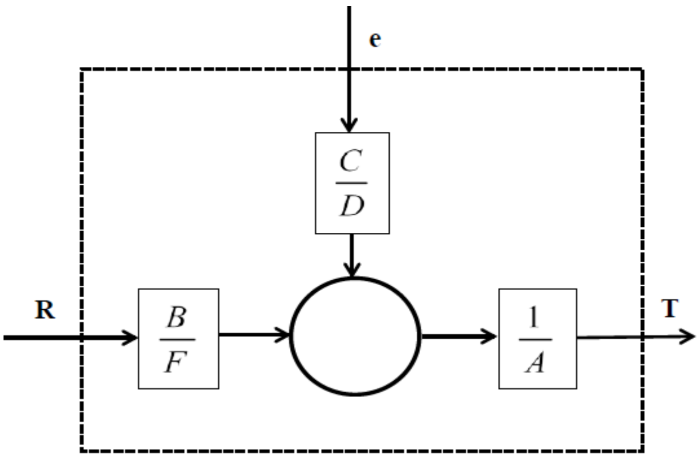

Figure 4. Black-Box model structure of process simulator

Considering the model structure shown in Fig. 3, the general mathematical expression for the black-box model of this process can thus be written as;

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$$A(q)T(t) = \frac{B(q)}{F(q)}R(t-n_k) + \frac{C(q)}{D(q)}e(t) \quad (1)$$

where n_k is the number of delay. The polynomial coefficients contained in the equation above are expressed as:

$$A(q) = 1 + a_1 q^{-1} + a_2 q^{-2} + \ldots + a_{na} q^{-na} \quad (2)$$

$$B(q) = b_1 + b_2 q^{-1} + b_3 q^{-2} + \ldots + b_{nb} q^{-nb+1} \quad (3)$$

$$C(q) = 1 + c_1 q^{-1} + c_2 q^{-2} + \ldots + c_{nc} q^{-nc} \quad (4)$$

$$D(q) = 1 + d_1 q^{-1} + d_2 q^{-2} + \ldots + d_{nd} q^{-nd} \quad (5)$$

$$F(q) = 1 + f_1 q^{-1} + f_2 q^{-2} + \ldots + f_{nf} q^{-nf} \quad (6)$$

For ARX model structure of this process, *C(q)*=*D(q)*=*F(q)*=1, while for the ARMAX model structure *D(q)*=*F(q)*=1. Based on Eq (1), for the process simulator with heater capacity being the input and three temperatures at different points on the process simulator being outputs, considered in this work, the structures of the ARX and ARMAX models to be developed are given as;

ARX models for the T2, T3 and T4 temperatures at different points on the process simulator given as respectively;

$$A(q)T_2(t) = B(q)R(t-n_k) + e(t) \quad (7)$$

$$A(q)T_3(t) = B(q)R(t-n_k) + e(t) \quad (8)$$

$$A(q)T_4(t) = B(q)R(t-n_k) + e(t) \quad (9)$$

ARMAX models for the T2, T3 and T4 temperatures at different points on the process simulator given as respectively;

$$A(q)T_2(t) = B(q)R(t-n_k) + C(q)e(t) \quad (10)$$

$$A(q)T_3(t) = B(q)R(t-n_k) + C(q)e(t) \quad (11)$$

$$A(q)T_4(t) = B(q)R(t-n_k) + C(q)e(t) \quad (12)$$

4) Determination of Model Orders

The determination of appropriate model orders (na, nb, nc and nk which stand for number of poles, number of zeros plus 1, number of C coefficients and number of delays respectively) is very important when developing any black-box model. During the model development, the optimum values of these model orders are necessary to be determined in order to avoid under-fitting or over-fitting of the developed model equation. Many criteria (such as AIC, BIC, and MDL) are available in the literature for the optimum selections of these model orders. In this work, the MDL (Rissanen's Minimum Description Length) criterion, shown in Eq. (13) below, was used because it allows the shortest possible description of the observed data[28]. In Eq. (13) V is the loss function; d is the total number of parameters in the structure; and N is the number of data points used for the estimation.

$$MDL = V\left(1 + \frac{d\log(N)}{N}\right) \quad (13)$$

III. RESULTS AND DISCUSSION

The wireless data acquired from the experiment carried out in the process simulator are as shown in Figure 5. It can be observed from Figure 5 that a change in the heater capacity between % 10-70 values to a unit step resulted in a change in the temperatures of the T2, T3 and T4. Using the wireless data acquired from the experiment, the model orders were estimated by optimizing the MDL criterion. The optimum model orders obtained from the optimization of the criterion were na=2, nb=3, and nk=3. Thereafter, the model orders were used to develop the black-box models (ARX and

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ARMAX) for the process simulator in MATLAB environment. That is, the polynomial coefficients of the models were estimated using the obtained model orders. The polynomial coefficients estimated are as outlined given in Table 1 and Table 2 for ARX and ARMAX models, respectively.

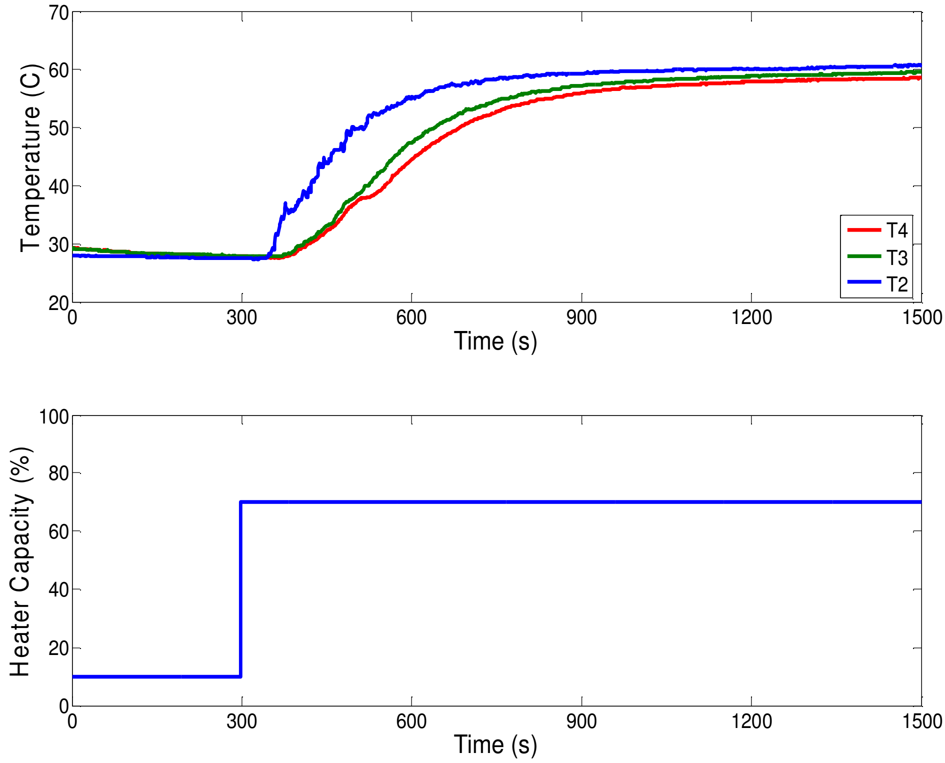

Figure 5. T2, T3 and T4 temperature changes according to given a step effect to the heater capacity between % 10-70 values

Table 1. Obtained ARX models for T2, T3, T4 temperatures

Temperature	ARX Model
T2	$\left(1-2.305q^{-1}+1.767q^{-2}-0.6174q^{-3}+0.155q^{-4}\right)y(t)=$ $(-0.000414q^{-1}+0.001469q^{-2}+0.0003432q^{-3}-0.001398q^{-4})u(t)+e(t)$
T3	$(1-1.998q^{-1}+0.7929q^{-2}+0.4079q^{-3}-0.2031q^{-4})y(t)=$ $(0.00008392q^{-1}-0.0002006q^{-2}+0.0009591q^{-3}-0.0008388q^{-4})u(t)+e(t)$
T4	$(1-1.857q^{-1}+0.5116q^{-2}+0.5474q^{-3}-0.2022q^{-4})y(t)=$ $(0.0001153q^{-1}-0.00004458q^{-2}+0.0005043q^{-3}-0.0005705q^{-4})u(t)+e(t)$

Table 2. Obtained ARMAX models for T2, T3, T4 temperatures

Temperature	ARMAX Model
T2	$(1-1.99q^{-1}+0.9897q^{-2})y(t)=(0.008831q^{-1}-0.008831q^{-2})u(t)$ $(1-0.6486q^{-1}-0.2763q^{-2})e(t)$
T3	$(1-2.0q^{-1}+1.0q^{-2})y(t)=(0.0002699q^{-1}-0.0002683q^{-2})u(t)$ $(1-1.13q^{-1}+0.1658q^{-2})e(t)$
T4	$(1-0.9497q^{-1}-0.0473q^{-2})y(t)=(0.349q^{-1}-0.3464q^{-2})u(t)$ $(1+0.002899q^{-1}+0.006569q^{-2})e(t)$

The developed models were then simulated and their simulated results were compared to the three different temperature points on the simulator. Shown in Figure 6 is the comparison between the experimental and the simulated T2-T3-T4 temperatures of the process simulator for the ARX and ARMAX models, respectively. As can be seen from Figure 6, there is a good agreement between the experimental and ARMAX model simulated T2-T3-T4 temperatures.

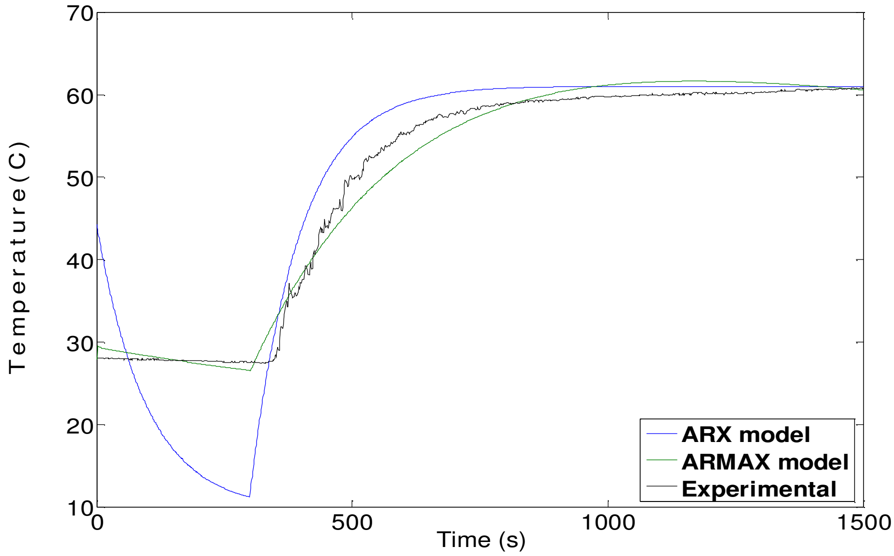

Figure 6. Comparison between the experimental and the simulated T2-T3-T4 temperatures

In order to have ideas about the dynamics of the developed models, the two models were simulated with the aid of MATLAB/Simulink by applying a step input to each of them and their dynamic responses were recorded. The obtained dynamic responses for the ARX and ARMAX models are as shown in Figures 7, 8 and 9 for temperatures T2, T3, and T4, respectively. From Figure 7 for temperature T2, ARX and ARMAX models step response results were stable because they were able to the steady state succesfully. ARMAX models results from Figure 8 and 9 for temperature T3 and T4 were stable because they were able to the steady state rapidly but ARX model results have big oscillations. From Figures 8 and 9, it was observed that the response of the developed ARX model to the applied step input resembled that of a first order system or of a higher order system with overdamped behavior. Therefore, it is very clear that the developed ARX model is a higher order model with overdamped response. Based on the simulation results, ARMAX models were discovered to be better than ARX models due to both faster than ARX models in getting to the steady-state and without any oscillations for this process simulator.

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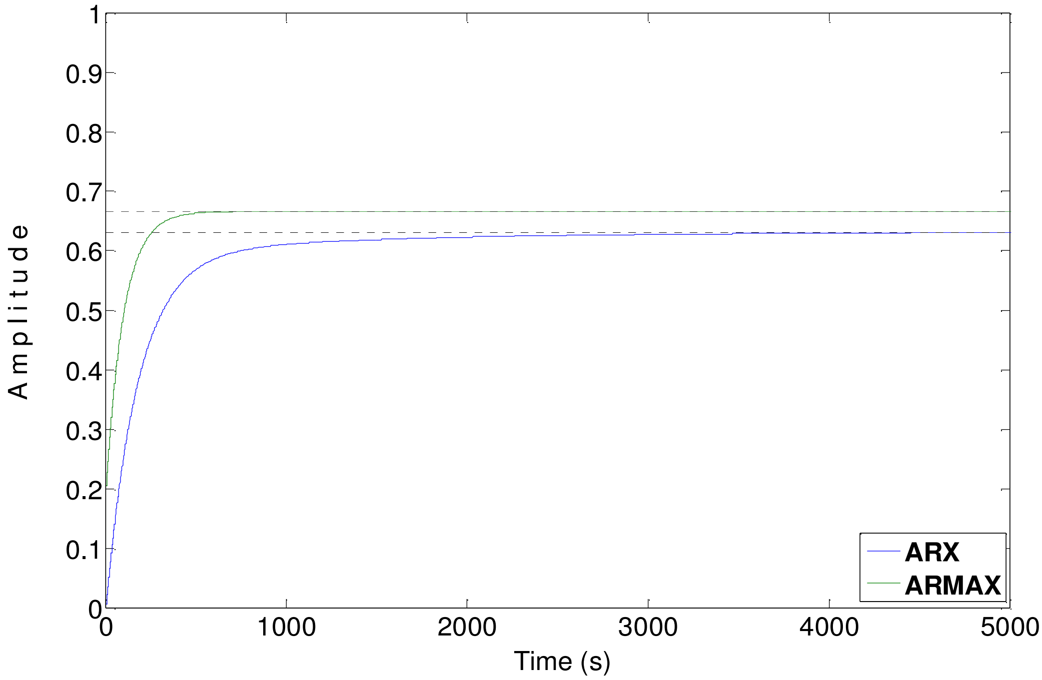

Figure 7. Comparison between the dynamic responses of ARX and ARMAX models to a step response for T2 temperatures

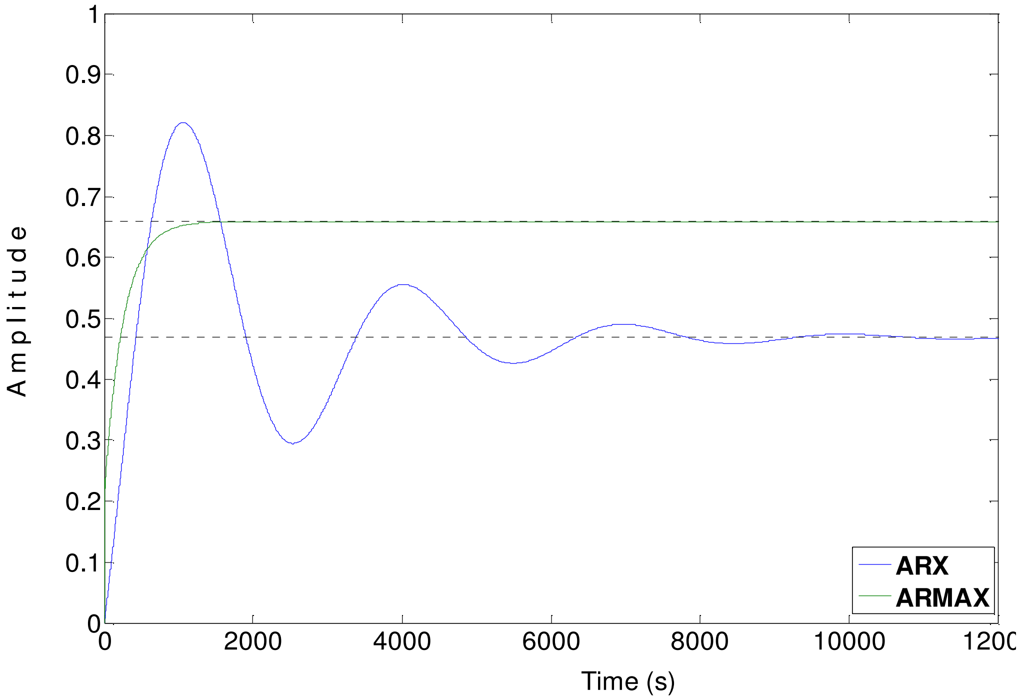

Figure 8. Comparison between the dynamic responses of ARX and ARMAX models to a step response for T3 temperatures

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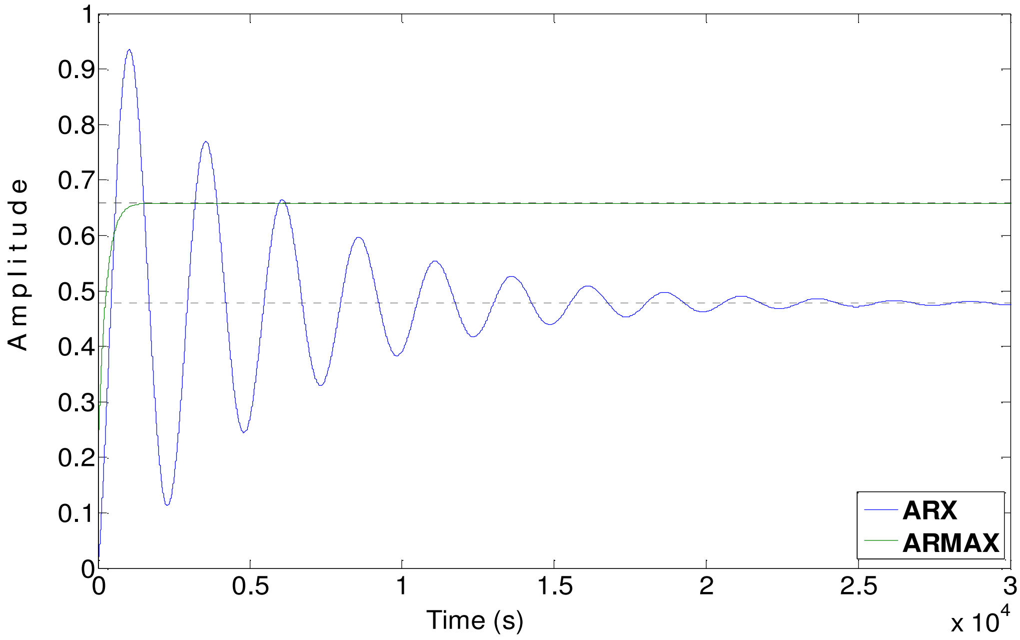

Figure 9. Comparison between the dynamic responses of ARX and ARMAX models to a step response for T4 temperatures

IV. CONCLUSION

In this study the development of two Black-Box (ARX and ARMAX) models for a process simulator has been carried out. Wireless temperature experiments were achieved by using MATLAB/Simulink program and wireless data transfer during the experiments were carried out using radio waves at a frequency of 2.4 GHz. The wireless data used for the models development were generated using a unit step change between % 10-70 values on the heater capacity of the process simulator. The model orders used for the estimation of the model polynomial coefficients were determined by optimizing the MDL with the aid MATLAB. The good comparisons between the wireless experimental and the simulated values of the temperatures (T2-T3-T4) of the developed ARX and ARMAX models for the process simulator have shown that the ARMAX models can be used to represent the behavior of the process simulator successfully. Based on simulation results, ARMAX models were discovered to be better than ARX models due to both faster than ARX models in getting to the steady-state and without any oscillations for this process simulator.

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