Scientific Journal Impact Factor (SJIF) : 1.711
International Journal of Modern Trends in Engineering and Research
ISSN (ONLINE) : 2349 - 9745
ISSN (PRINT) : 2393 - 8161

Nonlinear Identification of A Wireless Control System: Hammerstein-Wiener Modeling

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Abstract—This study proposes to modeling a process simulator that was used for the wireless control by using a nonlinear system identification technique based on Hammerstein-Wiener model. Wireless input/output data obtained from the Cussons P3005 type process control simulator. 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. Hammerstein-Wiener model orders and three estimator types were applied with the aid of System Identification Toolbox (SIT) of MATLAB using the wireless data acquired from the process simulator. It was observed that the fit values of the *piecewise linear* estimator type which was calculated for T2, T3 and T4 were higher than that of the *dead zone* and *saturation* model. According to the results the highest fit values are determined with *piecewise linear* estimator type which is calculated by 2, 2 and 1 model orders *nb, nf* and *nk*, respectively. The best accuracy, loss function and final prediction error values for T2 are determined 97.45, 0.249 and 0.252, for T3 are determined 92.72, 1.053 and 1.126 and for T4 are determined 86.56, 3.488 and 3.539, respectively. After determined of the best model order and estimator type for this wireless system was analyzed and characterized by graphical tools which can be used to design the linear controller, stability analysis, causality, system response analysis and signal processing.

Keywords—Nonlinear system identification, Hammerstein-Wiener model, MATLAB/Simulink, wireless process control, final prediction error, fit value, loss function

I. INTRODUCTION

Most industrial processes which have one or more physical systems, for instance, mechanical systems, control valves, sensors, and others are inherently nonlinear behavior. Nonlinear processes could be represented by uncertain linear models and thus the nonlinear control problem is converted into a robust linear control problem. It is necessary to pursue nonlinear modeling if the output of the linear model does not fit the measured output signal, or if the control performance of the linear model cannot be improved by changing only the order of the model [1]. Therefore, nonlinear estimator types and linear model orders should be changing simultaneously for better proces control.

Many methods such as Volterra series [2], neural networks [3], fuzzy logic systems [4], support vector machines [5] had been proposed to modeling of nonlinear systems in recent years. Nonlinear identification process based on Hammerstein-Wiener model structure which is consists of a linear dynamic block embedded between two nonlinear steady-state blocks, has been processed and synthesized yielding the modeling from only measured inputs and outputs of the dynamic systems. In this method, the system is considered as a black box of which it is not necesssary to know structures and parameters inside [6]. Hammerstein-Wiener models are popular because they have a convenient block representation, transparent relationship to linear systems, and are easier to implement than heavy-duty nonlinear models such as neural networks, Volterra models [7]. The Hammerstein–Wiener structure may be successfully used to describe various processes, e.g. the human's muscle [8], a continuous stirred tank reactor [9], a micro-scale polymerase chain reaction reactor [10], temperature variations in a silage bale [11], a DC motor [12], a pH neutralization reactor [13], a fuel cell [14], a photovoltaic system [6].

This paper describes modeling of a process simulator using nonlinear system identification based on Hammerstein-Wiener model. Modeling and analyzing of wireless control system carried out with the SIT of MATLAB (MathWorks 2011). Wireless 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. Hammerstein-Wiener model orders with model types are compared with the calculated fit values and loss function values of three temperature points on this wireless system.

1) Hammerstein-Wiener Modeling

A Hammerstein-Wiener model developed from a Hammerstein model and a Wiener model, shown in Fig. 1. The nonlinear blocks contain the nonlinear functions and the linear block is an output error (OE) polynomial model.

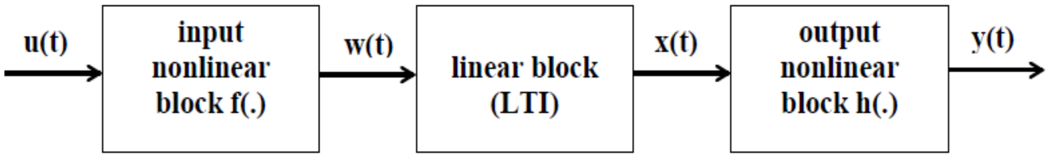

Figure 1. Structure of Hammerstein-Weiner model for SISO process

The following general equation describes the Hammerstein–Wiener structure are follow Eq. (1) and (2);

$$w(t)=f(u(t)), \quad \textbf{(1)}$$

$$y(t)=h(x(t)), \quad \textbf{(2)}$$

which *u(t)* and *y(t)* are the inputs and outputs for the system. *f(·)* and *h(·)* are nonlinear scalar functions that corresponding to the input and output nonlinearities. *w(t)* and *x(t)* are internal variables that define the input and output of the linear block. $w(t)=f(u(t))$ is a nonlinear function transforming input data $u(t)$. *w(t)* has the same dimension as *u(t)*. $x(t)=(B/F)w(t)$ is a linear transfer function. *x(t)* has the same dimension as *y(t)*. $y(t)=h(x(t))$ is a nonlinear function that maps the output of the linear block to the system output [7].

The nonlinear blocks which situated in the structure of Hammerstein-Wiener model are implemented using nonlinearity estimators, such as *Dead-Zone* which parametrize dead zones in signals as the duration of zero response, *Saturation* which parametrize hard limits on the signal value as upper and lower saturation limits, *Piecewise Linear* which parametrized by breakpoint locations, *One Dimensional Polynomial* [7]. These nonlinear estimators described in references [6, 15].

The linear block is similar to output error polynomial model which has structure shown in Eqs. (3), (4) and (5). The number of coefficients in the numerator polynomials *B(q)* is equal to the number of zeros plus 1, *nb* is the number of zeros. The number of coefficient in denominator polynomials *F(q)* is equal to the number of poles, *nf* is the number of poles. q is the time-shift operator and completely equivalent to the z transform form. *nk* is the delay from input to output in terms of the number of samples. *e(t)* is the error signal [6].

$$x(t)=\frac{B(q)}{F(q)}w(t-nk)+e(t) \quad \textbf{(3)}$$

$$B(q)=b_1+b_2q^{-1}+\cdots+b_{nb}q^{-nb+1} \quad \textbf{(4)}$$

$$F(q)=f_1+f_2q^{-1}+\cdots+f_{nf}q^{-nf} \quad \textbf{(5)}$$

II. WIRELESS CONTROL SYSTEM AND EXPERIMENTAL PROCEDURE

The experimental of system identification modeling use the process control simulator consists of two main units, an instrument console and a framework carrying the process equipment which is shown in Figure 2. The instrument console contains the electronic flow, level, temperature controllers and electrical switchgear. It is connected to the process equipment which consists of a water tank, water circulating pump, electrical heater, two vessels, two electrically positioned control valves and a heat exchanger. On process control simulator, twelve manual valves are available for different process experiment loops and temperature measurement and control can be made at four different points (T1, T2, T3 and T4) [16].

The wireless system constructed for transferring data between the computer and the simulator 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. Wireless temperature experiments were carried out by MATLAB/Simulink program and wireless data transfer during the experiments were achieved using radio waves at a frequency of 2.4 GHz [16].

The wireless data generated by operating the process simulator described above and shown in Figure 2. Wireless data were used for the development of the models of the three temperatures at different points on the process simulator using Process Identification Technique. Wireless 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. During the wireless experiments different effects were given to the heater and output temperatures taken with MATLAB/Simulink which block diagram shown in Figure 3 [16].

A step change effect was performed as input signal which apply the heater capacity and T2, T3 and T4 temperature changes with time as output signal which selected as the controlled variables while the heater capacity was chosen as the manipulated variable. Using SIT check accuracy of T2, T3 and T4 temperatures and find the maximum accuracy temperatures compare with real temperatures by changes the pole, zero and delay of linear terms.

The next process, iterative simulation temperatures and experimental temperatures compared until best model performances is derived by results include a quantitative measure of model quality in terms of goodness of fit to estimation data and loss function. The percentage of best fit accuracy in Eq. (6) is obtained from comparison between experimental and simulation modeling temperatures;

$$fit\ value\ (\%) = \frac{1 - norm(Ts - Te)}{norm(Te - \overline{Te})} * 100 \quad \textbf{(6)}$$

where Ts is simulated temperature, Te is measured temperature and $\overline{Te}$ is mean of temperature. The loss function V is follow in Eq. (7) where N is the number of estimation data and θ_N is represents the estimated parameters;

$$V = \det\left(\frac{1}{N}\sum_{1}^{N}\varepsilon(t,\theta_N)(\varepsilon(t,\theta_N))^T\right) \quad \textbf{(7)}$$

FPE is calculated for estimated model which the error calculation is defined as Eq. (8) where d is the number of estimated parameters, V is the loss function;

$$FPE = V\left(\frac{1 + d/N}{1 - d/N}\right) \quad \textbf{(8)}$$

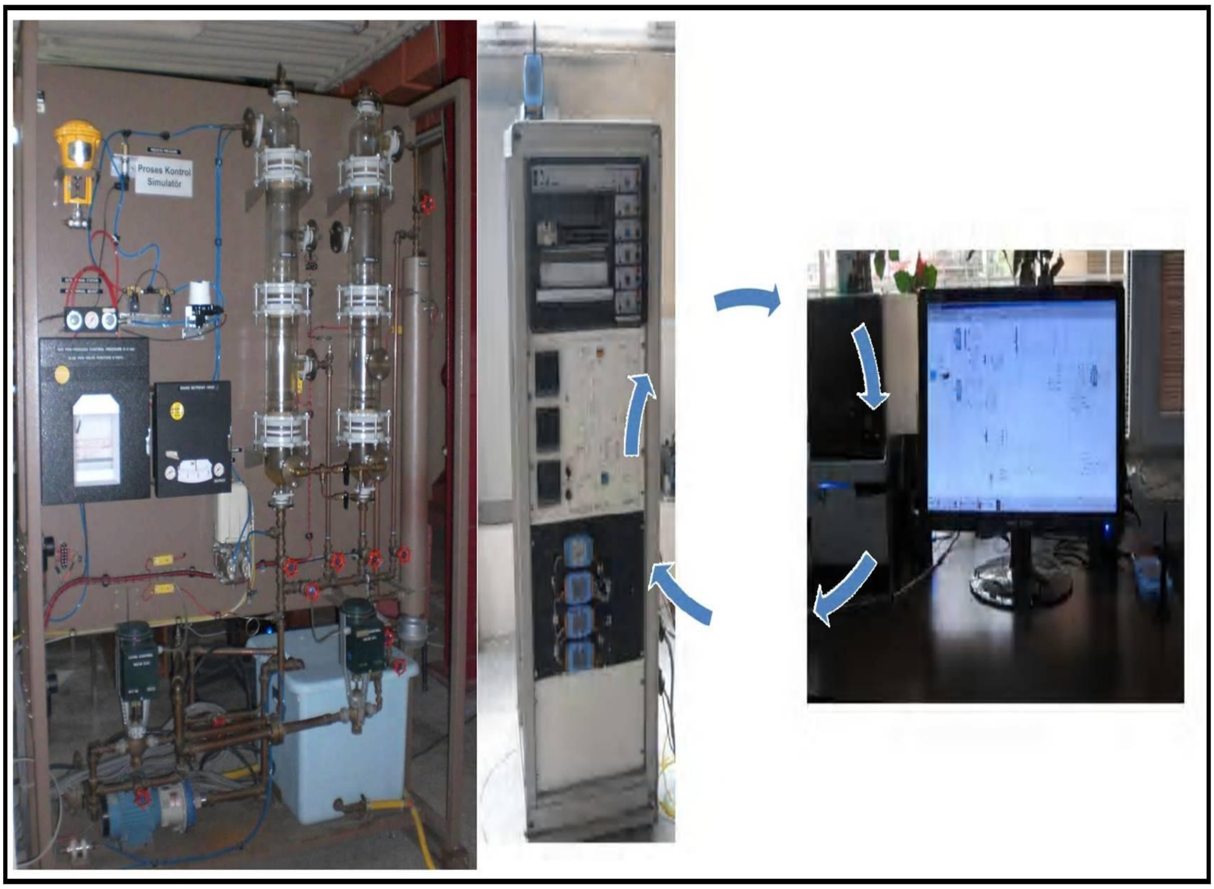

Figure 2. Experimental system: Process simulator, control panel and computer on-line connected to the process simulator with wireless technology [16]

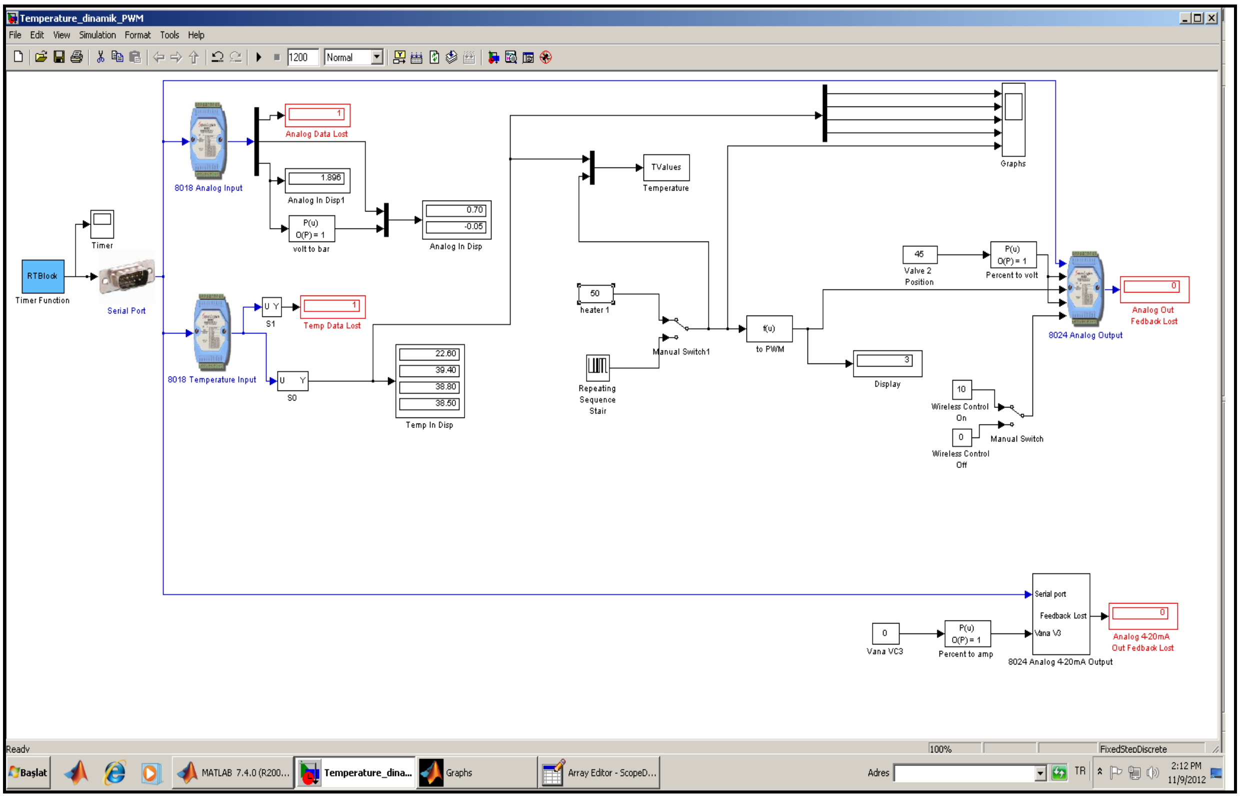

Figure 3. MATLAB/Simulink block diyagram for wireless temperature experiments [16]

III. RESULTS AND DISCUSSION

After obtained wireless measurement data and estimating data by system identification procedure, the validation of models are processed by considered;

i) the best model order which the system need the lowest-order model that adequately captures the system dynamics,

ii) the best fit value which mean the comparison between output modeling and experimental, need the highest fit value for the high accuracy of modeling,

iii) the best loss function and FPE values which using estimation data and estimated parameters, need the lowest loss function and FPE values for the high accuracy of modeling.

The model order values, % fit values (percentage of accuracy), loss function and FPE values are shown in Table 1, 2 and 3 for T2, T3 and T4 temperatures, respectively.

1) Comparison Studies Among Estimator Types and Model Orders

Shown in Table 1, 2 and 3 were comparison of among the three estimator types (*dead zone*, *saturation* and *piecewise linear*) and selected eight model order outputs for T2-T3-T4 temperatures, respectively. From the Table 1-3, it was observed that the fit values of the *piecewise linear* estimator type which was calculated for T2, T3 and T4 were higher than that of the *dead zone* and *saturation* model. According to the Table 1-3, the highest fit values are determined with *piecewise linear* estimator type which is calculated by 2, 2 and 1 model orders *nb*, *nf* and *nk*, respectively. % fit values of these three nonlinear estimator types are decreased while the model orders are increased.

The best accuracy, loss function and FPE values for T2 are determined 97.45, 0.249 and 0.252 (see Table 1), for T3 are determined 92.72, 1.053 and 1.126 (see Table 2) and for T4 are determined 86.56, 3.488 and 3.539 (see Table 3), respectively. As can be observed from the fit values shown in the tables below, some of the fit values are negative. These negative fit values which calculated with lowest model orders are belong to *dead zone* estimator type (see Table 1-2). Comparison of experimental and simulated temperatures determined with *piecewise linear* estimator which fit values are calculated by 2, 2 and 1 model orders shown in Figure 4.

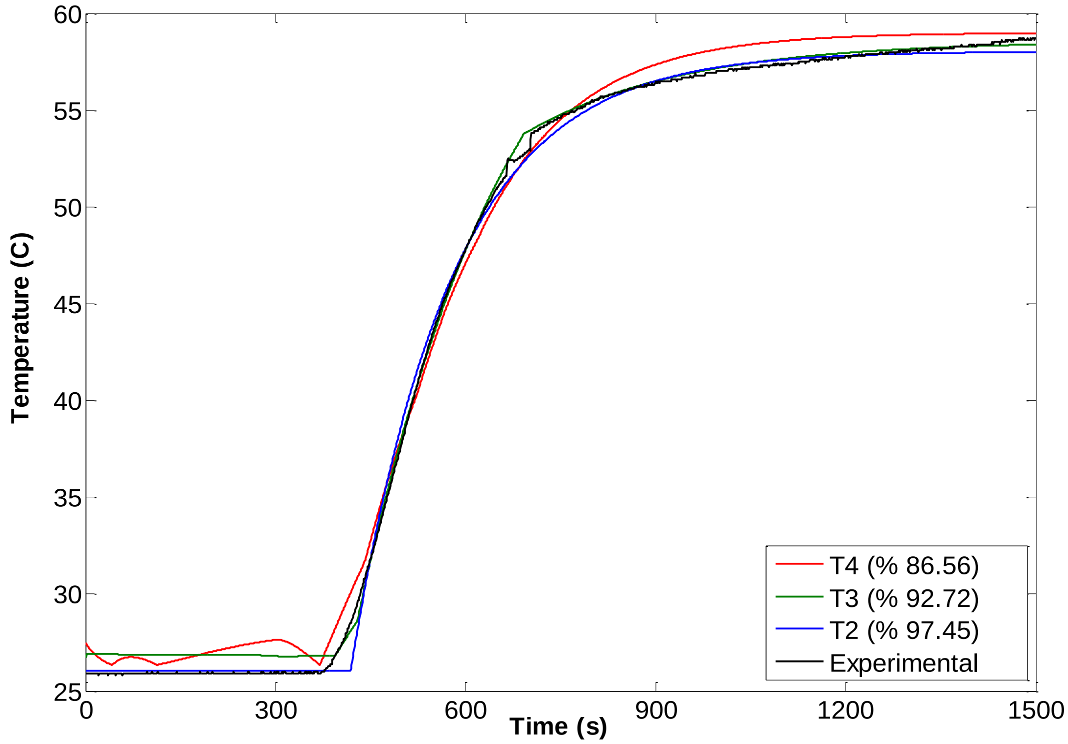

Figure 4. Comparison of experimental and simulated temperatures determined with piecewise linear estimator

Volume 02, Issue 09, [September – 2015] ISSN (Online):2349–9745 ; ISSN (Print):2393-8161

Table 1. Comparison of model types and model orders for T2 temperature

	Input/Output Nonlinear Model Type	***nb***	***nf***	***nk***	***% fit value***	***loss function value***	***FPE value***
1	*Dead zone* *Saturation* *Piecewise linear*	1	4	1	-73.80 68.95 77.49	3052 197.60 731.40	3089 210.20 740.20
2	*Dead zone* *Saturation* *Piecewise linear*	1	5	7	-85.40 40.16 67.42	2022 197.60 31.02	2049 210.50 31.43
3	*Dead zone* *Saturation* *Piecewise linear*	2	2	1	80.13 91.54 97.45	6.87 1.434 0.249	7.37 1.524 0.252
4	*Dead zone* *Saturation* *Piecewise linear*	2	4	3	70.44 74.52 92.15	37.60 4.737 1.384	38.10 4.800 1.477
5	*Dead zone* *Saturation* *Piecewise linear*	2	5	8	71.47 84.81 86.78	31.92 4.630 3.579	32.39 4.969 3.813
6	*Dead zone* *Saturation* *Piecewise linear*	3	2	8	69.67 11.65 80.65	26.98 222.40 5.994	27.30 236.60 6.066
7	*Dead zone* *Saturation* *Piecewise linear*	3	4	2	69.10 15.03 78.18	31.85 214.44 9.424	32.32 226.06 9.599
8	*Dead zone* *Saturation* *Piecewise linear*	4	3	5	67.37 13.55 72.51	29.58 207.10 344.20	30.01 220.80 349.20

Table 2. Comparison of model types and model orders for T3 temperature

	Input/Output Nonlinear Model Type	nb	nf	nk	% fit value	loss function value	FPE value
1	Dead zone	1	4	1	-5.846	2960	2995
	Saturation				11.27	417.60	444.30
	Piecewise linear				41.99	198.80	202.00
2	Dead zone	1	5	7	-43.81	2929	2968
	Saturation				20.31	297.70	317.10
	Piecewise linear				59.41	143.70	145.60
3	Dead zone	2	2	1	79.21	17.98	18.17
	Saturation				87.83	4.921	5.230
	Piecewise linear				92.72	1.053	1.126
4	Dead zone	2	4	3	69.21	21.81	22.10
	Saturation				65.69	81.20	88.66
	Piecewise linear				86.85	3.344	3.371
5	Dead zone	2	5	8	68.84	24.75	25.11
	Saturation				71.99	25.47	27.17
	Piecewise linear				83.60	5.215	5.541
6	Dead zone	3	2	8	74.67	51.56	52.18
	Saturation				61.12	29.31	31.30
	Piecewise linear				81.22	6.995	7.088
7	Dead zone	3	4	2	72.94	26.03	26.41
	Saturation				58.91	217.50	233.50
	Piecewise linear				81.37	6.907	6.999
8	Dead zone	4	3	5	15.94	158.50	160.90
	Saturation				27.81	109.60	116.90
	Piecewise linear				82.87	10.41	10.57

Volume 02, Issue 09, [September – 2015] ISSN (Online):2349–9745 ; ISSN (Print):2393-8161

Table 3. Comparison of model types and model orders for T4 temperature

	Input/Output Nonlinear Model Type	nb	nf	nk	% fit value	loss function value	FPE value
1	Dead zone Saturation Piecewise linear	1	4	1	34.84 38.85 50.01	289.90 251.90 2263	302.10 255.00 2290
2	Dead zone Saturation Piecewise linear	1	5	7	67.97 65.08 73.89	30.23 38.12 13.39	30.80 38.58 13.57
3	Dead zone Saturation Piecewise linear	2	2	1	71.19 74.63 86.56	42.44 24.72 3.488	42.89 25.28 3.539
4	Dead zone Saturation Piecewise linear	2	4	3	67.63 64.40 81.41	20.62 24.35 25.21	20.92 25.87 25.55
5	Dead zone Saturation Piecewise linear	2	5	8	62.91 67.96 76.47	24.11 19.64 22.05	24.26 19.93 22.55
6	Dead zone Saturation Piecewise linear	3	2	8	44.93 52.21 71.32	61.69 179.60 15.65	62.67 182.90 15.86
7	Dead zone Saturation Piecewise linear	3	4	2	22.27 29.15 64.63	137.20 100.10 24.64	140.40 106.90 25.00
8	Dead zone Saturation Piecewise linear	4	3	5	13.60 16.07 60.39	141.80 2133 32.03	145.60 2179 32.41

2) Analyzing Wireless System with Graphical Tools

This wireless control system can also be analyzed by graphical tools such as step response, impulse response, bode plot diagram, Nyquist plot, Nicholes chart and pole-zero map as shown in Figure 5, 6 and 7 for T2, T3 and T4 temperatures, respectively. These figures achieved with *piecewise linear* estimator and 2, 2 and 1 model orders using SIT of MATLAB. The interpretation and extraction the parameter of each graph can use the LTI theory [7]. These graphical linear tools can be used to design the linear controller, stability analysis, causality, system response analysis such as step response, impulse response and signal processing. The application of modeling form system identification is to create the control system and use the linear tools to design the controller and then system is controlled that method is known MPC. The other application is simulation output to analysis the accuracy of model, minimization of error, correct sizing and design of real system.

Nyquist stability criterion is a method that can be applied to judge the stability of the systems by frequency characteristic, which uses the open-loop Nyquist curve to judge the stability of the closed-loop system. Nyquist diagram contains curves and shows the frequency variations of the magnitude and phase of a transfer function as an ordered pair on the complex plane. Nichols charts are useful to analyze open- and closed-loop properties of SISO systems, but offer little insight into MIMO control loops. The Nichols chart contains curves of constant closed-loop magnitude and phase angle. A Bode plot is a useful tool that shows the gain and phase response of a given LTI system for different frequencies. The frequency of the Bode plots are plotted against a logarithmic frequency axis. The Bode phase plot measures the phase shift in degrees. A pole–zero plot is a graphical representation of a rational transfer function in the complex plane which helps to convey certain properties of the system such as: stability analysis, causality, region of convergence, minimum phase or non minimum phase.

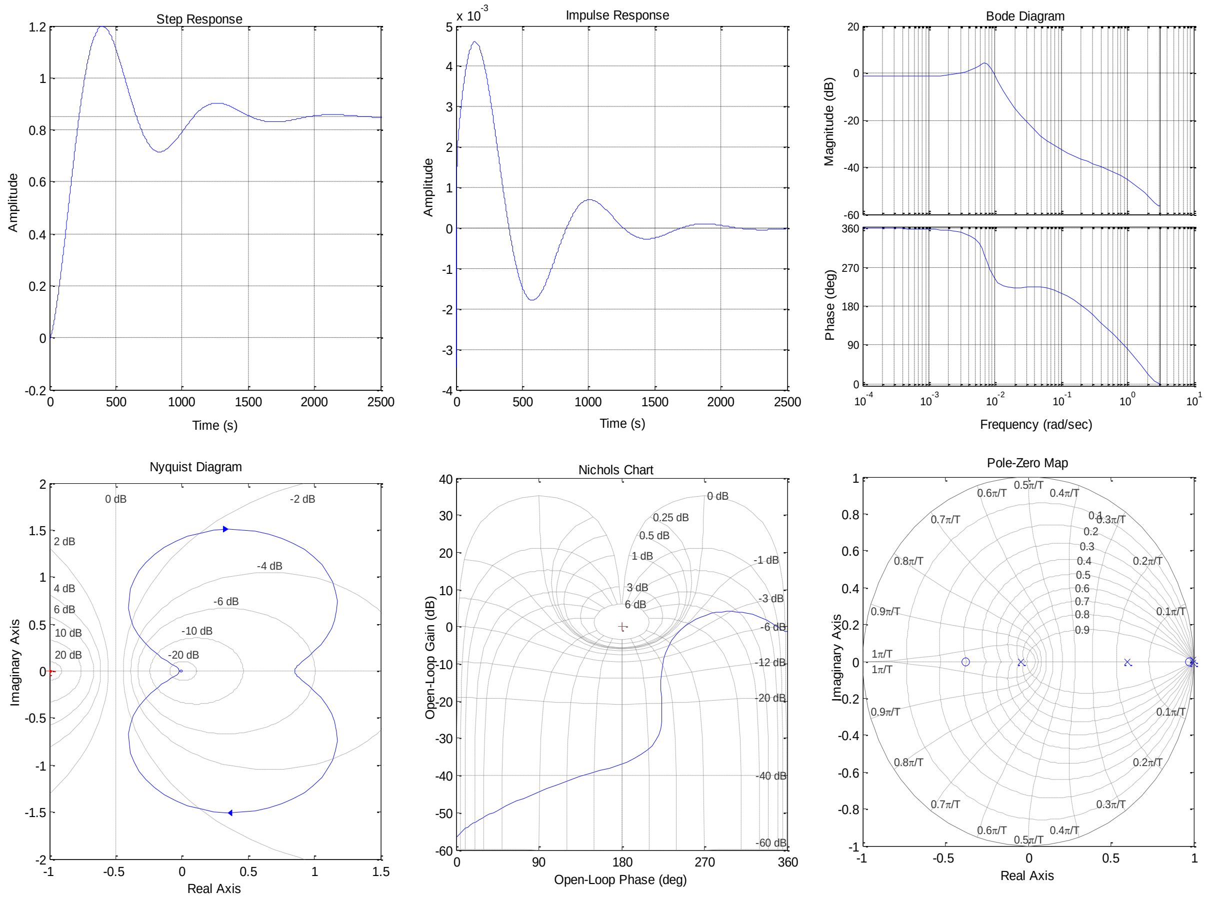

Figure 5. Graphical tools of wireless system analysis for T2 temperature

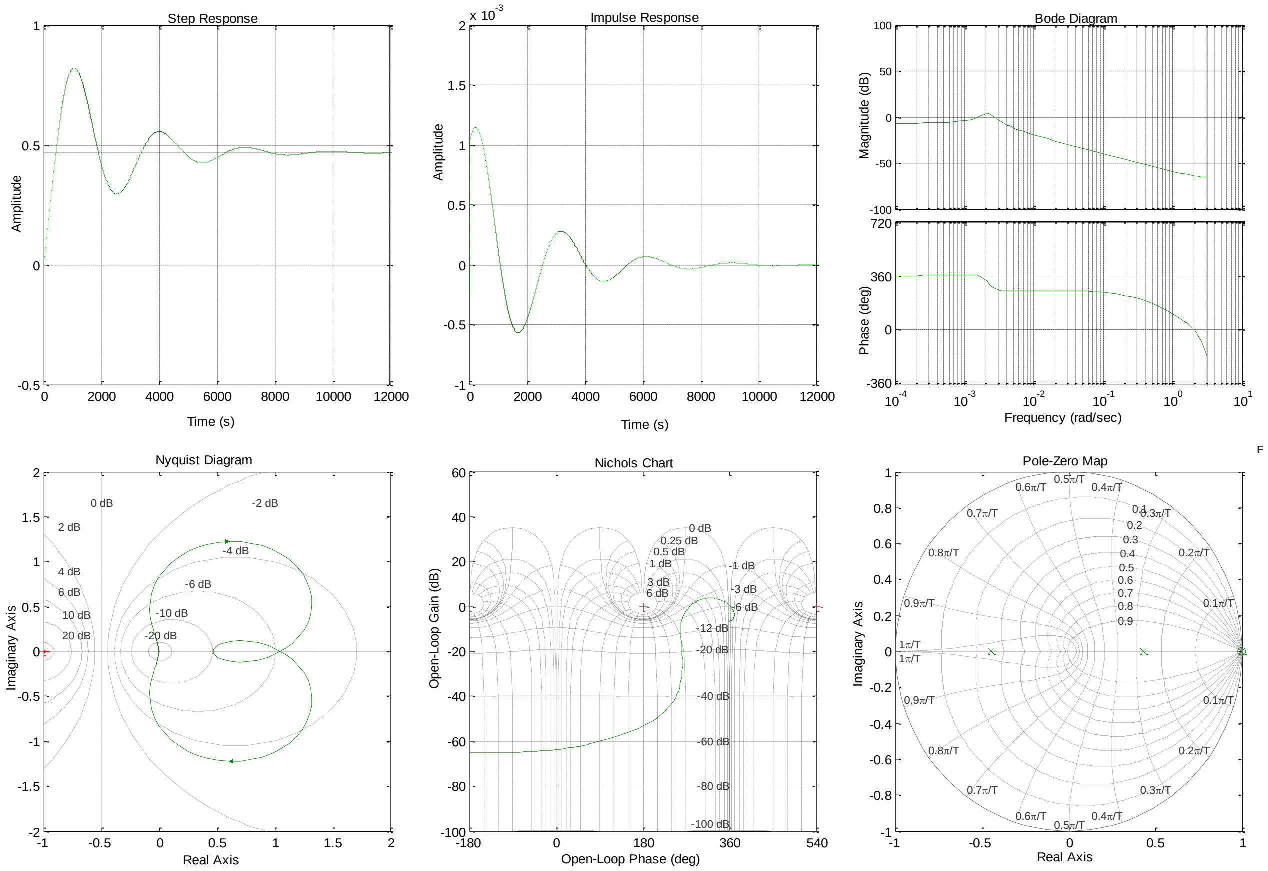

Figure 6. Graphical tools of wireless system analysis for T3 temperature

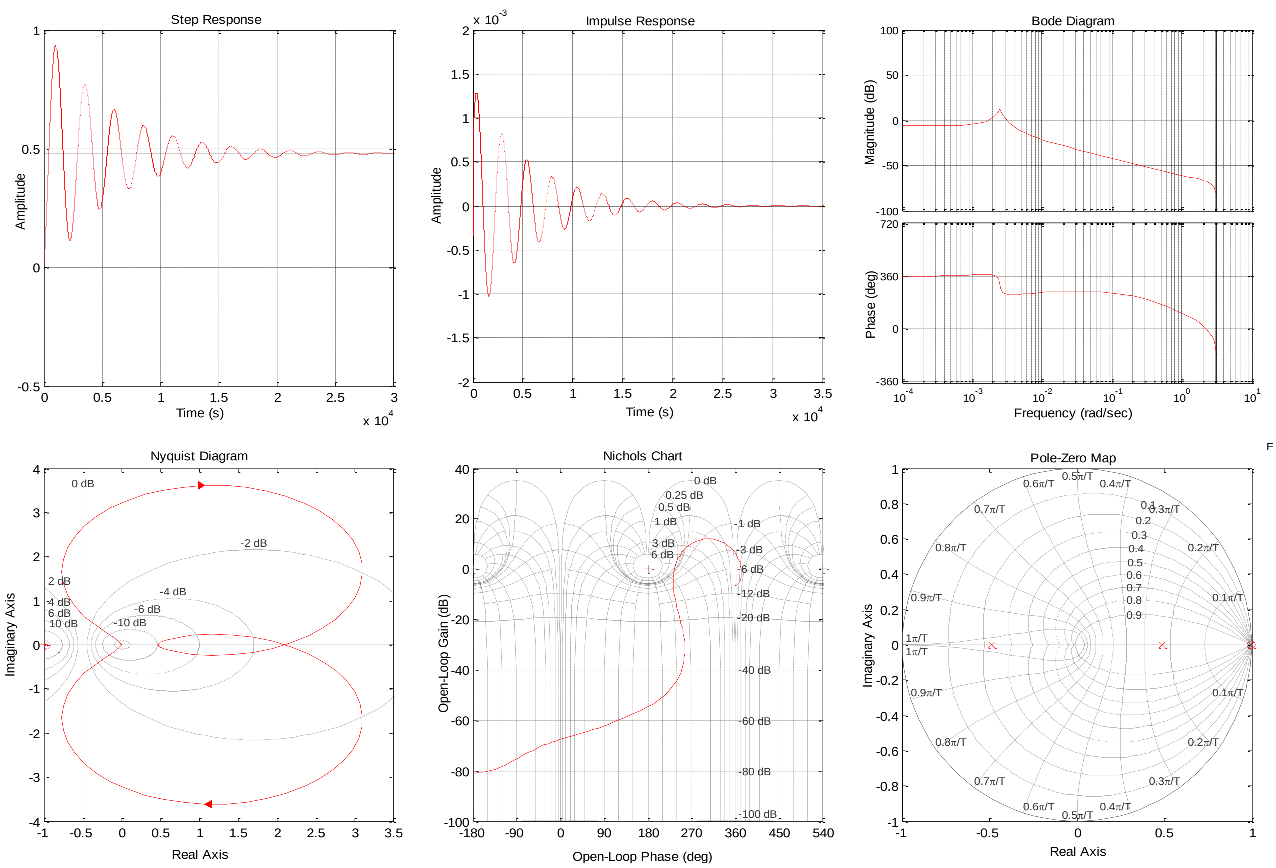

Figure 7. Graphical tools of wireless system analysis for T4 temperature

IV. CONCLUSION

In this study the comparison of among the three types of nonlinear estimators (*piecewise linear, dead zone, saturation)* and different model orders for a process simulator has been carried out, successfully. 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. Hammerstein-Wiener model orders and three estimator types were applied with the aid of System Identification Toolbox (SIT) of MATLAB using the wireless data acquired from the process simulator. It was observed that the fit values of the *piecewise linear* estimator type which was calculated for T2, T3 and T4 were higher than that of the *dead zone* and *saturation* model. According to the results the highest fit values were determined with *piecewise linear* estimator type which is calculated by 2, 2 and 1 model orders *nb*, *nf* and *nk*, respectively. % fit values of these three nonlinear estimator types were decreased while the model orders were increased. After determined of the best model order and estimator type for this wireless system was analyzed and characterized by graphical tools which can be used to design the linear controller, stability analysis, causality, system response analysis and signal processing.

Acknowledgements

The authors would like to thanks the Ankara University, Research Fund for providing financial support this research; Ankara, Turkey

Nomenclatures

FPE	Final Prediction Error
LTI	Linear Time Invariant
MIMO	Multi Input-Multi Output
MPC	Model Predictive Control
R	Heater Capacity (%)
SISO	Single Input-Single Output
SIT	System Identification Toolbox of Matlab
t	Time (s)
T_1	Storage tank temperature (ºC)
T_2	Heater output temperature (ºC)
T_3	Second tank input temperature (ºC)
T_4	Second tank output temperature (ºC)

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