

MODELING AND IDENTIFICATION OF HEAT EXCHANGER PROCESS USING LEAST SQUARES SUPPORT VECTOR MACHINES

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In this paper, Hammerstein model and Nonlinear AutoRegressive with eXogeneous inputs (NARX) model are used to represent tubular heat exchanger. Both models have been identified using least squares support vector machines based algorithms. Both algorithms were able to model the heat exchanger system without requiring any apriori assumptions regarding its structure. The results indicate that the blackbox NARX model outperforms the NARX Hammerstein model in terms of accuracy and precision.

Key words: Hammerstein model, heat exchanger, identification. support vector machine.

1. Introduction

In many engineering processes, heat exchangers are important thermal devices, such as power and chemical plants, oil refineries, gas turbines, boilers, and turbofans, etc. Tubular steam heat exchanger is one of the most common types of heat exchangers. The general function of the tubular steam heat exchanger is to transfer heat from a hot fluid flow to a cold fluid flow, in most cases through an intermediate metallic wall and without moving parts. From a modeling approach, heat exchangers are complex systems involving ill-defined dynamics, nonlinearities and time-varying characteristics ([1]-[5]). The non-linear behavior and complexity of heat exchangers make the control of a heat exchanger a complex process because of many phenomena such as leakage, friction, temperature-dependent flow properties, contact resistance, unknown fluid properties, etc. [6, 7]. The goal of system identification is to find mathematical equation that gives approximation to the actual behavior of a real system [8]. In [9], author gave subjective views on some essential feature in the area of non-linear models identification. Fu and Li [10], surveyed traditional methods of linear system identification and modern methods of nonlinear system identification, fuzzy logic, genetic algorithm, swarm algorithm, multi innovation algorithm and hierarchical algorithms in hopes of bringing benefits to related researchers and engineers. Identification of nonlinear systems is very challenging research area. Having an accurate system model is important but it is not easy to identify. Since the model is an approximation to the true system, there is trade-off between the simplicity of the model and the accuracy of its prediction. Block structure models, series of static nonlinearities and dynamic linear system might be compromise [11].

In this paper, Hammerstein model and Nonlinear AutoRegressive with eXogeneous inputs (NARX) model are used to represent tubular heat exchanger. Hammerstein models, cascade of

memoryless nonlinearity followed by a dynamic linear block is widely used to represent many practical systems [12-14]. Many identification algorithms have been developed for Hammerstein models since Narendra's Method [15]. Lovera et al. [16] proposed a recursive subspace identification algorithm for state space Hammerstein models using least squares support vector machines to estimate the nonlinear part of the system and ordinary least squares for recovering the linear part.

Jalaleddini et al. [17] extended Verhagen identification algorithm for Hammerstein system to estimate directly the coefficient of the basis function expansion of the nonlinearity and the state space model of the linear component and applied to stretch reflex identification. In [18], authors proposed an identification algorithm for Hammerstein systems with a symmetric two segment piecewise linear nonlinearities using improve particle swarm optimization algorithm. Simulation showed that the calculation complexity of the proposed algorithm is less than both the over parameter method and iteration algorithm. Most of these method assumes apriori knowledge about the structure of non linearity. Support vector machines (SVM) and least squares support vector machines (LS-SVMs) have the ability in approximating non linear function without requiring apriori structural information [19]. Goethals et. al. [20] proposed a method for the identification of Hammerstein models based on least squares support vector machines (LS-SVMs).

Leontaritis and Billings introduced Input–output parametric models for non-linear systems called black box Nonlinear AutoRegressive with eXogeneous inputs (NARX) models [21]. NARX model is widely used for identification of nonlinear single input single output systems [22]. Many papers have been published to propose algorithms for modeling and identification of black box NARX systems [23, 24].

In this work, two least squares support vector machines identification algorithms proposed in [20] and [24] are used to identify a Hammerstein model and a black box NARX model for heat exchanger process. The two models are going to be compared with each other in terms of accuracy and precision. The outline of this paper is as follows: Standard least squares support vector machines regression algorithm will be reviewed in Section 2. In Section 3, least squares support vector machines for system identifications are proposed. Section 4 presents process description. In Section 5, concluding remarks are given.

2. Standard Least Squares Support Vector Machines Regression Algorithm

The quadratic ε -insensitive loss function is selected in the least squares support vector machines (LS-SVM) regression. The optimization problem of the LS-SVM regression is formulated as

$$\min J(w, \xi) = \frac{1}{2} w^T w + \frac{c}{2} \sum_{i=1}^N \xi_i^2$$

subject to

$$y_i = w\varphi(x_i) + b + \xi_i, i = 1, \dots, N \quad (1)$$

The Lagrangian is defined as

$$L(w, b, \xi, a, c) = \frac{1}{2} w^T w + \frac{c}{2} \sum_{i=1}^N \xi_i^2 - \sum_{i=1}^N a_i (w\varphi(x_i) + b + \xi_i - y_i) \quad (2)$$

where a_i are Lagrange multipliers.

From the optimality conditions

$$\frac{\partial L}{\partial w} = 0, \frac{\partial L}{\partial b} = 0, \frac{\partial L}{\partial \xi_i} = 0, \frac{\partial L}{\partial a_i} = 0$$

we have

$$\begin{aligned} w &= \sum_{i=1}^N a_i \varphi(x_i), \sum_{i=1}^N a_i = 0, \\ a_i &= c\xi_i, w\varphi(x_i) + b + \xi_i - y_i = 0 \end{aligned} \quad (3)$$

From (3), the optimization problem can be rewritten as

$$\begin{aligned} \begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_1, x_1) + \frac{1}{c} & \cdots & K(x_1, x_l) + \frac{1}{c} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(x_l, x_1) + \frac{1}{c} & \cdots & K(x_l, x_l) + \frac{1}{c} \end{bmatrix} \begin{bmatrix} b \\ a_1 \\ \vdots \\ a_N \end{bmatrix} \\ = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_N \end{bmatrix} \end{aligned} \quad (4)$$

where $K(x_i, x_j)$ is kernel satisfying Mercer's condition **Error! Reference source not found.** defined as $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$

The LS-SVM model is

$$f(x) = \sum_{i=1}^N a_i K(x, x_i) + b \quad (5)$$

3. Least Squares Support Vector Machines for System Identification

This Section reviews two algorithms developed by Ivan Goethals et al. [20], and Tillmann Falck et al. [24]. In the first paper [20], authors proposed a technique for identification of Hammerstein systems. In [24], an identification algorithm for fully black-box NARX models has been considered.

3.1. Identification of Hammerstein Models Using Least Squares Support Vector Machines

The identification approach summarized in this section assumes a model structure of the form

$$y_t = \sum_{i=1}^n a_i y_{t-i} + \sum_{j=1}^m b_j f(u_{t-j}) + e_t, \quad (6)$$

with $u_t, y_t \in \mathbb{R}, \in \mathbb{N}, \{(u_t, y_t)\}$ a set of input and output measurements and e_t the equation error which is assumed to be white and n and m denote the order of the "Autoregressive part" and the "exogeneous part" respectively. The following structure is assumed for the static nonlinearity f :

$$f(u) = w^T \varphi(u) + b_0,$$

Hence, eq. (6) can be rewritten as

$$y_t = \sum_{i=1}^n a_i y_{t-i} + \sum_{j=1}^m b_j (w^T \varphi(u_{t-j}) + b_0) + e_t. \quad (7)$$

The proposed algorithm focuses on finding estimates for the linear parameters $a_i, i = 1, \dots, n$ and $b_j, j = 1, \dots, m$ and the static nonlinearity f .

Algorithm 1 *The algorithm for NARX identification of Hammerstein systems using least squares support vector machines can be summarized as follows*

1. Rewrite eq. (6) as

$$y_t = \sum_{i=1}^n a_i y_{t-i} + \sum_{j=1}^m w_j^T \varphi(u_{t-j}) + d + e_t. \quad (8)$$

2. Find Estimates for $a_i, i = 1, \dots, n$ and d by solving the following set of linear equations

$$\begin{bmatrix} 0 & 0 & 1_{N-r+1}^T & 0 \\ 0 & 0 & \mathcal{Y}_p & 0 \\ 1 & \mathcal{Y}_p^T & \mathcal{K} + c^{-1}I & K^0 \\ 0 & 0 & K^{0T} & 1_N^T K 1_N \cdot I_{m+1} \end{bmatrix} \begin{bmatrix} d \\ a \\ \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \mathcal{Y}_f \\ 0 \end{bmatrix}, \quad (9)$$

where

$$\mathcal{Y}_p = \begin{bmatrix} y_{r-1} & y_r & \cdots & y_{N-1} \\ y_{r-2} & y_{r-1} & \cdots & y_{N-2} \\ \vdots & \vdots & \ddots & \vdots \\ y_{r-n} & y_{r-n+1} & \cdots & y_{N-n} \end{bmatrix},$$

$$\begin{aligned}\mathcal{K}(p, q) &\ll \sum_{j=0}^m K(u_{p+r-j-1}, u_{q+r-j-1}), \\ K^0(p, q) &= \sum_{t=1}^N K(u_t, u_{p+r-q}), \\ \mathbf{y}_f &= \begin{bmatrix} y_r \\ y_{r+1} \\ \vdots \\ y_N \end{bmatrix}\end{aligned}$$

With $r = \max(m, n) + 1$.

3. Obtain estimates for b , and f from rank one approximation of

$$\begin{aligned}&\begin{bmatrix} b_0 \\ \vdots \\ b_m \end{bmatrix} \begin{bmatrix} \hat{f}(u_1) \\ \vdots \\ \hat{f}(u_N) \end{bmatrix}^T \\ &= \begin{bmatrix} \alpha_N & \cdots & \alpha_r & & 0 \\ & \alpha_N & \cdots & \alpha_r & \\ 0 & & \ddots & & \\ & & & \alpha_N & \cdots & \alpha_r \end{bmatrix} \\ &\times \begin{bmatrix} K(N, 1) & K(N, 2) & \cdots & K(N, N) \\ K(N-1, 2) & K(N-1, 2) & \cdots & K(N-1, N) \\ \vdots & \vdots & \ddots & \vdots \\ K(r-m, 1) & K(r-m, 2) & \cdots & K(r-m, N) \end{bmatrix} \\ &+ \begin{bmatrix} \beta_0 \\ \vdots \\ \beta_m \end{bmatrix} \sum_{t=1}^N \begin{bmatrix} K(t, 1) \\ \vdots \\ K(t, N) \end{bmatrix}^T, \tag{10}\end{aligned}$$

with $\hat{f}(u)$ an estimate for $f(u) = f(u) - (1/N) \sum_{t=1}^N f(u_t)$. After obtaining estimates of b_j , estimate \underline{f} for $\sum_{t=1}^N f(u_t)$ can be obtained as

$$\sum_{t=1}^N f(u_t) = \frac{Nd}{\sum_{j=0}^m b_j},$$

hence

$$f(u) = \underline{f}(u) + (1/N) \sum_{t=1}^N f(u_t).$$

4. Use the input sequence $[u_1, u_2, \dots, u_{n-1}]$ and the estimates of the response of the nonlinearity to this input $[f(u_1), f(u_2), \dots, f(u_{n-1})]$, to train a LS-SVM to approximate the nonlinear function f .

3.2. Identification algorithm for fully black-box NARX models

The NARX model is expressed as:

$$y_t = f(y_{t-1}, \dots, y_{t-n}, u_t, u_{t-1}, \dots, u_{t-m}) + e_t. \tag{11}$$

where $y_t \in R$ and $u_t \in R$ denote the measured output and input at time t respectively and $f: R^{n+m+1} \rightarrow R$ is an unknown function. The equation error e_t is assumed to be white noise with zero mean and finite variance.

The function f in eq. (11) is modeled as a least square support vector machine represented in eq. (5). In the sequel a proposed algorithm to estimate the function f is presented.

Algorithm 2 *The algorithm for identification of NARX models using least squares support vector machines can be summarized as follows*

1. Select model orders n and m .
2. Select regularization parameter c and a kernel function K (and its parameters).
3. Solve the linear system in eq. (4)

4. Process Description

The process chosen in this paper is the tubular steam heat exchanger (TSHE). It is one of the most common types of heat exchangers. The general function of the TSHE is to transfer heat from a hot fluid flow to a cold fluid flow, in most cases through an intermediate metallic wall and without moving parts. The basic component of a heat exchanger can be viewed as a tube with one fluid (steam) running through it and another fluid (liquid) flowing outside. The structure of the TSHE is shown in fig. 1, where liquid is heated by pressurized saturated steam through a copper tube.

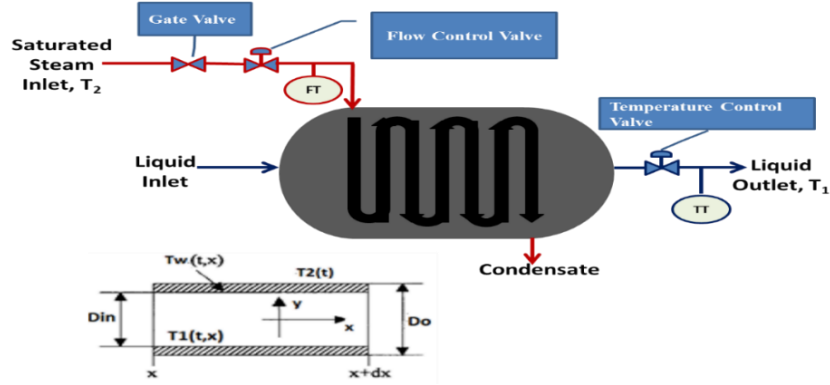


Figure 1: Structure of tubular steam heat exchanger

In this paper, a parallel flow tubes design has been considered. The main motivation for such design is its significance role in various industrial sectors such as process control industry (food manufacturing), superheating processes and thermal power plants [27].

4.1. Mathematical Model of Tubular Steam Heat Exchanger

A mathematical model of the tubular steam heat exchanger, shown in fig. 1, is presented in this section. The water is heated by pressurized saturated steam through a copper tube. The controlled variable is the outlet liquid temperature, $\vartheta_{10}(t)$. Among the input variables, the liquid flow rate, $q(t)$, is selected as the control variable, whereas the steam temperature, $\vartheta_s(t)$, and the inlet liquid temperature, $\vartheta_{li}(t)$ are disturbances. The tube is described by a linear coordinate x , which measures the distance of a generic section from the inlet. Here we assume that the liquid and metal temperatures (ϑ_1 and ϑ_m) are functions only of time and the axial coordinate x , whereas the saturated steam temperature $\vartheta_s(t)$ is uniform and independent of the shape of the tube. D_1 , and D_2 , are the internal and the external diameter of the tube, respectively. The liquid speed, $v(t) = q(t)/\mu_1$, where $q(t)$ is the liquid flow rate and μ_1 is the liquid density, is assumed to be uniform in the tube. The process equations due to [25] is given by:

$$\begin{cases} \tau_1 \frac{\partial \vartheta_1(t,x)}{\partial t} + \tau_1 v(t) \frac{\partial \vartheta_1(t,x)}{\partial x} + \vartheta_1(t,x) - \vartheta_m(t,x) = 0 \\ T_m \frac{\partial \vartheta_m(t,x)}{\partial t} + \beta [\vartheta_m(t,x) - \vartheta_1(t,x)] + \vartheta_m(t,x) - \vartheta_s(t,x) = 0 \end{cases} \quad (12)$$

the coefficients τ_1 , T_m and β are computed as follows:

$$\tau_1 = \frac{\mu_1 c_1}{\alpha_1 \pi D_1}, T_m = \frac{\mu_m c_m}{\alpha_s \pi D_s}, \beta = \frac{\alpha_1 D_1}{\alpha_s D_s},$$

where μ_1 and μ_m are linear densities (mass per length unit), c_1 and c_m are specific heats, α_1 is the liquid/metal heat transfer coefficient and α_m is the steam/metal heat transfer coefficient. Assuming

that the specific heats c_1 and c_m are constant, coefficient T_m is also constant, whereas τ_1 and β depend on the liquid speed $v(t)$ through tube with coefficient α_1 according to [26]:

$$\alpha_1 = Kv^\mu, \mu = 0.8.$$

The quantitative features of the considered heat exchanger in this paper are defined as follows: The tube length in the heat exchanger where the steam flows through is 2.44 meter, with an inner diameter $D_1 = 0.0547$ m and outer diameter $D_s = 0.0613$ m. The nominal heat transfer coefficients $\bar{\alpha}_1 = 754 [\text{Jm}^{-2}\text{s}^{-1}\text{°C}^{-1}]$ and $\bar{\alpha}_s = 3510 [\text{Jm}^{-2}\text{s}^{-1}\text{°C}^{-1}]$, the specific heats are $c_1=1 [\text{kcalkg}^{-1}\text{°C}^{-1}]$ and $c_m = 0.094 [\text{kcalkg}^{-1}\text{°C}^{-1}]$ respectively. The linear densities (mass per length unit) are given by 0.223 and 0.532 $[\text{kgm}^{-1}]$ [27].

4.2. LSSVM Modeling of Tubular Steam Heat Exchanger

To test performance of the proposed algorithm, the Heat Exchanger system presented in [27] is considered. The data were downloaded from the DAISY data base for system identification, (see [28]). The data were created as follows: the steady-state corresponding to $\bar{v} = 0.3\text{m/s}$, $\bar{\vartheta}_{1i} = 65^\circ\text{C}$, $\bar{\vartheta}_{1u} = 98.765^\circ\text{C}$, $\bar{\vartheta}_v = 120^\circ\text{C}$ is taken as the nominal point. A sample of 4000 input-output data points was generated at the rate of 1 Hz. The input signal $u(k)$ is made up of 100 steady-state samples in the nominal point, followed by 100 Gaussian distributed samples centred on the nominal steady-state speed, 600 beta-distributed samples with $a = 2.142, b = 1.415$, weighted towards low speed values, 1200 beta-distributed samples with $a = 1.621, b = 3.829$, which privilege high speeds, and finally 2000 uniformly distributed samples. The disturbances ϑ_{1i} and ϑ_s , are kept constant and equal to their nominal values. The first 1000 samples were reserved for testing and the rest for training. The training and testing data sets are shown in figs. 2 and 3 respectively.

The NARX Hammerstein model LSSVM identification algorithm presented in Section 3.1, and the LSSVM identification algorithm for fully Black-box NARX model presented in Section 3.2 were employed to the training data. The LSSVM hyperparameters and the NARX orders (n and m) were chosen based on cross-validation method.

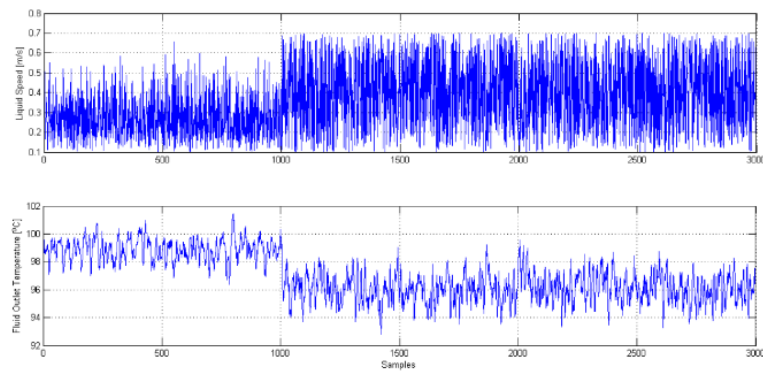


Figure 2: Training data

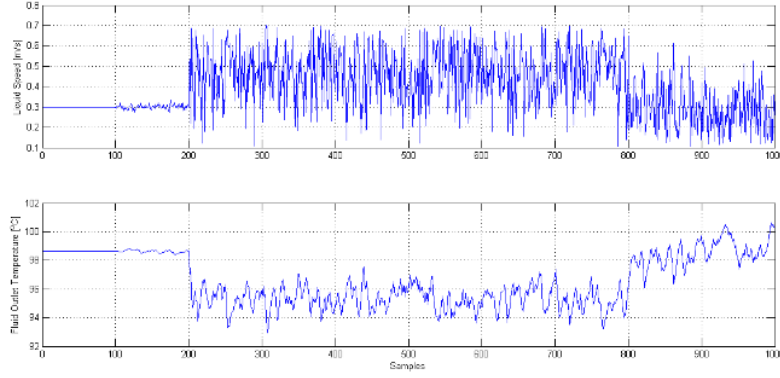


Figure 3: Testing data

4.2.1. Case 1: The NARX Hammerstein Model

The NARX Hammerstein model LSSVM identification algorithm presented in Section 3.1 is applied to the training data. The hyperparameters governing the algorithm were selected based on cross validation test as follows. The ARX orders were selected as $n = 6$ and $m = 0$ as presented in tab. 1 and the LSSVM hyperparameters were chosen to be $C = 0.1$, and $\sigma = 0.01$ as shown in tab. 2. fig. 4 shows Hammerstein model identification algorithm estimate together with measured output for the test data. The identified model accounted for 80.93 percent of the actual output variance.

Table 1: Case 1: RMSE between true and estimated output for test data set using various values for ARX orders (n and m). The other hyperparameters were fixed as $C=10$ and $\sigma=0.1$

C	σ	n	m	RMSE
10	0.01	5	0	11.06
			6	10.69
			7	10.81
			8	10.93
10	0.1	6	0	10.69
			1	10.69
			2	11.30

Table 2: Case 1: RMSE between true and estimated output for test data set using various values of LSSVM hyperparameters were fixed as C and σ . The ARX orders were fixed as $n=6$ and $m=0$

C	σ	n	m	RMSE
0.01	0.01	6	0	14.72
0.1				10.56
1				10.74
10				10.69
100				10.70
0.1	0.01	6	0	10.56
	0.1			11.06
	1			13.13
	10			30.20

4.2.2. Comparison between Case 1 and Case 2

The LSSVM identification algorithm for fully black-box NARX model presented in Section 3.2 is employed to the training data. The hyperparameters were chosen based on cross-validation method which resulted in $C = 10000$, and $\sigma = 100$ as shown in tab. 4. The NARX orders n and m were chosen to be 9 and 6 respectively (see tab. 3). The black-box NARX model identification algorithm estimate together with measured output for the test data is shown in fig. 5. The algorithm gave 97.57 percent fit of the identified model to the testing data.

Table 3: Case 2: RMSE between true and estimated output for test data set using various values for ARX orders (n and m). The other hyperparameters were fixed as $C=10$ and $\sigma=10$

C	σ	n	m	RMSE
10	10	7	0	4.93
				4.88
				4.77
				4.78
				4.82
10	10	9	4	2.87
			5	2.42
			6	2.42
			7	2.54

Table 4: Case 2: RMSE between true and estimated output for test data set using various values of LSSVM hyperparameters were fixed as C and σ . The ARX orders were fixed as $n = 9$ and $m = 6$

C	σ	n	m	RMSE
0.01	10	9	6	23.90
	100			18.96
	1000			39.76
100	100	9	6	2.13
1000				1.56
10000				1.35
100000				1.37

4.2.3. Comparison between Case 1 and Case 2

Table 5 represents statistical measures of performance of NARX Hammerstein model and black-box NARX model. The performance measures which are used to evaluate the two cases are defined as:

1. Sum Squared Error (SSE) of testing samples ($SSE = \sum_{i=1}^N (y_i - \hat{y}_i)^2$). Where y_i , and \hat{y}_i denote the measured and estimated outputs respectively.
2. (SSE/SST), which is defined as the ratio between sum squared error and sum squared deviation of testing samples ($SST = \sum_{i=1}^N (y_i - \bar{y})^2$). Where \bar{y} denotes the arithmetic mean of the measured output.
3. (SSR/SST), which is defined as the ratio between sum squared deviation that can be explained by the estimator and sum squared deviation of testing samples ($SSR = \sum_{i=1}^N (\hat{y}_i - \bar{y})^2$).
4. Percent fit = $100 \left(1 - \frac{\|y - \hat{y}\|}{\|y - \bar{y}\|} \right)$.

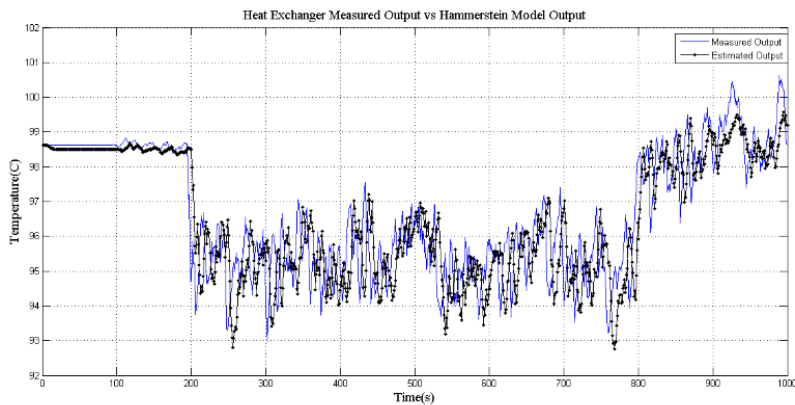


Figure 4: Outlet temperature of the simulated process (continuous line) and the Hammerstein model prediction (dashed).

Table 5: SSE, SSE/SST, SSR/SST, and Percent Fit of Case 1 and Case 2

Data set	Regressor	SSE	SSE/SST	SSR/SST	Percent Fit
Heat Exchanger	Case 1	111.55	0.0364	0.9854	80.93
	Case 2	1.81	5.93e-4	0.9967	97.57

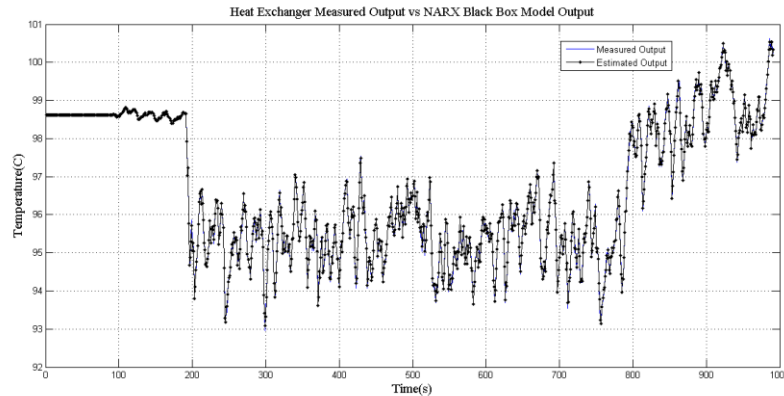


Figure 5: Outlet temperature of the simulated process (continuous line) and the Black box NARX model prediction (dashed).

It is important to note that the smaller SSE, the better the approximating function fits the data. Also, a lower value of SSE/SST reflects precision in agreement between the estimated and regressor values, while higher value of SSR/SST shows higher statistical information being accounted by regressor. Moreover, the higher value of percent fit indicates the better match between the actual system and the identified model. It is clear from tab. 5 that the black-box NARX model outperforms the NARX Hammerstein model in all aspects.

5. Conclusion

In this paper, two models have been used to represent tubular steam heat exchanger, black-box NARX model and NARX Hammerstein model. Both models have been identified using least squares support vector machines based algorithms. Both algorithms were able to model the heat exchanger system without requiring any apriori assumptions regarding its structure. The results indicated that the black-box NARX model outperforms the NARX Hammerstein model in terms of accuracy and precision.

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Nomenclatures

c_1, c_m - specific heats [$\text{kcal kg}^{-1} \text{ } ^\circ\text{C}^{-1}$]	NARX- Nonlinear AutoRegressive with eXogeneous inputs
D_1, D_s -inner and outer diameters [m]	SVM Support vector machines
m- Exegeonous part order[-]	TSHE- tubular steam heat exchanger

n – Autoregressive part order [-]
 RMSE – Root Mean Square Error [-]
 SST - sum squared deviation [-]
 SSE - Sum Squared Error [-]
 SSR - sum squared deviation [-]
 $v(t)$ – Liquid speed [m/s]

Abbreviation

LS-SVMs - least squares support vector machines

Greek letters

α_1 - liquid/metal heat transfer coefficient [$\text{Jm}^{-2}\text{s}^{-1}\text{C}^{-1}$]
 α_m -steam/metal heat transfer coefficient [$\text{Jm}^{-2}\text{s}^{-1}\text{C}^{-1}$]
 ϑ_1 - Liquid temperatures [°C]
 $\vartheta_{10}(t)$ - Outlet liquid temperature [°C]
 $\vartheta_s(t)$ - Steam temperature [°C]
 ϑ_m – metal temperatures [°C]
 $\vartheta_{li}(t)$ - inlet liquid temperature [°C]

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