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Recursive Least Square Identification of Heat Exchanger System using Block-Structured Models

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***Abstract*—This study provides a recursive parametric identification scheme for a liquid-saturated steam heat exchanger system. The recursive identification scheme uses block-structured Wiener and Hammerstein model as model structure and recursive least square estimation scheme as the parameter estimation method. The estimated block-oriented model provides higher accuracy of estimation than linear models provided in the literature. From the simulation results, it is observed that the Wiener model can provide 88% goodness-of-FIT, whereas Hammerstein model can provide 96% goodness-of-FIT using the said technique.**

***Index Terms*—Wiener model, Hammerstein model, Heat exchanger, recursive parameter estimation**

I. Introduction

Chemical processing plants are generally complex, multi-input and multi-output, ill-conditioned systems (higher condition number) and non-linear entities with inherent dead time. Efficient control of chemical processing plants is essential because of the following reasons (a) improves the quality of the end product, (b) decreases the number of shut-down, (c) provides an economic advantage, and (d) provides environmental and operational safety. A control engineer faces different challenges while designing a model-based control mechanism for the chemical processing plants. One of the most challenging aspects of model-based control system design is to obtain an accurate mathematical model of the plant. A precise plant model is not always available due to various factors such as the complexity of the plant, interaction between state variables, transport delay, measurement noise, and disturbance. Models of a chemical plant can be classified as (a) theoretical model, (b) empirical model, and (c) semi-empirical model. The theoretical model provides physical insight into the process, and these models are applicable over a wide range of operating conditions. But building theoretical models are expensive and time and computationally intensive work. The second type of model is an empirical model, which is easier to build than the theoretical model. Still, the main problem in the empirical model is the lack of extrapolation capability. A semi-empirical model is the combination of the theoretical model and the empirical model [1].

The first principle modeling technique is the systematic approach of building a mathematical model for a system. The first principle modeling technique uses ordinary differential equation to capture nonlinear relationship among the process variable and it considers three different types of parameters i.e. geometrical, physical, and phenomenological. Geometrical and physical parameters are deduced from operational documents of the plant setup whereas phenomenological parameters are estimated from the known parameters [2]. For chemical process modeling, the first principle model uses the principle of mass balance and energy balance equations to capture the dynamics. These transport mechanisms find the relationship between state variable, manipulated variable and disturbance variable. To reduce the modeling error and improve the accuracy, the models developed using first principle approach is adjusted using the trial-error method. Due to the inherent limitations of the trial and error method, the least square approximation technique and its different variants are used [3], [4]. Though the first principle model provides a greater insight into the system dynamics, it is an expensive procedure as it requires expert knowledge to derive an accurate mathematical model from transport phenomena and physical laws.

One of the other approaches of modeling, is known as data-driven modeling technique (also called as data-based system identification technique) where input and output data of the system is used to find a suitable mathematical model. There are two basic types of system identification i.e. parametric system identification and non-parametric system identification. In the parametric system identification approach, a known mathematical model is considered, and a parameter estimation technique is used to build a mathematical model of acceptable accuracy [5], [6]. A significant amount of research has been going on to implement different system identification approaches in chemical processing plants. A detailed review of different system identification and control schemes of a nonlinear physical system have been provided in [7]. For a complex technical system operating under an operational point of view, the estimation of the different state variable is one of the crucial tasks which has been thoroughly discussed in [8]. System identification of any chemical plant is carried out either in an open-loop or in a closed-loop environment. In many real-world problems, a controller is required to keep the plant in a steady-state condition; therefore, closed-loop system identification is more preferred than open-loop identification. In closed-loop identification, the correlation between the input signal and undesired noise signal creates a significant challenge in estimating parameters. There are different methods to overcome such issues. In the direct method, the feedback loop is neglected, and the estimation method is applied directly to the open-loop measurement data while properly describing the noise model. In the indirect method, a linear control law is used, and the open-loop plant model is estimated from the closed-loop measurement data. In the joint-input-output method, exact knowledge of the controller is not required [9], [10]. In the closed-loop system identification approach, a-*priori* knowledge of pole-zero cancellation, time delay, polynomial order, and proper external excitation signal is required. The parameter-based closed-loop system identification approach explicitly considers the system's parameters and doesn't consider the identifiability of the system [11]. For a complex system with strategic significance, fuzzy-based identification scheme is used to find the operational status of different state variables [12], [13]. System identification of a process helps to design a robust controller as well as helps to estimate fault in the system [14] [15].

Heat exchangers are one of the most critical components in the chemical industry, which performs heat transfer operation between two fluids through an intermediate solid surface. Mechanical design, geometry, and classical modeling techniques of heat exchangers are well documented in standard textbooks [16]. Mathematical modeling of heat exchangers can be accomplished by coupled hyperbolic and parabolic partial differential equations [17]. Another way to model the heat exchangers can be done using distributed parameter modeling technique where the output variables are a function of time and position. The conventional methods of modeling are time and computational intensive in nature, therefore, data-based modeling approaches are applied to obtain a mathematical model of the system. In data based modeling scheme, a parameter estimation algorithm is used to estimate the parameters of the system. For a sampled-data system with uniform sampling time, maximum likelihood estimation method, prediction error method [18], instrumental variable method [19], [20], and subspace identification methods [21] are used for parameter estimation. In [22], the authors have compared the performance of different estimation methods such as maximum-likelihood, instrumental variable and refined instrumental variable approach to obtain a time-continuous model. A survey of different parameter estimation techniques of continuous-time models is available in [23]. The parameter estimation aspect of a multi-stage, multi-load demand experimental refrigeration plant has been addressed in [24]. Stochastic identification of heat exchangers has been reported in [25]. Recently, a two-step system identification technique is proposed for estimating physical parameters of the partial differential equations governing the dynamical behavior of a co-current flow heat exchanger from input-output dataset sampled w.r.t time and space, respectively [26]. Bilinear system identification algorithm based on the uniformly convergent sequence of the linear deterministic, stochastic state-space model has been presented in [27]. The said identification algorithm is based on Picard decomposition, and it is applied to a heat exchanger case study. Linear parameter varying identification of cross-flow heat exchanger has been discussed in [28]. Use of programmable logic controller and National Instruments Data Acquisition System along with LabVIEW has been used for real-time open-loop system identification and control of heat exchanger system in [29], [30]. In [31], the authors provided the system identification of a pilot-scale heat exchanger system and computed the state-space analysis of the plant. Identification of liquid-saturated steam heat exchanger using ARMAX model has been discussed in [32], where extended least square method is used for parameter estimation. Extended Kalman filter [33] and statistical approach [34] to estimate the dynamics of heat exchanger systems have been presented in the literature. Parametric system identification of a heat-exchanger system using linear models (ARX, ARMAX, OE, and BJ) has been studied in [35]. As system identification of nonlinear plants are complicated in nature, some authors used artificial neural networks [36]–[38]. In [39], the authors developed time-lagged recurrent neural network with gamma memory to learn the dynamics of liquid saturated steam heat exchanger system. One of the major limitation of neural network-based identification procedure is the need for training, testing, and validation of the data which takes considerable time.

As heat exchanger is a nonlinear entity, the nonlinear models have to be investigated in the parametric system identification step. Block-oriented model (Wiener and Hammerstein models) are the special type of nonlinear model which posses the functionality of both linear as well as nonlinear models. Different parameter estimation techniques such as the instrumental variable method have been used for continuous-time model identification of hammerstein-wiener model in [40]. In [35], the authors provided a procedure that uses linear time series models and prediction error method to identify the dynamics of heat exchanger, but the said technique is not recursive and the linear models do not always justify the actual dynamics of complicated nonlinear dynamic system.

Therefore, this paper provides recursive parametric system identification of heat exchanger system using Wiener model and Hammerstein model using recursive least square identification technique. The online identification scheme used on the block-oriented model provides reasonable model accuracy compared to the offline identification scheme used on linear models in [35]. Parameter estimation of the Wiener model using the least mean square (LMS) method has been discussed in [41]. The model validation is performed using goodness-to-FIT measure, and the Wiener and Hammerstein models provide better FIT% than linear models shown in [35].

This paper is structured as follows. Section II provides the problem formulation. Section III provides the details of system identification where the Wiener and Hammerstein model has been discussed. Section IV presents the simulation results whereas Section V concludes the paper.

II. Problem Formulation

Figure 1 presents the cascade control and system identification concept of an industrial heat exchanger system. Considering the heat exchanger as a control problem, the controlled variable is output temperature, manipulated variable is hot water or saturated steam flow rate and disturbance variable is process fluid flow rate. In cascade control, two control loops are considered. The outer-loop or primary loop is for control of outlet temperature whereas secondary loop is used for control of flow of manipulated variable. The temperature and flow rate of input fluid is considered as constant. The output temperature is measured using a 3-wire RTD and with the help of temperature transmitter TT-101, temperature data is provided to the temperature controller TIC-101. The output of temperature controller is considered as the reference to the flow controller FIC-100. The flow rate of manipulated variable is measured using orifice plate and flow transmitter FT-100. The flow controller FIC-100 provides actuating signal (4–20 mA) to the control valve via a current-pressure converter. The current-pressure converter converts the actuating signal (4–20 mA) to proper pneumatic signal (3–15 psig).

For system identification purpose, an identification enable signal is initiated at any point of time. Once the identification enable is initiated a high frequency signal is injected to the system without causing any major disturbance to the normal closed-loop operation of the process. The input and corresponding output data is acquired by the system identification module. Once the data is acquired, a model structure is used and parameters of the model needs to be estimated and model needs to be validated.

III. System Identification

Figure 2 provides the basic flow chart of system identification. The first step of parametric system identification is the design of identification experiment. In this step a persistently excited signal is injected in to the process for a certain duration to excite the whole range of dynamics of the said system. Necessary precautions need to be taken such that while the injection of the signal is done, the normal process output shouldn't be effected. So design of identification experiment is one of the crucial phase of system identification experiment. System identification can be enabled at any moment of the process operation. Once the corresponding output signal is acquired at a particular sampling time, the data is checked for required quality and pre-processing of the data is carried out. Cross-correlation analysis is carried out to find whether there is sufficient impact of process input on the corresponding process output. Once the input and output dataset are obtained, a proper model structure

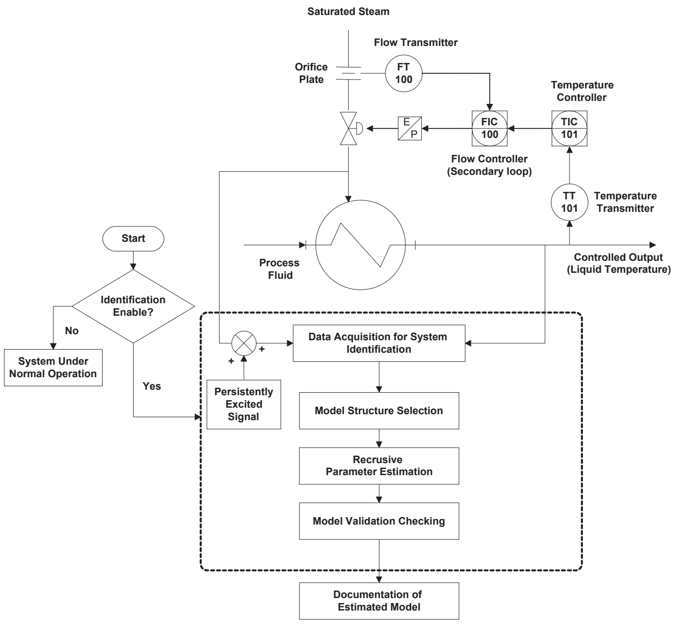

Fig. 1: Cascade Control and System Identification of Heat Exchanger System

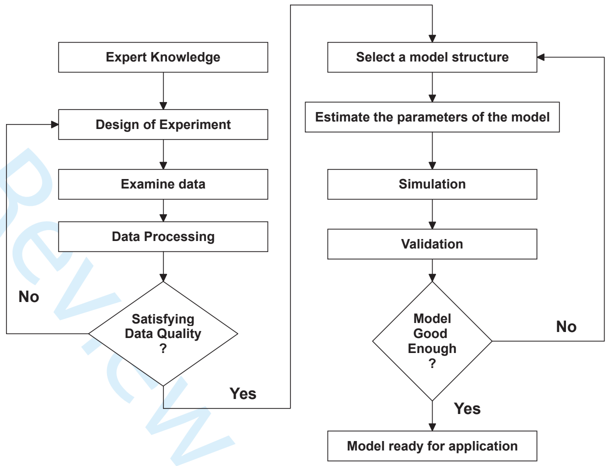

Fig. 2: Flow chart of parametric system identification [5]

is selected using a-*priori* knowledge which is then used for construction of estimated model. For the purpose of parameter estimation, different estimation schemes are used which may be recursive or non-recursive in nature. The estimated model is checked for validity in the model validation step.

The following subsection provides the preliminary idea about some widely used block-oriented models [42].

A. *Wiener model*

Fig. 3 illustrates the block diagram of Wiener model which comprises of a nonlinear function and a linear time invariant (LTI) model.

$F(\cdot) : \mathbb{R} \to \mathbb{R}$ represents the nonlinearities. $G(q)$ is the LTI subsystem, $u(t)$ and $y(t)$ denote input and output respectively. $v(t)$ represents stochastic white Gaussian noise. The mean value of the gaussian noise is 0. $G(q)$ can have any form

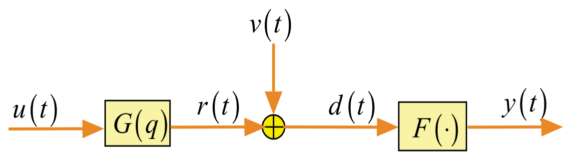

Fig. 3: Block diagram of Wiener model [43]

such as rational functions, Laguerre functions etc where q is a forward shift operator

The output of LTI system $r(t)$ can be expressed as

$$r(t) = \frac{\beta(q)}{\alpha(q)} u(t). \tag{1}$$

$$y(t) = F(d(t)), \tag{2}$$

where

$$d(t) = r(t) + v(t) = \frac{\beta(q)}{\alpha(q)} u(t) + v(t). \tag{3}$$

$$\begin{aligned} \alpha(q) &= 1 + \alpha_1 q^{-1} + \alpha_2 q^{-2} + \ldots + \alpha_{n_\alpha} q^{-n_\alpha} \\ \beta(q) &= \beta_1 z^{-1} + \beta_2 q^{-2} + \ldots + \beta_{n_\beta} q^{-n_\beta}. \end{aligned} \tag{4}$$

The orders n_α and n_β are assumed to be known, and $F(\cdot)$ is assumed to be invertible. The relationship between $d(t)$ and $y(t)$ is

$$d(t) = F^{-1}(y(t)) = \sum_{k=1}^{m} c_k f_k(y(t)), \tag{5}$$

where $f_k(\cdot)$ are the nonlinear basis functions correspond to nonlinearity of the system. The order of nonlinearity m is considered to be foreknown. Using Eq. (4) in (3),

$$d(t) = \sum_{i=1}^{n_\alpha} \alpha_i [v(t-i) - d(t-i)] + \sum_{j=1}^{n_\beta} \beta_i u(t-j) + v(t). \tag{6}$$

From Eq. (5) and (6)

$$\begin{aligned} \sum_{k=1}^{m} c_k f_k(y(t)) &= \sum_{i=1}^{n_\alpha} \alpha_i [v(t-i) - d(t-i)] \\ &\quad + \sum_{j=1}^{n_\beta} \beta_i u(t-j) + v(t). \end{aligned} \tag{7}$$

Assuming $c_1 = 1$, Eq.(7) can be rewritten as

$$\begin{aligned} f_1(y(t)) &= \sum_{i=1}^{n_\alpha} \alpha_i [v(t-i) - d(t-i)] + \sum_{j=1}^{n_\beta} \beta_i u(t-j) \\ &\quad - \sum_{k=2}^{m} c_k f_k(y(t)) + v(t). \end{aligned} \tag{8}$$

Eq. (8) is in the linear regression form and can be written in a simplified form as

$$y(t) = \bar{\phi}^T(t)\bar{\theta} + v(t) \tag{9}$$

where

$$\bar{\theta} = \left[\bar{\theta}_1^T, c_2, \ldots, c_m\right]^T \in \mathbb{R}^{n = n_\alpha + n_\beta + m - 1} \tag{10}$$

$$\bar{\theta}_1 = \left[\alpha_1, \ldots, \alpha_{n_\alpha}, \beta_1, \ldots, \beta_{n_\beta}\right]^T \in \mathbb{R}^{n_1 = n_\alpha + n_\beta} \tag{11}$$

$$\bar{\phi}(t) = \left[\bar{\phi}_1^T(t), -f_2(y(t)), \ldots, -f_m(y(t))\right] \in \mathbb{R}^n \tag{12}$$

$$\bar{\phi}_1(t) = \begin{bmatrix} v(t-1) - d(t-1), .., v(t-n_\alpha) \\ -d(t-n_\alpha), u(t-1), .., u(t-n_\beta) \end{bmatrix} \in \mathbb{R}^{n_1}. \tag{13}$$

Let's assume that the nonlinear basis functions are of polynomial type as they are simple and easier to be analyzed. So, the generalized regression vector in (12) can be expressed as

$$\bar{\phi}(t) = \left[\bar{\phi}_1^T(t), -y^2(t), \ldots, -y^m(t)\right] \in \mathbb{R}^n \tag{14}$$

From Eq. (6), (11) and (13), the intermediate unknown variable $d(t)$ can be expressed as

$$d(t) = \bar{\phi}_1^T(t)\bar{\theta}_1 + v(t). \tag{15}$$

Eq.(15) represents linear regression form of intermediate variable

The quadratic cost function on prediction error for a data length of L is

$$J(\bar{\theta}) = \sum_{t=1}^{L} \left(y(t) - \bar{\phi}^T(t)\bar{\theta}\right)^2. \tag{16}$$

This model is simple to implement, also it has the ability to capture complex nonlinear dynamics of the systems and is suitable for control design [44]. The objective is to find the model parameter vector $\bar{\theta}$ in an adaptive recursive way so as to track and control the system adaptively.

The recursive least square (RLS) update expression can be obtained recursively by the minimization of quadratic problem on prediction error as given below

$$\bar{\theta}(t) = \arg\min_{\bar{\theta}} \sum_{m=0}^{t} \lambda^{t-m} \left(y(m) - \bar{\phi}^T(m)\bar{\theta}\right)^2 \tag{17}$$

where λ is the forgetting factor which is basically used to practically compromise between tracking and misadjustment [45]. The Wiener optimal solution at any instant of time is given by

$$\bar{\theta}(t) = R^{-1}(t) P(t), \tag{18}$$

where $R(t) = \sum_{m=0}^{t} \lambda^{t-m} \bar{\phi}(m) \bar{\phi}^T(m)$,

$P(t) = \sum_{m=0}^{t} \lambda^{t-m} y(m) \bar{\phi}(m)$.

With the use of inversion lemma [46, pg.571], the recursive update of R^{-1} can be expressed as

$$R^{-1}(t) = \lambda^{-1} R^{-1}(t-1) - \lambda^{-1} k(t) \bar{\phi}^T(t) R^{-1}(t-1), \tag{19}$$

where

$$k(t) = \frac{\lambda^{-1} R^{-1}(t-1)\bar{\phi}(t)}{1 + \lambda^{-1}\bar{\phi}^T(t) R^{-1}(t-1)\bar{\phi}(t)}$$

The RLS update expression to recursively estimate $\bar{\theta}$ can be given as [47]

$$\bar{\theta}(t+1) = \bar{\theta}(t) + k(t)\left(y(t) - \bar{\theta}^T(t)\bar{\phi}(t)\right). \tag{20}$$

B. Hammerstein Model

Hammerstein model has an LTI subsystem block and static nonlinear function block. The cascade order of these blocks are reversed to that of Wiener model as shown in Fig. 4. The relationship between input and output of a traditional

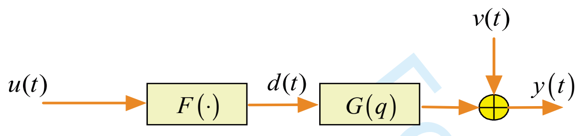

Fig. 4: Hammerstein nonlinear system.

Hammerstein model is given as

$$y(t) = G(q)\,d(t) + v(t) = G(q)\,F(u(t)) + v(t) \tag{21}$$

where $u(t) \in \mathbb{R}$ represents the modified temporal input, $y(t) \in \mathbb{R}$ is the temporal output, $d(t) \in \mathbb{R}$ denoting the intermediate variable and $v(t) \in \mathbb{R}^r$ is the process noise at any particular instant $'t'$. Assuming the transfer function matrix of LTI dynamical system has the form

$$G(q) = \frac{b(q)}{a(q)} \tag{22}$$

where

$$\begin{aligned} a(q) &= 1 + a_1 q^{-1} + a_2 q^{-2} + \dots + a_{n_y} q^{-n_y} \\ b(q) &= b_1 q^{-1} + b_2 q^{-2} + \dots + b_{n_u} q^{-n_u} \end{aligned} \tag{23}$$

with $a_i \ (i = 1, \dots, n_y)$ and $b_j \ (j = 1, \dots, n_u)$ are unknown parameter having input and output lags of n_u and n_y respectively. Let us assume that the static nonlinear function $F(u(t))$ can be approximated as

$$d(t) = F(u(t)) = \sum_{k=1}^{n_f} c_k f_k(u(t)) \tag{24}$$

where $f_k(\cdot) : \mathbb{R} \to \mathbb{R}$ represent the nonlinear basis functions, which can be polynomials type, radial basis functions etc. $c_k \in \mathbb{R}$ are unknown parameter coefficients associated to nonlinear basis functions and n_f are the total number of nonlinear basis functions.

With the use of (22), (23) and (24) in (21), we can write it as

$$\begin{aligned} y(t) = &\sum_{i=1}^{n_y} a_i\left(v(t-i) - y(t-i)\right) \\ &+ \sum_{j=1}^{n_u} b_j \sum_{k=1}^{n_f} c_k f_k\left(u(t-j)\right) + v(t) \end{aligned} \tag{25}$$

.

Define $\rho_{jk} = b_j c_k \in \mathbb{R}$, hence (25) can be rewritten as

$$\begin{aligned} y(t) = &\sum_{i=1}^{n_y} a_i\left(v(t-i) - y(t-i)\right) \\ &+ \sum_{j=1}^{n_u}\sum_{k=1}^{n_f} \rho_{jk} f_k\left(u(t-j)\right) + v(t). \end{aligned} \tag{26}$$

Now, let us define

$$\bar{\varkappa} = \begin{bmatrix} a_1, \dots, a_{n_y}, \rho_{11}, \dots \rho_{n_u 1}, \rho_{12}, \dots, \rho_{n_u 2}, \\ \dots\dots\dots, \rho_{1 n_f}, \dots, \rho_{n_u n_f} \end{bmatrix}^T \in \mathbb{R}^{(n_y + n_u n_f)} \tag{27}$$

$$\bar{\psi}(t) = \begin{bmatrix} (v(t-1) - y(t-1)), \dots, \\ (v(t-n_y) - y(t-n_y)), \\ f_1(u(t-1)), \dots, f_1(u(t-n_u)), \\ f_2(u(t-1)), \dots, f_2(u(t-n_u)), \dots. \\ \dots, f_{n_f}(u(t-1)), \dots, f_{n_f}(u(t-n_u)) \end{bmatrix}^T \in \mathbb{R}^{(n_y + n_u n_f)} \tag{28}$$

hence expression (26) can be written as

$$y(t) = \bar{\varkappa}^T \bar{\psi}(t) + v(t) \tag{29}$$

The aim is to adaptively estimate parameter vectors $\bar{\varkappa}$ in a recursive manner. The RLS update expression can be obtained recursively by the minimization of quadratic problem on prediction error as given below

$$\bar{\varkappa}(t) = \arg\min_{\bar{\varkappa}} \sum_{m=0}^{t} \lambda^{t-m}\left(y(m) - \bar{\psi}^T(m)\bar{\varkappa}\right)^2 \tag{30}$$

where λ is the forgetting factor which is basically used to practically compromise between tracking and misadjustment [45]. The Wiener optimal solution at any instant of time is given by

$$\bar{\varkappa}(t) = R^{-1}(t)\,P(t), \tag{31}$$

where $R(t) = \sum_{m=0}^{t} \lambda^{t-m}\bar{\phi}(m)\,\bar{\phi}^T(m)$,
$P(t) = \sum_{m=0}^{t} \lambda^{t-m} y(m)\,\bar{\phi}(m)$.

With the use of inversion lemma [46, pg.571], the recursive update of R^{-1} can be expressed as

$$R^{-1}(t) = \lambda^{-1} R^{-1}(t-1) - \lambda^{-1} k(t)\,\bar{\phi}^T(t)\,R^{-1}(t-1), \tag{32}$$

where

$$k(t) = \frac{\lambda^{-1} R^{-1}(t-1)\bar{\phi}(t)}{1 + \lambda^{-1}\bar{\phi}^T(t) R^{-1}(t-1)\bar{\phi}(t)}$$

The RLS update expression to recursively estimate $\bar{\varkappa}$ can be given as [47]

$$\bar{\varkappa}(t+1) = \bar{\varkappa}(t) + k(t)\left(y(t) - \bar{\varkappa}^T(t)\bar{\phi}(t)\right). \tag{33}$$

C. Cross Validation

As the overall dataset is sufficiently large, it is subdivided in to two different subsets such as estimation data and validation data. Estimation data is used to estimate the model whereas validation data is not used to build any model. The performance of the estimated model is evaluated by computing mean square error (MSE) on the validation data only. Final prediction error (FPE) and goodness to FIT are two the well-known cross validation indices which are represented as

$$\mathrm{FPE} = \left| \frac{1}{N} \sum_{1}^{N} e(k,\theta)\left(e(k,\theta)\right)^{T} \right| \left(\frac{1+\frac{d_m}{N}}{1-\frac{d_m}{N}} \right) \tag{34}$$

where estimated parameters is d_m and $e(k)$ denotes the prediction error vector and θ represents estimated parameters.

$$\mathrm{FIT} = 100\left(1 - \frac{\sqrt{\sum_{k=1}^{N}\left(y(k)-\hat{y}(k)\right)^2}}{\sqrt{\sum_{k=1}^{N}\left(y(k)-\bar{y}\right)^2}}\right) \tag{35}$$

where measured output of the system is denoted as $y(k)$ and predicted output of the estimated model is denoted as $\hat{y}(k)$. Mean value of the measured data is denoted as $\bar{y}$

IV. Simulation Results

For simulation analysis of identification algorithm, a liquid-saturated steam heat exchanger is considered. In this heat exchanger system, the water is heated by pressurized saturated steam via a copper tube. The heat exchanger system is considered as a benchmark problem of nonlinear control system because the dynamics of the system depicts non-minimum phase behavior.

The input and output data which is considered for system identification purpose is taken from DaISy (Database for the identification of Systems) data repository. Experimental data of heat exchanger system considered in this case comprises of 5000 data samples and the sampling rate is 0.0016667 [38], [48]. The experimental data is represented in Figure 5.

Figure 6 presents the prediction output of Wiener model using RLS estimation technique. For wiener model, the RLS estimation technique provides a model validation FIT % of 88.0619 %. Figure 7 presents the prediction output of Hammerstein model using RLS technique. In Hammerstein model, the model validation FIT % is 96.6232 %. In [41], the authors considered the same heat exchanger case study and developed different linear models (ARX, ARMAX, OE and BJ) using prediction error method. But the validation FIT% is not accurate as the paper only considers the linear dynamics of the model. The other major limitation of [41] is that the identification process is offline in nature. But this paper provides an online data driven identification framework for heat exchanger system where the estimation process is recursive in nature. This paper considers block-oriented model and using recursive estimation technique, gets accurate validation FIT%. From the simulation results, it can be

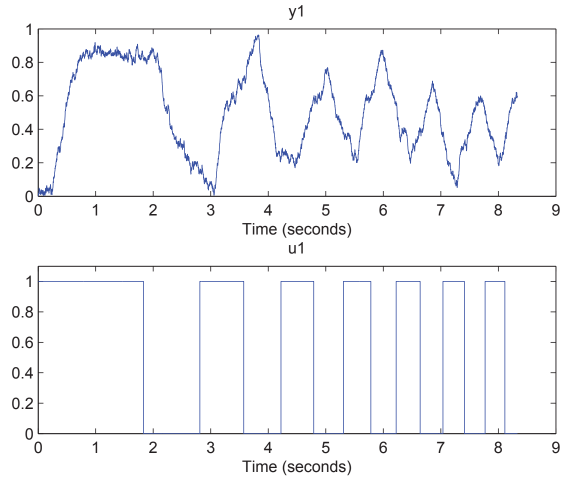

Fig. 5: Experimental (Output and Input) data of heat exchanger system [38], [48]

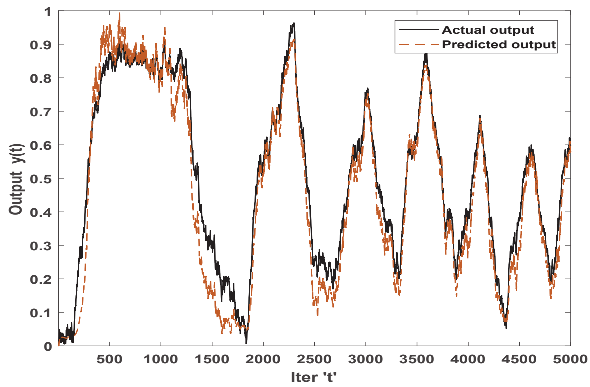

Fig. 6: Prediction output of Wiener model for heat exchanger system FIT percentage is 88.0619%

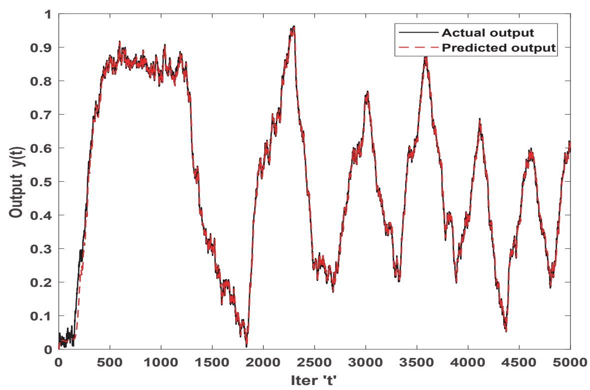

Fig. 7: Prediction output of Hammerstein model for heat exchanger system FIT percentage is 96.6232%

observed that the Hammerstein model provides better model estimation as well as model validation than Wiener model for a heat exchanger system.

V. Conclusion

This study provides a recursive parametric identification approach to model heat exchanger system from experimental input-output data. Due to the nonlinear dynamics of heat exchanger system, block-oriented models (Wiener and Hammerstein model) is considered as model structure. For online parameter estimation, recursive least square algorithm is considered. The salient features of the paper are as follows

- A benchmark problem of heat exchanger system is considered and data-driven recursive identification procedure is implemented to estimate the model dynamics.
- Block-oriented models such as Wiener and Hammerstein model is considered for the model structure and this model provides better FIT%
- In literature, the heat exchanger dynamics were identified using linear models using prediction error method and extended least square method respectively [32], [41].
- The estimation results using linear models are inaccurate and the estimation techniques are non-recursive
- The current paper proposes a recursive identification technique and from the simulation results, it can be observed that the Hammerstein model provides a better estimation as well as model validation than the Wiener model for the considered case study of heat exchanger system.

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