Parallel OBF-Wavelet Network Model for Nonlinear Systems Identification

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Abstract—In the present work, a linear Orthonormal Basis Filters (OBF) model is integrated with nonlinear Wavelet Network (WN) model in parallel structure for nonlinear systems identification. The overall nonlinear model is taken as the sum of these two models and analyzed using two case studies. The effectiveness and the model performance within the model development region as well as under extrapolating conditions are studied. The results showed that the proposed parallel OBF-WN performed better than other conventional models in both regions of operations.

Key-Words: -Modeling Nonlinear systems, OBF, Wavelet networks

1 Introduction

In control area, mathematical modeling is a backbone in determining the capacity and capability of the system [1-2]. Mathematical models are classified into two categories: black box (purely empirical model) and white box (traditional physical modeling) [3]. White box models are derived from fundamental principles such as mass and energy balances. However, they tend to be highly complex and, generally, are difficult and very time consuming to be developed. Nonlinear black box models, on the other hand, mainly aim to determine a mathematical model of process dynamics that matches observed input/output data according to some objective matching criteria. Hence, they have certain advantages over the white box models in terms of development time and efforts [4].

In nonlinear system identification using black box models such as neural networks (NN), one possible approach is to use a parallel combination of linear and NN models[5]. This parallel combination through the usage of residuals is very attractive in two ways: viz. (1) a nonlinear model that is not properly developed performs worse than a linear one, hence by having a linear model developed in the first step ensures that reasonable models are obtained, and (2) applying the NN on the residuals (inputs and residuals as network input and output) ensures that the overall nonlinear model performs at least as good as or better than the linear model. One recent approach is the parallel OBF-NN model developed by [4](see Figure 1). The developed OBF-NN model has been shown to have better extrapolation capability in comparison to the conventional NN model.

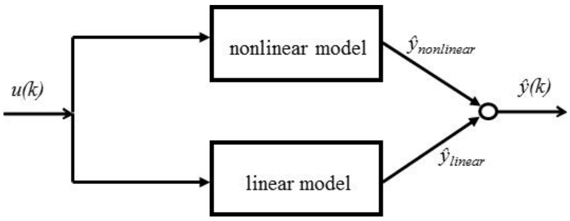

Fig. 1 The linear and nonlinear models in parallel

Though NN has been recognized as a successful class of nonlinear models, there is no structured construction procedure for determining the number of hidden layers and neurons in the network model [6]. Wavelet networks, on the other hand, do not suffer from such drawback, and are also efficient in approximating any static nonlinearity [6]. Efficient construction algorithms for defining the Wavelet networks structure are available [7].

Wavelet networks have been proven successful in the areas of classification and identification problems [8-9]. Development of wavelet networks comes from combination of neural networks and wavelet theory. Thesetype of nonlinear models have their own capabilities of capturing essential features in “frequency-rich” signals that contribute to their strength. Wavelet networks have advantages over neural networks where both the position and the dilation of the wavelets are optimized besides the weights.

In this paper, the performance of the previously developed parallel OBF-NN model is evaluated by replacing the nonlinear NN model with Wavelet networks (WN), resulting in parallel OBF-WN model. The proposed model is shown in Figure 2. The objective of the paper is to analyze whether the proposed OBF-WN model can simultaneously identify nonlinear systems aswell as improving the extrapolation capability of the previous models.

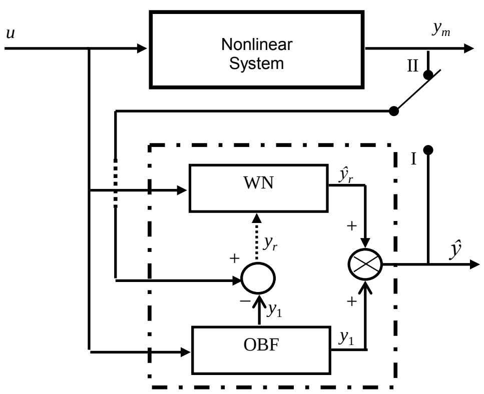

Fig. 2 The proposed sequential identification of residuals-based parallel OBF-plus-WN models (I: simulation, II: prediction configuration)

2 Methodology

Parallel combination of OBF and WN models to describe a nonlinear system is developed using the following procedure that is divided into two major parts: (A) Training and Validation and (B) Extrapolation Analysis.

2.1 Training & Validation

As stated before, in order to develop a parallel proposed model, a parsimonious linear Laguerre model is identified first. The single-input single-output (SISO) for Orthonormal Basis Filter (OBF) model can be expressed as follows:

$$\hat{y}(k+1) = \left(\sum_{i=1}^{N} c_i L_i(q) \right) u(k) + e(k) \quad (1)$$

where N is the number of orthonormal basis filters, c_i are the optimal OBF model parameters, $L_i(q)$ are the orthonormal basis filters, q is forward shift operator, $u(k)$ is input to the system, and $e(k)$ is the system white noise.

For SISO nonlinear model, the wavelet network (WN) function is based on the following function expansion:

$$f(x) = \sum_i w_{a,b}{}^i a_i^{-n/2} \psi((x - b_i)/a_i) \quad (2)$$

where$a$ and b are the dilation and translation parameters, respectively. Function Ψ is termed as "mother wavelet" and is selected as radial function [7] and w represents the weights.

The overall model output then is the summation of both the linear dynamic model and the nonlinear model.

$$\hat{y}_f(k) = y(k) + f(k) \quad (3)$$

The algorithm to identify the OBF-WN model is described as follows:

1. Develop OBF model to get y_{OBF}
2. Calculate the predicted residuals using

   $y_{RES} = y_{ACTUAL} - y_{OBF}$
3. Develop the WN model using y_{RES} as outputs of the WN model.

75% of the generated data is used for training while 25% is used for validation. The aim is to evaluate how effective the model generalizes (predicts) when subjected to out-of-sample data that is not used during the identification stage. In this step, the the graphical plots between model output and measured process output are compared as well as by the Root Mean Square Error (RMSE) defined as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y - \hat{y})^2}{n}}$$

where

y is the measured output, and
$\hat{y}$ is predicted value of y.

2.2 Extrapolation Analysis

Extrapolation is a term used when a model is forced to perform prediction in regions beyond the space of the original training data. New out-of-sample data are generated by forcing the system to operate beyond the original training range of the model. Once the model development and validation are done as outlined in the previous section, then the performance of the proposed model is compared against the previously established parallel OBF-NN model in these extrapolation regions. The parallel OBF-NN model is developed using the same training, validation and configurations as reported in [4].

3 Results and Discussion

3.1 Parallel OBF-WN model development

Two case studies have been used for the development of parallel OBF-WN model. Continuous stirred tank reactors (CSTR) are often encountered in industrial applications and one of the operating units widely considered in the control literature. Case 1 represents the CSTR model taken from Neural Network Control System Toolbox in MATLAB [4]. The second case study, refers to as Case 2 in this paper, is the van de Vusse reactor, a highly nonlinear system, which is frequently used as benchmark problem for various identification and control strategies. For details of the equations describing the system and parameters used refer to [4]. The corresponding input-output data used to develop the proposed model is as shown in Figure 3 (case 1) and Figure 4 (case 2).

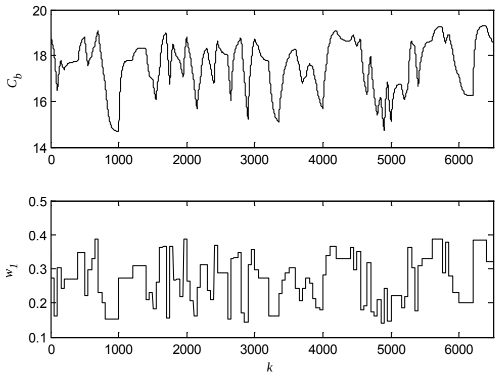

Fig. 3 Input-output data set (case 1)

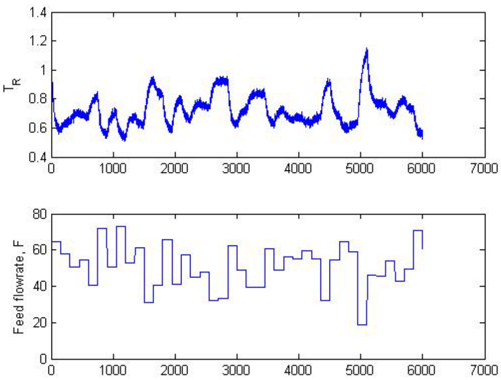

Figure 4 Input-output data set (case 2)

Developing the linear OBF model using the above data, it is observed that the linear OBF model seem to be able to identify only 69% and 73% of the process variations as shown in Figures 5 and 6, respectively, for case 1 and case 2. Moreover, Figure 7 and Figure 8 indicate the significant presence of nonlinearity in the system due to a strong pattern in the residual behavior.

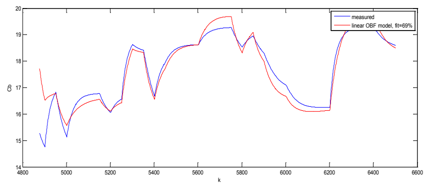

Fig. 5 Measured and estimated output for linear Laguerre model (case 1)

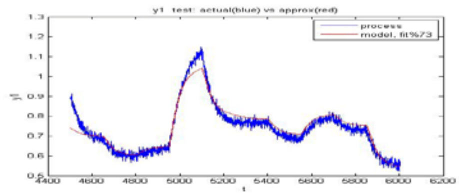

Fig. 6 Measured and estimated output for linear Laguerre model(case 2)

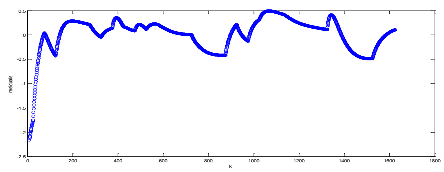

Fig. 7 Residuals of the linear OBF model (case 1)

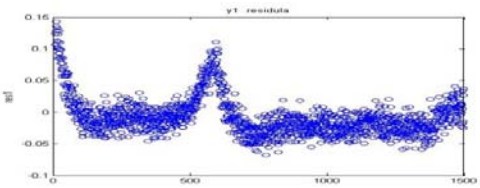

Fig 8 Residuals of the linear OBF model (case 2)

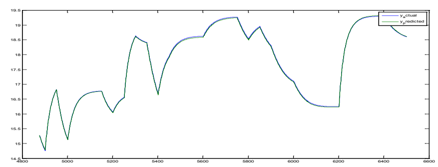

Fig. 9 Measured and estimated output for the OBF-WN model for model development (case 1)

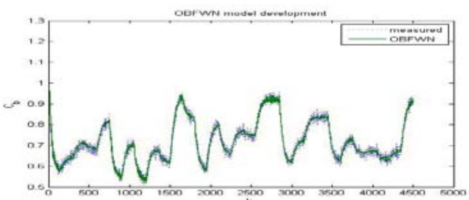

Fig. 10 Measured and estimated output for the OBF-WN model for model development (case 2)

The analysis in Tables 1 and 2 show the performance comparisons between the previously developed parallel OBF-NN and the proposed parallel OBF-WN model done on the validation data set.

Table 1 Identification RMSE: Comparison on the validation sets (case 1)

Case Studies	Parallel OBF-NN	Parallel OBF-WN
Plant	0.0008	0.000574

Table 2 Identification RMSE: Comparison on the validation sets (case 2)

Case Studies	Parallel OBF-NN	Parallel OBF-WN
Plant	0.0253	0.0157

From the tables, it is shown that the proposed OBF-WN model is able to identify the nonlinear CSTR systems in both cases since the error on the validation data set is comparably similar to OBF-NN.

In order to apply this model under extrapolating conditions, this identification result is important to ensure that both models are comparably similar in the model development stage. Using the same optimal parameters obtained in this stage, both models are then subjected to the extrapolating conditions in the next section.

3.2 Extrapolation analysis using Parallel OBF-WN model

Figures 11, 12 and 13 show the measured and predicted values of the product outlet concentration, $\underline{C_b}$ for decrease of 9%, 20% and 28% in the w_1 below the original training range. Subsequently, Figure 14, 15 and 16 show the measured and predicted values of the product outlet concentration $\underline{C_b}$ for decrease of 9%, 22% and 30% in the w_1 below the original training range. The resulting RMSE comparison between the two models for the three test sets are shown in Figure 17 and 18. Parallel OBF-WN seems to show an excellent prediction performance with the RMSE is 0.186, 0.1814 and 0.1803 for case 1 and 0.0153, 0.0152 and 0.0151 for case 2 which are generally smaller in comparison to the previously established parallel OBF-NN.

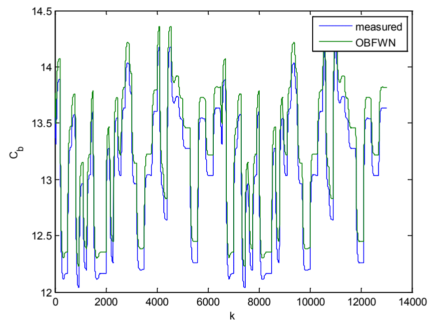

Fig. 11 An average of 9% decrease in w_1

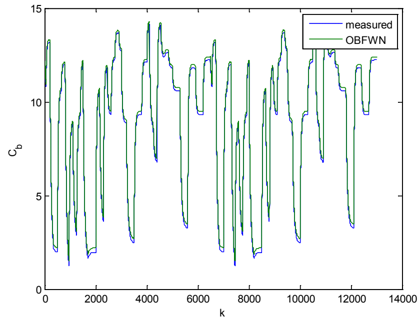

Fig. 12 An average of 20% decrease in w_1

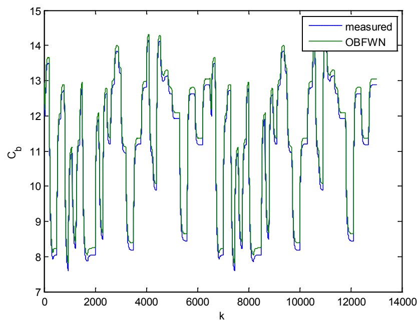

Fig. 13 An average of 28% decrease in w_1

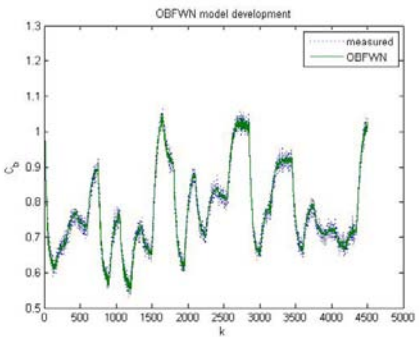

Fig 14 An average of 9% decrease in w_1

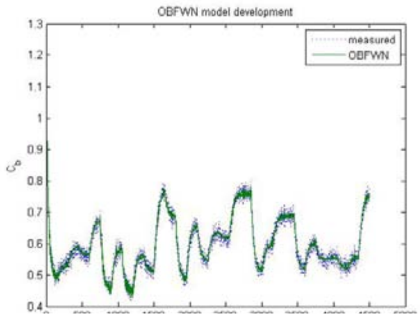

Fig. 15 An average of 22% decrease in w_1

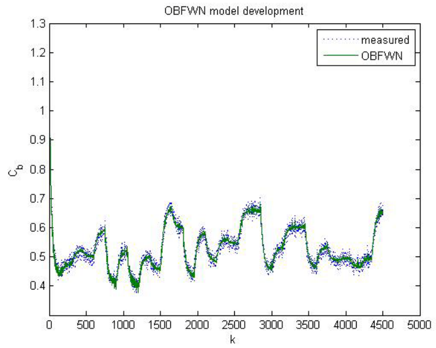

Fig. 16 An average of 30% decrease in w_1

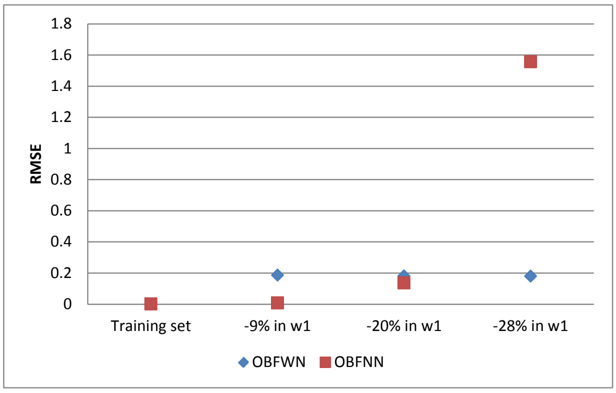

Fig. 17 Prediction errors for the training and extrapolation data sets (case 1)

Fig. 18 Prediction errors for the training and extrapolation data sets (case 2)

4 Conclusion

In this study, it has been shown that the Orthonormal Basis Filter (OBF) plus Wavelet Networks (WN) model is able to identify nonlinear systems efficiently and to extrapolate beyond the regions of original range encountered during the model development phase. Future works may involve the integration of the proposed model in a closed-loop nonlinear predictive controller environment to test its capability under control loop.

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