Multi-step ahead predictions of Integrated OBF-NN models

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***Abstract*—In this paper the multi-step ahead prediction of the recently developed integrated OBF-NN models is studied and applied to the nonlinear Van de Vusse reactor. Results show comparable multi-step ahead predictions of the method in comparison to conventional MLP NN.**

I. Introduction

Predictive control, or better known as Model Predictive Control (MPC), is widely used in industry and extensively studied in literatures [1]. At the core of the MPC algorithm is the dynamic model of the system to be controlled. In fact, modeling and system identification are an indispensable part of the analysis and controller design of APC. Both the accuracy of the model and its simplicity are important in application. Until recently, industrial applications of MPC have relied on linear dynamic models even though most processes are nonlinear because of the simplicity in developing the model and implementation. MPC based on linear models are acceptable when the process operates at a single set point and the primary use of the controller is the rejection of disturbances. Many chemical processes especially in complex chemical plants, however, are nonlinear in nature. Because these processes make transitions over the nonlinearity of the system, linear MPC often results in poor control [2-4], which is later translated to poor overall performance of the plant including energy efficiency. This, together with higher product quality specifications, increased productivity demands, tighter environmental regulations and demanding economical considerations in the process industry necessitates the systems to operate closer to the boundary of the admissible operating region. Hence, to maintain the energy conservation benefits, more efficient MPC algorithms are required [5-7]. These are the main factors why modeling and identification of nonlinear systems have been the primary focus in recent years [8].

Recently, neural networks have become an attractive tool in the construction of models for complex non-linear systems, because of their inherent ability to learn and approximate non-linear functions. From model-based control strategies point of view, algorithms based on neural networks (NN) models are preferred [9], and a large number of control and identifications structures based on neural networks has been presented in literatures. NN models are highly efficient in learning data from complex processes with significant nonlinearity [9, 10-13]. Training of NN models requires no technical knowledge about the process and the corresponding models usually have a small number of parameters with simple structure [9]. However one of the significant drawbacks of NN as a model is that they have poor extrapolation property in regions outside those that are used during training [9, 11].

Recently, a nonlinear system identification approach has been proposed by [14] that provides an interesting alternative in overcoming the extrapolation weakness of NN. The proposed integrated structure of OBF-NN models have shown enhanced extrapolation behavior on open loop identification data. However, for the proposed model to be of significant advantage especially in the predictive controller framework, it has to be able to able to provide consistent multi-step ahead prediction.

Hence, in this paper, the multi-step ahead prediction of the integrated OBF-NN models are studied and compared to the more conventional NN models.

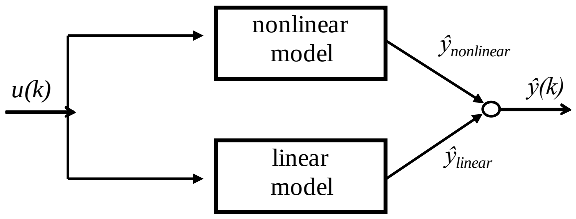

Figure 1. The schematic diagram of the integrated structure of OBF-NN models [14].

In this paper, the material is organized as follows. Section 2 presents the procedure of obtaining the OBF-NN predictors starting from the design of a non-linear OBF-NN-based model of the process. Finally, Section 3 gives a simulated example using a non-linear system taken from literature to show the multi-step ahead prediction performance.

obf-nn prediictors

A. *Nonlinear system modeling using OBF-NN models*

For a SISO system with an MLP neural network with one hidden layer (with reference to Figure 2), the output of the nonlinear OBF-NN models can be given as follows (for details, readers are referred to 14]:

$$\hat{y}(k) = \left(\sum_{j=1}^{N} c_j L_j(q) \right) u(k-1) + \beta \left[b^2 + \sum_{i=1}^{K} w_i^2 \varphi(b_i^1 + w_{i,1}^1 x(k-1)) \right] \quad (1)$$

where nonlinear neural network function approximation is trained with regression vectors consisting of previous plant inputs and previous residuals of the linear model, $x(k-1) = [u(k-1), \ldots, u(k-m), \hat{y}_r(k-1), \ldots, \hat{y}_r(k-m)]$. Also $\varphi, \beta : R \to R$ are the nonlinear activation functions (e.g. hyperbolic tangent etc.), b are the biases, K is the number of hidden neurons, and the weights of the network are denoted by $w^1_{i,j}, i = 1,\ldots,K$ (with ith neuron and jth input, in this case $j = 1$) for the first layer, and $w^2_i, i = 1,\ldots,K$ for the second layer.

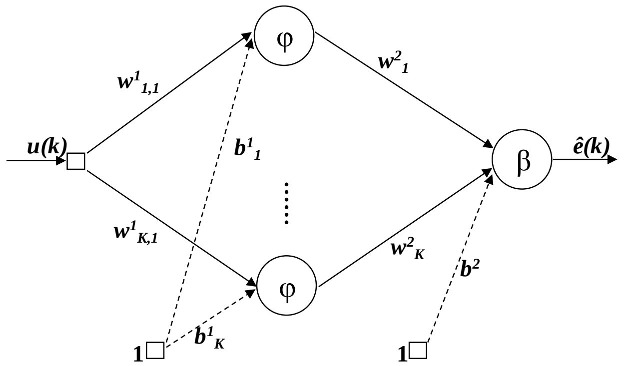

Figure 2. The structure of one hidden layer MLP neural network (a single input single output (SISO) example).

B. OBF-NN based predictors

The predictors are necessary for the prediction of future values of the plant output that are considered in the predictive control strategy. The implementation approach proposed in this paper uses OBF-NN predictors obtained by appropriately shifting the inputs of the neural based model. The OBF-NN predictors rely on the OBF-NN model of the process, as is usually done in NN [1]. In order to obtain the model of the non-linear system, the same structure of the OBF-NN given by (1) is considered. A sequential algorithm based on the knowledge of current values of u and y together with the OBF-NN system model gives the i-step ahead *OBF-NN predictor*. From Eq. (1), one can properly derive the model output at the $k + 1$ time instant:

$$\hat{y}(k) = f_1(u(k-1)) + \beta[b^2 + f_2(x(k-1))] \qquad (2)$$

(1)

$$\hat{y}(k+1) = f_1(u(k)) + \beta[b^2 + f_2(x(k))] \qquad (3)$$

Extending the prediction one-step further, $y(k+2)$ can be obtained, and generally, the i-step ahead predictor can be calculated as follows:

$$\hat{y}(k+2) = f_1(u(k+1)) + \beta[b^2 + f_2(x(k+1))] \qquad (4)$$

$$\hat{y}(k+i) = f_1(u(k+i-1)) + \beta[b^2 + f_2(x(k+i-1))] \qquad (5)$$

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where

$$\begin{aligned} x(k-i-1) = [&u(k+i-1),\ldots,u(k+i-m),\ldots \\ &..\hat{y}_r(k+i-1),\ldots,\hat{y}_r(k+i-m)] \end{aligned} \qquad (6)$$

In the next section, the multi-step ahead predictions will be compared against that of the conventional Multi-layer Perceptron (MLP) NN. *4*-step ahead prediction is considered, with m set at a value of 2. It is assumed that for both MLP NN and OBF-NN, the previous two values of u and y are available. In both cases, the future values are set to be equal to the latest value available at the current time. In other words, for N-step ahead predictions,

$$y = \begin{bmatrix} y(k-2) \\ y(k-1) \\ y(k)_1 \\ y(k)_2 \\ y(k)_3 \\ \vdots \\ y(k)_N \end{bmatrix} \quad \text{and} \quad u = \begin{bmatrix} u(k-2) \\ u(k-1) \\ u(k)_1 \\ u(k)_2 \\ u(k)_3 \\ \vdots \\ u(k)_N \end{bmatrix}$$

II. RESULTS AND DISCUSSIONS

To demonstrate and compare the multi-step ahead predictions of the OBF-NN models, Van de Vusse reactor case study is considered. The performance of the proposed method is compared with the conventional MLP NN model.

In all cases, the number of Laguerre filters is fixed at six (wherever applicable). For both the conventional NN and the proposed OBF-NN models, a single-hidden layer standard MLP network is adopted. The determination of the relevant inputs for the nonlinear NN function, $\gamma(\cdot)$, is essentially equivalent to the problem of dynamic order selection. In this work, the dynamic orders are arbitrarily selected, where two sets of regression vectors are considered for the conventional NN and parallel OBF-NN models, with increasing complexity or dynamic order from m=1 to 2. On both models, the number of hidden layer neurons is selected via trial-and-error, and the one that gives the lowest error is selected. The number of hidden layer neurons is 20 for the conventional NN, whilst the proposed OBF-NN model has 24.

The Van de Vusse CSTR is a nonlinear process and frequently used as a benchmark problem for various identification and nonlinear control strategies. In this isothermal CSTR, reactant A is to be converted to the desired product B, but the product B is degraded to product C. In addition to this consecutive reaction, a high-order parallel reaction occurs by which the reactant A is converted to by-product D.

$$A \xrightarrow{k_1} B \xrightarrow{k_2} C$$

$$2A \xrightarrow{k_3} D$$

The mathematical model of this reactor is described by the following set of ordinary differential equations (ODE):

$$\frac{dc_A}{dt} = \frac{q_r}{V_r}(c_{A0} - c_A) - k_1 c_A - k_3 c_A{}^2$$

$$\frac{dc_B}{dt} = -\frac{q_r}{V_r} c_B + k_1 c_A - k_2 c_B$$

$$\frac{dT_r}{dt} = \frac{q_r}{V_r}(T_{r0} - T_r) - \frac{\Delta h_r}{p_r c_{pr}} + \frac{A_r U}{V_r p_r c_{p_r}}(T_c - T_r)$$

$$\frac{dT_c}{dt} = \frac{1}{m_c c_{pc}}(Q_c + A_r U(T_r - T_c))$$

The net heat of reaction (Δh_r) for the above reactions is expressed as:

$$\Delta h_r = h_1 k_1 c_A + h_2 k_2 c_B + h_3 k_3 c_A{}^2$$

where h_i refers to respective heat of reactions. Nonlinearity can be found in reaction rates (k_j) which are described via the Arrhenius expression:

$$k_j(T_r) = k_{0,j} \exp\left(\frac{-E_j}{RT_r}\right), \text{ for } j = 1, 2, 3$$

where $k_{0,j}$ represents the pre-exponential factors and E_j are activation energies. Fixed parameters of the system are taken from [15]. The nonlinear identification is carried out for SISO system by considering the dynamic characteristics from the changes of the feed flow rate, F, and the product outlet concentration, C_B.

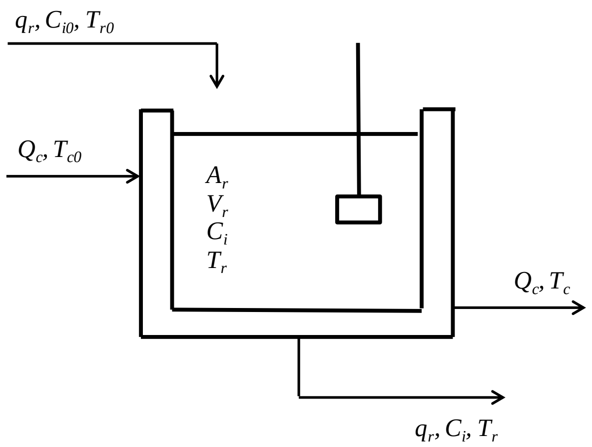

Figure 3. The schematic diagram of the Van de Vusse CSTR reactor.

Figures 4-5 shows the multi-step ahead prediction for both the conventional MLP NN and the integrated OBF-NN models for *4*-step ahead prediction. It can be seen that the recently developed OBF-NN is capable of providing satisfactory multi-step ahead predictions. This is a necessary requirement that has to be considered if the model is to be applied in the predictive control strategy..

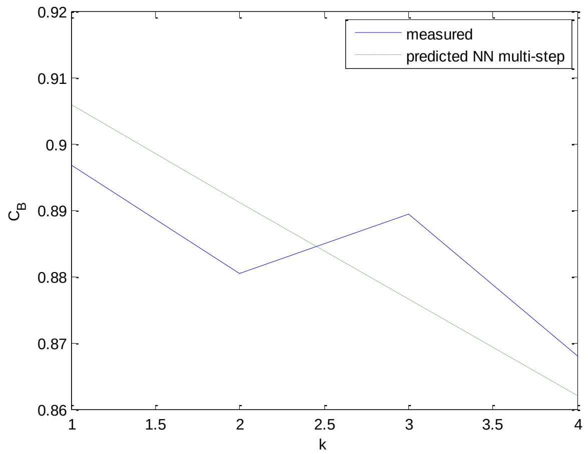

Figure 4. Conventional MLP NN model.

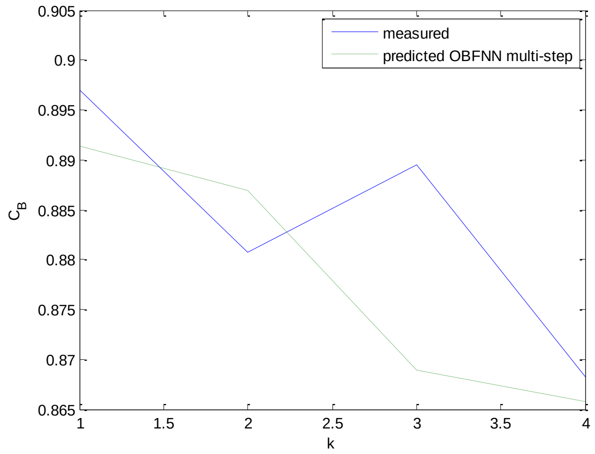

Figure 5. Integrated OBFNN model.

CONCLUSION

This paper presented a study on the multi-step ahead prediction capability of the recently developed integratd OBF-NN models. Results show comparable performance when compared against that of the more conventional MLP NN. This characteristic is essential in determining the suitability of the integrated OBF-NN models in the predictive controller framework.

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