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Application of Radial Basis Function Neural Networks in Modeling of Nonlinear Systems with Deadband

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Abstract

Presence of dead-band in engineering process decreases the system performance. Modeling of systems with such nonlinear properties is a key factor in model-based control and in fact a challenging task by conventional mathematic methods. In this paper, application of radial basis neural networks in such systems is investigated. The nonlinear static part of the system can be decoupled first from linear dynamic part and then modeled using Radial Basis Function (RBF) network; the dynamic linear part of the system can be identified using linear models. Results show that RBF can capture well, the key model of the systems with dead band.

Keywords: Radial Basis Function, Deadband, Modeling, Static, Dynamic.

1. Introduction

For many manufacturers, high quality of products is a very important factor as it increases efficiency and profitability of the products. In many factories, the plant includes hundreds or thousands of control loops. Maintaining the process at proper operating conditions is the aim of control systems in such factories as any failure of its will spread undesirable impact of one loop to the other part of the plant.

Different kinds of observed fluctuations in the signals of a control system are considered as a result of unsatisfactory performance. These deviations from desired values may have different root causes. Presence of dead-band in control loops is one of the major factors which are investigated here.

Model-based control is a key factor of preventing systems from oscillations. In this regard, good model of nonlinear behaviour of the system is a key factor to designing a good controller and therefore to eliminate undesirable performance of the system.

Recently, artificial neural networks have attracted attention of many researches. It has been shown that because of their capability in learning, adaptation, and classification, neural networks can approximate any nonlinear continuous function arbitrarily well on a compact set [1]. They are also very effective for modeling the complex nonlinear systems [2–3]. In this paper, we take advantages of special case of neural networks named Radial Basis Function (RBF) neural networks in modelling processes with dead-band.

The rest of this paper is organised as follows: In section II, explanation on problem statement is given. Section III describes radial basis function network. Section IV describes the application of radial base function network to nonlinear static part of a process for modelling and finally some concluding remarks useful for future works are given in last section of this paper.

2. Problem Statement

Nonlinearity problems always occur in the components used to implement the control or dynamics of the plant to be controlled. For an example, a valve actuator may have a dead-band due to friction effect. In most closed-loop applications, dead-band has undesirable effects on the

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feedback loop dynamics and control system performance. It represents a "loss of information" when the signal falls into the dead band and can cause limit cycles, tracking errors, and so forth. Identification of precise form of this nonlinearity is a challenge.

We start with well-known model of this nonlinearity, according to [4] simple one parameter e.g. dead-band model can be mathematically expressed by the following equation:

$$x(t)=\begin{cases} x(t-1), & if\,|x(t)-d|<d \\ u(t) & otherwise \end{cases} \tag{1}$$

x(t) and x(t-1) are the valve output (stem position) at time 't' and 't-1' respectively, u(t) is the controller output at time 't' and 'd' is the valve Dead-band. The block diagram representation of this model is given in Figure 1. In this model, when control Output Signal (OP) increases the valve position remains unchanged. The valve will start to move only after the controller output overcomes the dead-band (d) of the valve, the valve jumps to a new position. Instead of having a fixed signal at the output of the process, the output is oscillating. The goal is to keep the process variable (PV) in fixed point or desired point (SP).

The presence of the dead band decreases the performance of the control loop as described above. Modeling of the behavior of the system is a crucial factor in model-based control of this process. In practice valve position (MV) is not available and is not usually measured in most real processes. Therefore, modeling of nonlinear part of the process is a hard task. Instead of using valve position, the corresponding flow rate can be used as an alternative as the flow rate is almost proportional to the valve position [5]. Without losing generality, we consider the flow rate to have positive response to the valve input, otherwise we assume it is available or can be obtained by some techniques such as dividing the system in two parts including nonlinear static and linear dynamic e.g. Hammerstein model [6, 7] and decoupling this two parts by using special test signal [8].

3. Radial Basis Function Neural Networks

This three layers network first proposed by [9] has been used to apply successfully on many applications such as pat-tern recognition and classification [10, 11], function

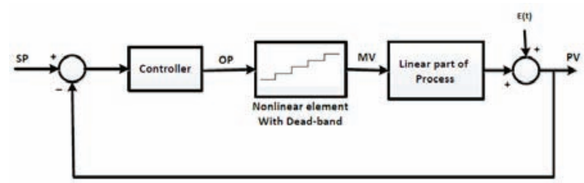

Figure 1. Process control loop in the presence of dead-band.

approximation [12], modeling [13] and control [14]. Comparing with the other neural networks such as feed forward and multi-layer perceptron neural networks, RBF neural networks has some better approximation properties [15].

A three-layer RBF neural network has an input layer, a nonlinear hidden layer (RBF) and a linear output layer as shown in Figure 2. The nodes within each layer are fully connected to the previous layer nodes. The inputs of hidden layer are the linear combinations of scalar weights, where the scalar weights are usually assigned unity values and the input vector $X=\left[x_1,x_1,\ldots,x_N\right]^T$ therefore the whole input vector appears to each neuron in the hidden layer. The hidden layer nodes are RBF units. The nodes calculate the Euclidean distances between the centers and the network input vector, and pass the results through a nonlinear function [16]. The output layer yields a vector $y=\left[y_1,y_1,\ldots,y_M\right]^T$ to produce the final output. The network output can be obtained by

$$y=yf(X)=\sum_{i=1}^{K} w_i\phi_i(X) \tag{2}$$

where, $\phi_i\,(X)$ denotes the radial basis function of the i-th hidden node, W_i denotes the hidden-to-output weight corresponding to the i-th hidden node, and k is the total number of hidden nodes. There are different types of radial basis function. A normalized Gaussian function usually used as the radial basis function, that is:

$$\phi_i(X)=exp\left(-\frac{\|x-\mu_i\|^2}{2\sigma_i^2}\right) \tag{3}$$

where, μ_i and σ_i denote the center and spread width of the i-th node, respectively.

As we can see because of simple structure of these networks the training time is reduced, and this has led to the application of such networks to many practical problems.

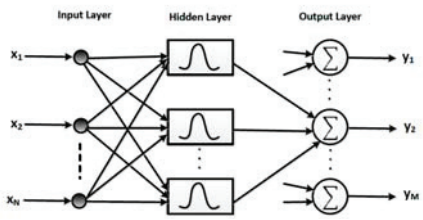

Figure 2. Structure of a radial basis function (RBF) neural network.

4. Modeling of Nonlinear Static Part of the Process using RBF Network

We want to use radial basis function network to model nonlinear part of the process. The system includes two parts, nonlinear static and linear dynamic. The first task in this identification is to decouple the two parts. MV-OP is the nonlinear static part, while MV-PV is the linear dynamic part. In most real system, MV cannot be measured except for smart valves. As stated in previous section, instead using the valve position the corresponding flow rate can be used as an alternative because the flow rate is almost proportional to the valve position [5].

First we assume the valve position is not available. Therefore, we have to identify linear part before identification of other part.

The linear dynamic part is represented by ARMAX model [17]

$$A(q^{-1})y(k) = B(q^{-1})u(k) + C(q^{-1})e(k) \tag{4}$$

where, q^{-1} is the backward shift operator $q^{-i}\mathrm{u(k)} = \mathrm{u(k-i)}$, and ε the unmeasured disturbance. $A(q^{-1}), B(q^{-1})$ and $C(q^{-1})$ are polynomials in q^{-1} of specified order n, m and p, respectively:

$$\begin{aligned} A(q^{-1}) &= 1 + a_1 q^{-1} + a_2 q^{-2} + \cdots + a_{na} q^{-na} \\ B(q^{-1}) &= b_0 + b_1 q^{-1} + b_2 q^{-2} + \cdots + b_{nb} q^{-nb} \\ C(q^{-1}) &= 1 + c_1 q^{-1} + c_2 q^{-2} + \cdots + c_{nc} q^{-nc} \end{aligned} \tag{5}$$

where,

$$\Theta = \left[a_1 \dots a_{na}, b_0 \dots b_{nb}, c_1 \dots c_{nc} \right]^T \tag{6}$$

Now identification can be restricted to finding optimal values for equation (6).

Identification of this linear dynamic part of the process is not the aim of this research and readers are suggested to refer [17] for further details.

For identification of nonlinear static part, a set of 181 pairs generated based on equation (1) with ramp input is used. Among these pairs, 54 were used for testing and 127 were used for training the network. Since most systems working in real atmosphere have unknown noise, performance of the network has to be tested with noisy data. White noise with variance 0.02 was added to the data. RBF network with different number of neurons in hidden layer was used for approximation of this part. During the training procedure, the adjustable parameters such as centers and spreads can be estimated. There are three performance indexes for evaluating the model: First, the Mean Squared Error (MSE) of an estimator quantifies the difference between values implied by an estimator and the true values of the quantity being estimated. It is usually used for function approximation, modeling and so on. Taking the square root of MSE yields the Root Mean Square Error (RMSE) which is another similar performance index. Second, Regression (R) which is used to validate the network performance displays the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data fitting a function should fall along a 45 degree line, where the network outputs are equal to the targets. Third, the error histogram for obtaining additional verification of network performance shows distribution of error. Smooth distribution is a result of good model while non-smooth distribution shows that modeling process in some part is not so good. Three performance indexes of the network on testing data are given in Figure 3 along with the model. In this figure it is obvious that the shape of outputs and targets are approximately the same and without other three mentioned indexes, it is difficult to find out how good the model is. The regression is much closed to one and the MSE and RMSE show accuracy of the model; finally, the error histogram shows distribution of error which is smooth and in uniform shape. Performance of RBF neural network based model on sets of training data is given in Figure 4. The amount of RMSE and SME on sets of training data is smaller than testing data, which is normal as the amount of data in training section is more than the testing section. Distribution of error in training section and testing section is approximately same and the regression is closed to one as it should be. Performance of the model on all data is given in Figure 5 which reveals the good performance of the model. Number of neuron is very important factor as it has a nonlinear function which increases complexity of the model. The above performance of the model is obtained by at most 10 numbers of neurons (Figure 6). However, with only 6 neurons it can reach good amount of MSE and it is up to user and application to define how much the model should be accurate and therefore how many neurons have to be used.

This approach is a data-driven supervised learning approach since the radial basis function network attempts to mimic and existing process from being exposed to the process data.

At the implementation stage, this model must be incorporated with a model-based control scheme. It is usually employed in a nonlinear model predictive control scheme in the most process industry as shown in Figure 7 [18]. In this case the model predictive control is an optimization problem. The optimizer uses the model that we have obtained using RBF and ARMAX. For further details readers are suggested to refer [18].

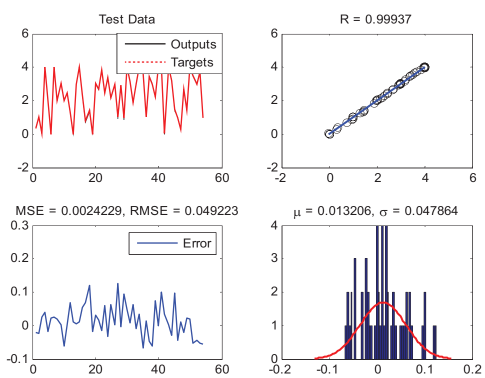

Figure 3. Performance of RBF neural network based model on sets of testing data.

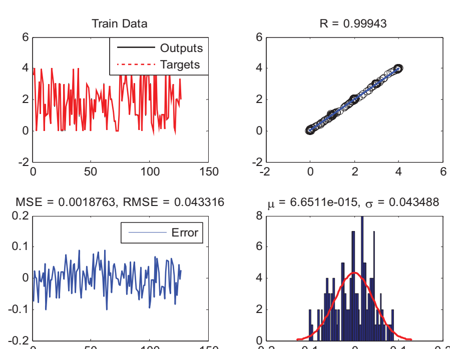

Figure 4. Performance of RBF neural network based model on sets of training data.

5. Conclusion and Future Work

Due to undesirable impact of dead-band on performance of control loops, modeling of such nonlinearity is an interesting subject which impact can be mitigated in model-based control. While mathematical approach is not effective tools, application of radial basis function neural network in modeling static nonlinear part of processes with dead-band were investigated. It can be seen that neural network can successfully model system with dead-band. For processes with the presence of dead-band and jump which have non smooth function, these networks have to be modified.

Our method is applicable for smart valve and also for valves in which position can be replaced with the

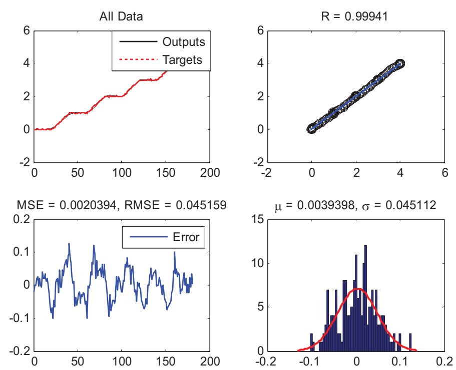

Figure 5. Performance of RBF neural network based model on sets of all data.

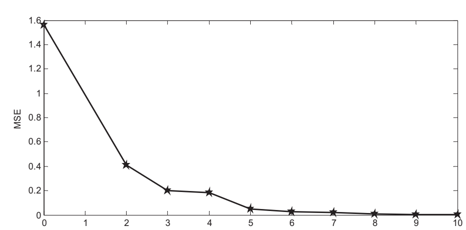

Figure 6. Performance of RBF neural network based model on number of neurons in hidden layer.

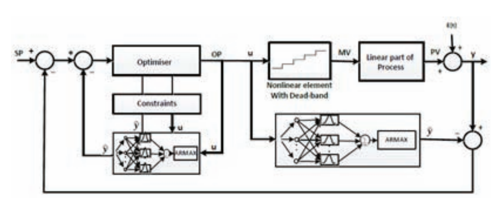

Figure 7. A RBF neural network model can be incorporated into linear model predictive control scheme.

corresponding flow as an alternative. However for cases that do not match the above conditions, we suggest using dynamic neural network instead of static radial basis since for many processes decoupling of the two parts is a huge challenge. However, in implementation stage, these dynamic neural networks have to be modified to model the system.

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7. References

1. Haykin S (1994). Neural Networks: A Comprehensive Foundation, Chapter 2, Pearson Eduvation Publication, 72–133.
2. Wang H, Oh Y et al. (1998). Strategies for modeling and control of nonlinear chemical processes using neural networks, Computers & Chemical Engineering, vol 22(Sup 1), S823–S826.
3. Han X, Xie W et al. (2011). Nonlinear systems identification using dynamic multi-time scale neural networks, Neurocomputing, vol 74(17), 3428–3439.
4. Stenman A, Gustafsson F et al. (2003). A segmentation-based method for detection of stiction in control valves, International Journal of Adaptive Control and Signal Processing, vol 17(7–9), 625–634.
5. Yamashita Y (2006). An automatic method for detection of valve stiction in process control loops, Control Engineering Practice, vol 14(5), 503–510.
6. Fruzzetti K, Palazoğlu A et al. (1997). Nolinear model predictive control using Hammerstein models, Journal of Process Control, vol 7(1), 31–41.
7. Srinivasan R, and Rengaswamy R (2005). Control Loop Performance Assessment. 2. Hammerstein Model Approach for Stiction Diagnosis, Industrial & Engineering & Chemistry Research, vol 44(17), 6719–6728.
8. Bai E-W (2004). Decopling the linear and nonlinear parts in hammerstein model identification, Automatica, vol 40(4), 671–676.
9. Broomhead D S, and Lowe D (1988). Multivariable functional interpolation and adaptive networks, Complex Systems, vol 2(2), 321–355.
10. Krzyzak A, Linder T et al. (1996). Nonparametric estimation and classification using radial basis function nets and empirical risk minimization, IEEE Transactions on Neural Networks, vol 7(2), 475–487.
11. Mali K, and Mitra S (2005). Symbolic classification, clustering and fuzzy radial basis function network, Fuzzy Sets and Systems, vol 152(3), 553–564.
12. Hou M, and Han X (2010). Constructive approximation to multivariate function by decay RBF neural network, IEEE Transactions on Neural Networks, vol 21(9), 1517–1523.
13. Shen C, Cao G-Y et al. (2002). Nonlinear modeling and adaptive fuzzy control of MCFC stack, Journal of Process Control, vol 12(8), 831–839.
14. Bahita M, and Belarbi K (2012). Radial basis function controller of a class of nonlinear systems using mamdani type as a fuzzy estimator, International Symposium on Robotics and Intelligent Sensors Procedia Engineering, vol 41, 501–509.
15. Qiao J-F, and Han H-G (2012). Identification and modeling of nonlinear dynamical systems using a novel self-organizing RBF-based approach, Automatica, vol 48(8), 1729–734.
16. Warwick K (1996). An introduction to radial basis functions for system identification: a comparison with other neural networks methods, Proceedings of the 35th Conference on Decision and Control, Kobe, Japan, vol 1, 464–469.
17. Ljung L (1999). System Identification: Theory for the User, 2nd Edn., Chapter 4, Prentice Hall PTR, New Jersey, 69–115.
18. Sut H-T, and McAvoy T I (1993). Neural model predictive control of nonlinear chemical processes, IEEE International Symposium On Intelligent Control, Chicago, USA, 358–363.