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Neural Network Modeling of Valve Stiction Dynamics

H. Zabiri, Y. Samyudia, W. N. W. M. Zainudin

Abstract—**Stiction is the most commonly found valve problem in the process industry. Valve stiction may cause oscillations in control loops which increases variability in product quality, accelerates equipment wear and tear, or leads to system instability. In this paper, we present a new approach in control valve stiction modeling using Recurrent Neural-Network with NARX structure. It is shown that the performance of the developed model is comparable to other models reported in literature.**

Index terms— **Control valve stiction, neural network, modeling**.

I. Introduction

Oscillations in process variables are widely encountered in process plants [1]. The presence of oscillations in a control loop enhances the variability of the process variables hence creating inferior quality products, higher rejection rates, increased energy consumption and reduced average throughput. Interactions among process units further facilitate the propagation of oscillations across the plant.

There are many causes that may contribute to the oscillatory behavior observed in control loops. These include poorly tuned controllers, presence of oscillatory disturbances and nonlinearities [2]. A survey reported in [1] found that 30% of the loops are oscillatory due to control valve problems. Control valves constitute an important element in chemical process control systems. Through a control valve, control actions are implemented on the process. They manipulate energy flows, mass flows or forces as a response to low energy input signals, for example, electrical voltages or currents, pneumatic and hydraulic pressures or flows [3].

Due to their continuous motions, control valves tend to undergo wear and aging. In general, they contain static and dynamic nonlinearities including saturation, backlash, stiction, deadband and hysteresis [4]. Among the many types of nonlinearities in control valves, stiction is the most commonly encountered in the process industry [4]. In general, stiction is a phenomena that describes the valve's stem (or shaft) sticking when small changes are attempted [4]. Stiction causes fluctuation of process variables, which lowers productivity. The variability of process variables makes it difficult to keep operating conditions close to their constraints, and hence causes excessive or unnecessary energy consumption. It is therefore desirable to understand and study the dynamics behavior of stiction so that necessary actions can be implemented to eliminate or hinder its deleterious effect before it propagates.

Several valve stiction models have been proposed in the literature. Muller [5] described a detailed physical model that formulates the stiction phenomenon as precisely as possible. However this type of model is not only impractical, it is also time-consuming since there are a number of unknown physical parameters that must be solved. On the other hand, Choudhury et al. [4] proposed a data-driven model that describes the relationship between a controller output and a valve position. An extended version of Choudhury's model that includes the flexibility of processing deterministic and stochastic signals has been proposed in Kano et al. [6]. However, both these empirical approaches involved with a rather complex logic making them difficult to implement.

In this paper, a much simpler black-box approach for control valve stiction modeling is proposed using Neural-Network. The outline of this paper is as follows: Section II describes stiction in general. In Section III, the Neural-Network algorithm is presented. Section IV illustrates the proposed method in numerical simulations and benchmarked against the proven and validated data driven model of [4]. Finally, the conclusions are presented.

II. Control Valve Stiction

Fig. 1 shows the general structure of a pneumatic control valve. Stiction happens when the smooth movement of the valve stem is hindered by excessive static friction at the packing area. The sudden slip of the stem after the controller output sufficiently overcomes the static friction causes undesirable effect to the control loop.

Fig. 2 illustrates the input-output behavior for control valve with stiction. The dashed line represents the ideal control valve without any friction.

Stiction consists primarily of deadband, stickband, slip jump and the moving phase [7]. For control valve under stiction resting at point (a), the valve position remains unchanged even when the controller output increases due to the deadband caused by the static friction. Only when the controller output

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exceeds the maximum static frictional force, f_S, the valve starts to respond (point(b)).

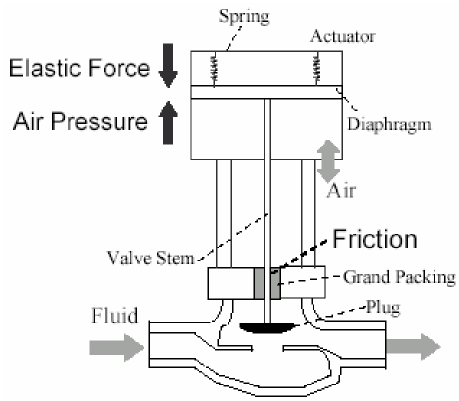


Fig. 1 Structure of pneumatic control valve adapted from [6].

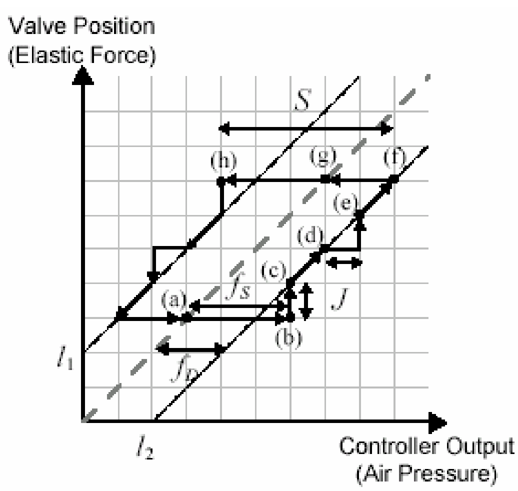


Fig. 2 Typical input-output behavior of a sticky valve adapted from [6].

A slip jump of magnitude J is incurred when the valve starts to move at point (b) when the frictional force f_S is converted to kinetic force f_D. From points (c) to (d), the valve position varies linearly. The same scenario happens when the valve stops at point (d), and when the controller output changes direction. Parameter S represents the deadband plus stickband regions.

III. Neural-Network

An artificial neural network (ANN) or commonly just neural network (NN) is an interconnected group of artificial neurons that uses a mathematical model or computational model for information processing based on a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network.

In this paper, two types of NN for modeling the control valve stiction are investigated.

A. Feedforward-Backpropagation Neural Network

Feedforward backpropagation neural networks (FF networks) are the most popular and most widely used models in many practical applications. They are known by many different names, such as "multi-layer perceptrons." The following diagram illustrates a FF networks network with three layers:

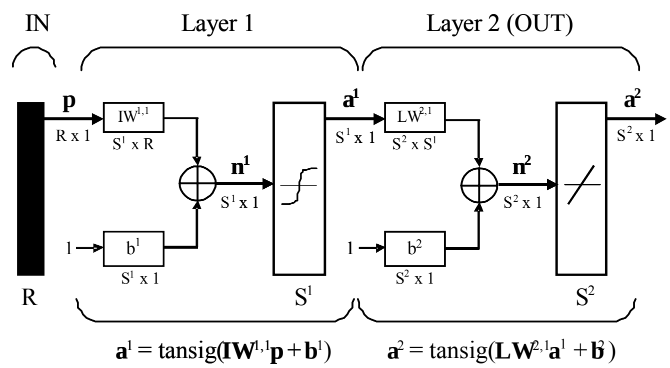


Fig. 3 Graphical representation of a BP network architecture.

Backpropagation (BP) network was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear but differentiable transfer functions [8]. BP network with biases, a sigmoid (‘tansig’ or ‘logsig’) transfer functions at the hidden layers, and a linear transfer function at the output layer is capable of approximating any functions.

BP networks architecture is slightly more complex than a single layer network. In addition to a single (hidden) layer consisting nodes with sigmoid transfer function, another layer called the output layer is required. The output layer is usually kept linear to produce output values in the similar range as the target values. However, the sigmoid transfer functions (either ‘logsig’ or ‘tansig’) are often used if the outputs need to be constrained to the range of [0,1] or [-1,1].

The minimum architecture of BP networks is illustrated as layer diagram in Fig. 3. The (R x 1) inputs p are fed to Layer 1 (hidden layer) consisting of S^1 ‘tansig’ nodes. The resulting outputs a^2 with ‘linear’ transfer function retain the same size (S^2 x 1) as the net inputs n^2 to Layer 2 (output layer). With this architecture, the BP networks are capable of approximating any linear and nonlinear functions given adequate number of hidden nodes.

B. Recurrent Neural Network with NARX Structure (NARX network)

In Feedforward NN, the neurons in one layer receive inputs from the previous layer. Neurons in one layer deliver its output to the next layer; the connections are completely unidirectional; whereas in Recurrent NN, generally, some connections are present from a layer to the previous layers. The next value of output is regressed on previous values of input signal (see Fig.4).

NARX Network

The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network [9-11].

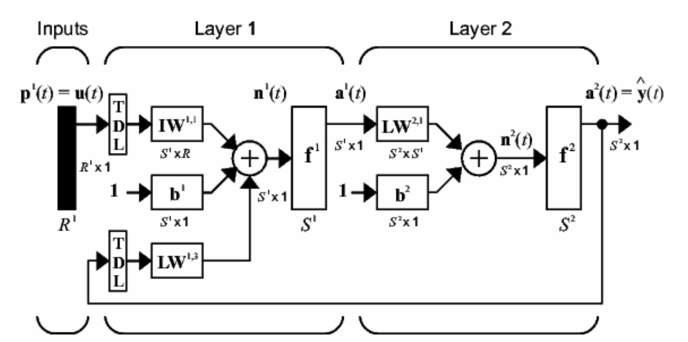


Fig. 4. NARX network structure.

The NARX model is based on the linear ARX model, which is commonly used in time-series modeling. The defining equation for the NARX model is shown in (1), where the next value of the dependent output signal $y(t)$ is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal.

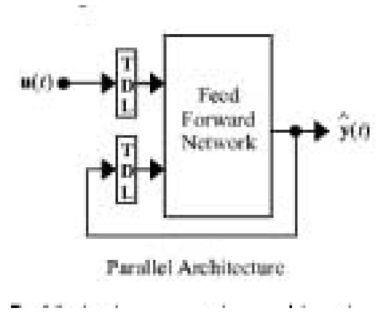
$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u)) \tag{1}$$

Standard NARX architecture is as shown in Fig. 5(a). It enables the output to be fed back to the input of the feedforward neural network. This is considered a feedforward backpropagation network with feedback from output to input. In series parallel architecture, Fig. 5(b), the true output which is available during the training of the network is used instead of feeding back the estimated output. The advantage is that the input to the feedforward network is more accurate. Besides, the resulting network has a purely feedforward architecture, and static backpropagation can be used for training.

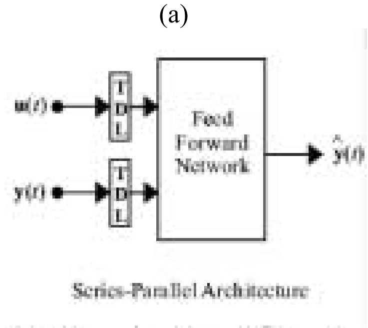
IV. Numerical Evaluations

In this section, the two types of NN for modeling valve stiction are applied to simulated data generated using the validated and proven data-driven model of Choudhury et al. [4] from a simple sine wave function. The four cases of stiction are investigated, namely, deadband (*J=0*), stiction undershoot (*S>J*), stiction no offset (*S=J*) and stiction overshoot (*S<J*). The performances of the two NN models are benchmarked against that of the data-driven model.

Note that the NN architecture summary for all the four cases of stiction is described in TABLE 1.



(a)



(b)

Fig. 5. NARX network architecture.

A. Deadband

Figs. 6 and 7 show the performance comparison between feedforward backpropagation and NARX with data-driven model of [4] for a pure deadband case.

Note that in all the figures in this section onwards, only the control valve stiction output signals are plotted.

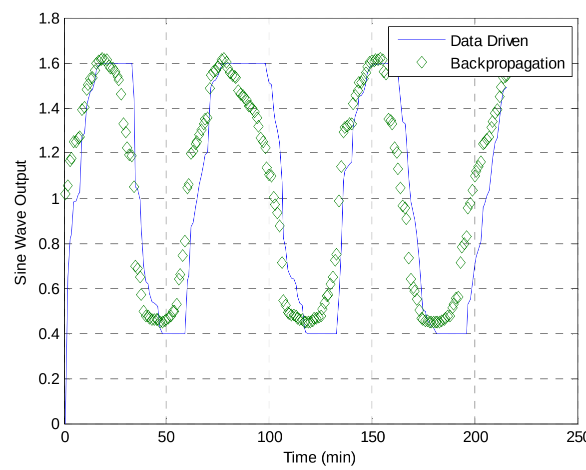


Fig. 6. Data driven vs. feedforward backpropagation for pure deadband case.

From the figures, it can be clearly observed that NARX model followed closely the behavior of the data driven model of [4]. Feedforward backpropagation model displayed good directional change in the signal, however, the model is unable to track the constant sine wave output signal whenever it changed directions.

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TABLE 1.
NN ARCHITECTURE FOR THE STICTION MODELS.

	Feedforward Backpropagation model				NARX model			
Transfer functions	Deadband	Stiction undershoot	Stiction no offset	Stiction overshoots	Deadband	Stiction undershoot	Stiction no offset	Stiction overshoots
Layer 1	Log sigmoid	Log sigmoid	Linear	Linear	Linear	Log sigmoid	Linear	Linear
Layer 2	Tangent sigmoid	Linear	Linear	Linear	Log sigmoid	Linear	Linear	Tangent sigmoid
Layer 3	Linear	Log sigmoid	Log sigmoid	Log sigmoid	Linear	Log sigmoid	Linear	Linear

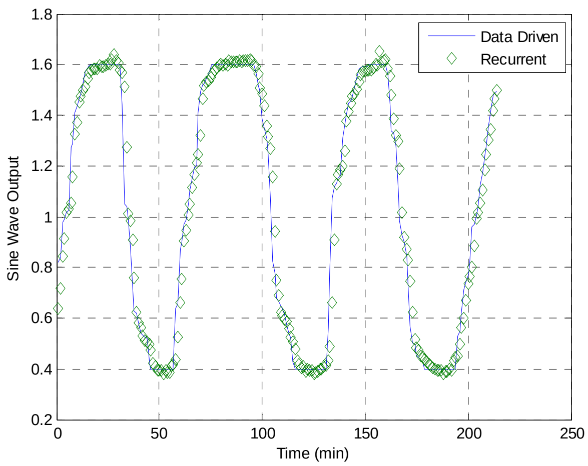

Fig. 7. Data-driven vs. NARX for pure deadband case.

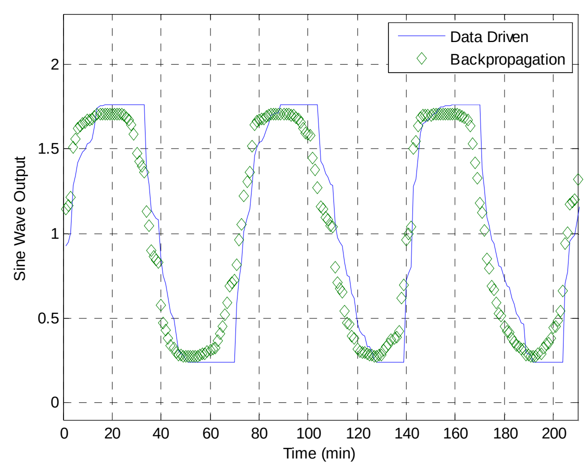

Fig. 8. Data driven vs. feedforward backpropagation for stiction undershoot.

Statistical analysis for the Root Mean Squared Error (RMSE) confirms the visual inspection, with values of 0.2336 and 0.0869 for feedforward backpropagation and NARX, respectively.

Correct Directional Change (CDC) [9] values are approximately the same for both networks as expected. This is because both networks predict the direction of change satisfactorily.

B. Stiction undershoot

In stiction undershoot case, the valve output can never reach the valve input, i.e, there will always be some offset. Fig. 8 and 9 show the resulting performance of the three stiction models.

Again, similar performance as observed earlier can be seen. NARX model with output feedback feature tracks the stiction behavior as efficient as the data driven model. RMSE of 0.1990 and 0.0907, and CDC values of 61% and 59% are obtained for the feedforward backpropagation and NARX models, respectively.

C. Stiction no offset

Stiction no offset produces a pure stick-slip behavior with no offset between the input and output signals. The moment stiction is overcome, valve output tracks the valve input signal perfectly. Fig. 10 and 11 display the corresponding behavior for both the networks.

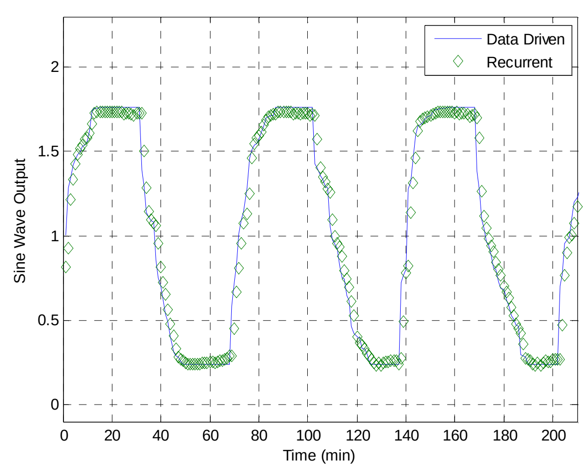

Fig. 9. Data driven vs. NARX for stiction undershoot.

In this case, precise matching between the feedforward backpropagation and data driven stiction models outputs can be perceived in all the moving phase regions.

However, in the deadband area, the same poor performance as seen in earlier sections is again encountered. In contrast, NARX stiction model accurately predicts the stiction output signal.

CDC of 62% are obtained for both NN stiction models, with comparable RMSE of 0.1793 and 0.1262.

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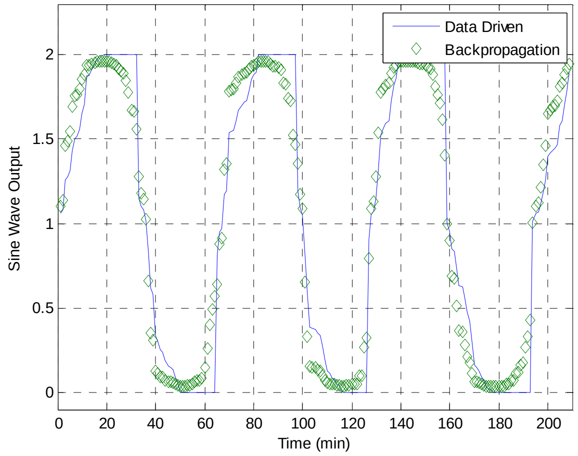

Fig. 10. Data driven vs. feedforward backpropagation for stiction no offset.

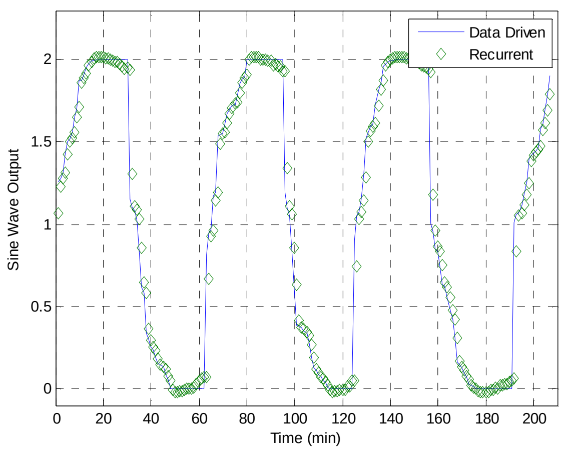

Fig. 11. Data driven vs. NARX for stiction no offset.

D. Stiction overshoot

For control valve with stiction overshoot, the valve output overshoots the valve input due to excessive stiction.

Stiction model developed using NARX network provides excellent prediction of the control valve output as can be seen from Fig. 12 and 13. Feedforward backpropagation stiction model is unable to capture the sharp edges of the control valve output as satisfactorily as exhibited by the data driven model.

RMSE values for the feedforward backpropagation model is 0.2179, whilst the NARX stiction model is 0.1428. Directional changes of the signal, however, are predicted accurately by both the NN models.

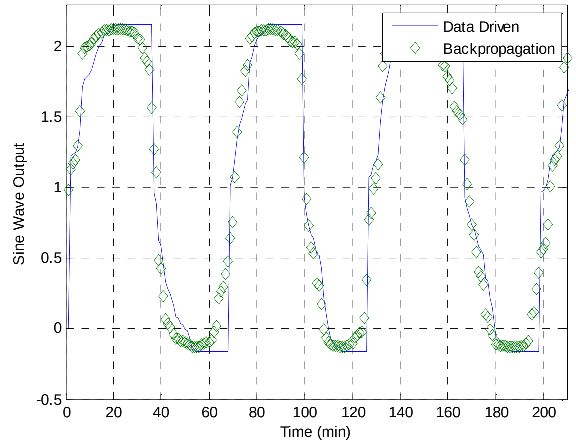

Fig. 12. Data driven vs. feedforward backpropagation for stiction overshoots.

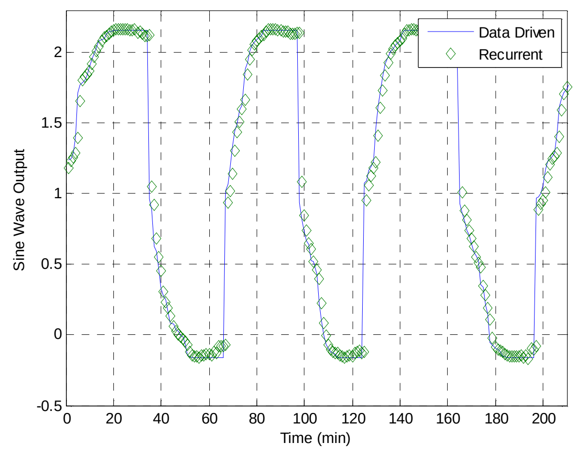

Fig. 13. Data driven vs. NARX for stiction overshoot.

I. Conclusion

In this work, a simple Neural Network-based modeling approach is proposed in modeling control valve stiction. The validity of the model is demonstrated by benchmarking the performance with the proven data driven model of stiction developed by [4]. Numerical evaluations showed that Recurrent NN stiction model is able to predict the control valve behavior in all four types of stiction to sufficient accuracy. Comparable results are obtained for both the Recurrent NN and data driven models. The use of a purely black-box NN models avoid the use of complex logics as encountered in other models.

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REFERENCES

[1] Kariwala, V., M. A. A. S. Choudhury, H. Douke, S. L. Shah, H. Takada, J. F. Forbes and E. S. Meadows, Detection and diagnosis of plant-wide oscillations: An application study, In: *Proceedings of IEEE APC 2004,* Vancouver,BC,Canada,2004, http://citeseer.ist.psu.edu/kariwala04detection.html.3

[2] Choudhury, M. A. A. S., Shah, S. L., and Thornhill, N. F., Diagnosis of poor control-loop performance using higher-order statistics, *Automatica*, 40, 2004, pp. 1719-1728.

[3] Zabiri, H., and Samyudia, Y., A hybrid formulation and design of model predictive control for systems under actuator saturation and backlash, *Journal of Process Control*, 16, 2006, pp. 693-709.

[4] Choudhury, M. A. A. S., Thornhill, N. F., and Shah, S. L., Modeling valve stiction, *Control Engineering Practice*, 13, pp. 641-658.

[5] Muller, F., Simulation of an air operated sticky flow control valve, *Proceedings of the 1994 Summer Computer Simulation Conferences*, 2005, 1994, pp. 742-745.

[6] Kano, M., H., Kugemoto, H., and Shimizu, K., Practical model and detection algorithm for valve stiction, In *Proceedings of the Seventh IFAC-DYCOPS Symposium*, Boston, USA, 2004.

[7] Choudhury, M A. A. S., Kariwala, V., Shah, S. L., Douke, H., Takada, H., and Thornhill, N. F., A simple test to confirm control valve stiction. IFAC World Congress, Praha, 2005.

[8] Hagan M.T., Demuth H.B., Beale M.H., *Neural Network Design*, PWS Publishing Company, Boston, MA, 1996.

[9] Radhakrishnan, V. R., Zabiri, H., and Thanh, D. V., Application of Multivariable Modeling in the Hydrocarbon Industry, *International Conference on Computer Process Control*, Lake Louise, Alberta Canada, January 10-16, 2006.

[10] Lin, T., Bill, G. H., Peter, T., Giles, C. L., Learning long-term dependencies in NARX recurrent neural networks, *IEEE Tr. On Neural Networks*, 7(6), 1996.

[11] Walter, M. Bernhard, S., Recurrent and Non-recurrent Dynamic Network Paradigms: A Case Study, *ijcnn, p. 6073, IEEE-INNS-ENNS International Joint Conference on Neural Networks (IJCNN'00),* 6, 2000.

[12] Catfolis, T., Meert, K., Implementing Empirical Modeling Techniques with recurrent Neural Networks, *Proceedings of Eight International Conference on Tool with Artificial Intelligence*, November 16-19, 1996.