ADAPTIVE-PREDICTIVE CONTROL WITH INTELLIGENT VIRTUAL SENSOR

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Abstract: In many industrial plants, some key variables cannot always be measured on-line and for the purpose of control, a virtual sensing system is often required. This paper is concerned with a development of an alternative intelligent control strategy, which is an integration between adaptive-predictive based controller and intelligent virtual sensing system. This allows an immeasurable variable to be inferred and used for control. The neuro-fuzzy approach is used for modelling the process as it has learning capability from the numerical data obtained from the measurements and subsequently used as process model in the generalized predictive control scheme. The intelligent virtual sensor is composed of the Diagonal Recurrent Neural Network (DRNN) and the Extended Kalman Filter (EKF) as the estimator with inputs from DRNN. The integration between virtual sensor and the controller enables the development of an on-line control scheme involving the immeasurable variable. Experimental results show some potential benefits on applying the proposed technique using the real-world process plant.

Keywords : intelligent control, predictive control, neuro-fuzzy, virtual sensor, extended Kalman Filter, real-time control

1. INTRODUCTION

Generalized Predictive Control (GPC) strategy which is considered as a universal method for model-based predictive control, is proven to be successful in handling various kinds of processes and has also been successfully applied in industry. It can be used either to control a simple plant with little prior knowledge or a complex plant, such as nonminimum-phase, open-loop unstable and a process having variable dead-time (Clarke, et al., 1987; Garcia, et al., 1989). A very critical step towards the success of the implementation of GPC is the availability of a reliable process model as an accurate plant model is necessary to drive a set of future plant outputs close to its corresponding reference signal sequence. As most processes in industry have nonlinear behaviour, then the modelling process is even more difficult.

In recent years, different studies have revealed that the integration of the strength of the neural network and fuzzy systems methodologies, producing the so-called neuro-fuzzy systems, could be used as the plant model development for control system design purposes. The main advantage of the neuro-fuzzy methodology is its learning capability from the numerical data obtained from the measurements and hence no mathematical model of the plant to be controlled is required, which is very advantageous for nonlinear plants where the mathematical models are difficult to derive (Jang, et al., 1997; Nazaruddin and Tjandrakusuma 2001; Nazaruddin and Maulana, 2002).

Moreover, in many industrial control plants, some key variables are not always available for control purposes. These variables, in general, cannot always be measured on-line, while they are difficult to measure, the sensing elements are expensive or lack of any reliable sensors. Another problem appears if the sensors performance decline, undetected disturbance comes out or even equipments degradate. These will cause the decreasing of the overall system performance. In such a case, a virtual sensing system is usually required. Virtual sensing system or virtual sensor will infer values of complex process variables by integrating information from easily made measurements using software.

In this paper, an intelligent control scheme which is an integration between the Generalized Predictive Control (GPC) strategy with neuro-fuzzy based modelling and virtual sensing elements is proposed. The modelling process will be performed on-line at each control action and this will allow the control to be done adaptively. The virtual sensor consists of Diagonal Recurrent Neural Network (DRNN) for modelling the plant as part of the sensing algorithm and the Extended Kalman Filter (EKF) as the estimator with inputs from DRNN and plant output.

The overall adaptive predictive controller algorithm with virtual sensing scheme has been implemented as a real-time control software developed using graphical-based programming language LabVIEW (LabVIEW, 1998) and then it was tested in a real-time environment to control the water level in tanks of a process mini-plant which has strongly inherent mechanical nonlinearities. The experiments will show the real application of the integration of the strength of adaptive-predictive control scheme with virtual sensing in real-time environment.

2. PREDICTIVE-ADAPTIVE CONTROL STRATEGY

Generalized predictive control is a control strategy that works based on a process model. This model is used to calculate a series of output predictions, and based on these predictions a series of control signals is determined by minimizing a cost function, so that the difference between predicted output and set-point, and also the change of control signal are minimum. The cost function to be minimized can be written as

$$J = \sum_{j=N_1}^{N_2} \left[\hat{y}(t+j) - w(t+j)\right]^2 + \sum_{J=1}^{N_U} \lambda(j)\left[\Delta u(t+j-1)\right]^2 \tag{1}$$

where $\hat{y}(t+j)$, $w(t+j)$ and $\Delta u(t+j)$ are predicted output, set-point and the change of control signal at $t + j$, respectively. N_1, N_2, N_u, and $\lambda(j)$ are the minimum horizon ($1 \le N_1 \le N_2$), the maximum horizon ($N_2 \ge 1$), the control horizon ($1 \le N_u \le N_2$) and the control-weighting sequence ($\lambda \ge 0$) respectively.

In an adaptive control system, changes of the controller's parameters occur as a response of a change in process dynamics or process parameters. In the proposed control algorithm this adaptive characteristics of the controller is realized by identifying the process model at each control action. Here, the certainty equivalence principle is assumed.

3. NEURO-FUZZY BASED MODELLING

Since all calculation is based on the process model, it is very important to have a reliable and efficient process model. Ideally, the process model should be derived from physical and chemical consideration. However, in many cases, this approach of modelling is not favorable as the lack of process knowledge contributes mostly to the difficulties. Therefore an empirical process modelling approach is used in many cases in which the plant dynamics can be inferred from the measured plant data directly. A parametric model of process identification is favorable to be used in industrial practice. Since most of the process models in industrial control show a strongly nonlinear behaviour, a popular Nonlinear Auto-Regressive with eXogeneous Variable (NARX) parametric model form is widely used to represent nonlinear systems. In this model, the output is a nonlinear function of previous outputs and inputs of the system, or

$$y(t) = F(y(t-1),\ldots,y(t-n),u(t-d-1),\ldots,u(t-d-n)) + e(t) \tag{2}$$

Here *y(t)* and *u(t)* are the sampled process output and input at time instant *t* respectively, *e(t)* is the equation error, *n* denotes the order of the process, *d* represents the process dead time as an integer number of samples and *F(.)* is an unknown nonlinear function to be identified.

The modelling of nonlinear process is not a simple task. One of the methods that is successfully used is neuro-fuzzy (Jang, et al., 1997). An architecture called Adaptive Neuro-Fuzzy Inference System (ANFIS), which is an integration between neural network and fuzzy inference system, will be further explored. Here, the mechanism of fuzzy inference is described in a neural network architecture. The structure of first order TSK (Takagi-Sugeno-Kang) fuzzy system with two inputs and one output can be seen in Figure 1.

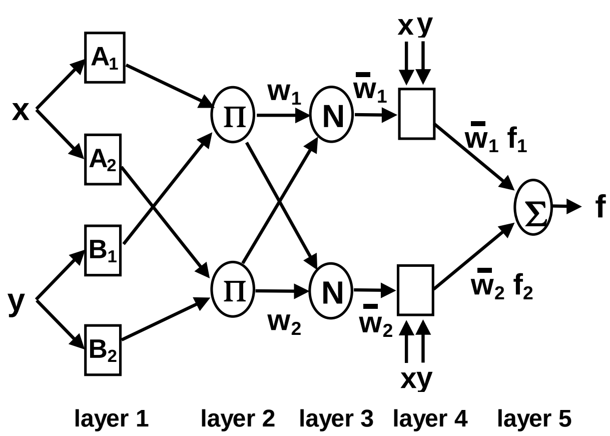


Fig. 1. Structure of ANFIS TSK

This architecture consists of five layers with different function in each layer. The adaptive network is manifestated only in the first and the fourth layer. In the first layer, the adaptive parameters are the parameters of the membership function of input fuzzy set, which are nonlinear function of the system output, also known as premise parameters. The parameters in the fourth layer are the linear function of the system output assuming that the parameters of the membership function are fixed. These parameters are determined using hybrid learning, which involves backward pass for linear parameters and forward pass learning for nonlinear parameters. Due to the linear relationship with respect to the output parameters, then a least-square estimator can be applied for the learning process. Whereas the learning process for the nonlinear parameters employs the simple steepest descend method.

4. INTELLIGENT VIRTUAL SENSOR

The objective of using virtual sensing system is to estimate the input variable which can not be measured on-line. In such a case, an artificial neural network technique can be applied to model the relation which is difficult to derive analyticaly. By deriving the inverse model of the process, the artificial neural network can be used to model the immeasurable variable, which is called the primary variable, from a measurable variable, which is called secondary variable. The scheme of virtual sensing system employs an artificial neural network with Diagonal Recurrent Neural Network (DRNN) structure as model of the plant and the Extended Kalman Filter (EKF) as the estimator (Habtom, 1999), as shown in Fig. 2. The first step to be done is to identify the plant which its immeasurable variable will be estimated off-line. In this process, the immeasurable variable should be included in the process. After the model is obtained, the next step is to design an estimator based-on the Extended Kalman Filter (Kalman, 1960) without inserting the immeasurable variable in the model input.

In developing the plant model using DRNN, during the learning phase, as input variables are the measurable input u_M (secondary variable) and immeasurable input u_i (primary variable), and as the output variable of the plant is y. The learning phase will be performed using the backpropagation method with adaptive learning rate. After the modelling process and validation, the weighting of DRNN will not be changed or in the on-line phase, the weighting should not be adaptive. The architecture of the DRNN can be seen in Fig. 3 and its mathematical representation can be written as

$$S_j(n) = \sum_{k=1}^{N} W_{jk}^{10} I_k(n) + W_j^{Z} Z(n) + W_j^{11} X_j(n-1) + W_j^{1b} \quad (1)$$

$$X_j(n) = f(S_j(n)) \quad (2)$$

$$Y(n) = \sum_{j=0}^{M} W_j^{21} Xj(n) \quad (3)$$

where in every discrete-time n, $I_k(n)$ is *measureable* input to k^{th} neuron in input layer, Z(n) is *immeasureable* input to neuron in input layer, $S_j(n)$ is input to j^{th} neuron in hidden layer, $X_j(n)$ is j^{th} output neuron in hidden layer, Y(n) is network output and f is activation function, with $0 \le k \le N$, N is the number of neuron in input layer, and $0 \le j \le M$, M is the number of neuron in hidden layer.

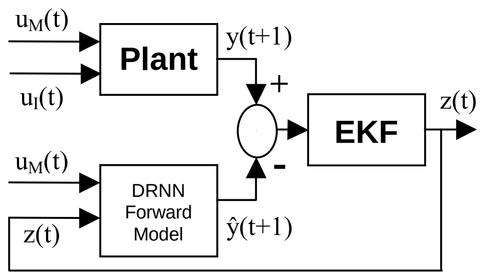


Fig. 2. *Virtual sensor* with EKF as an estimator

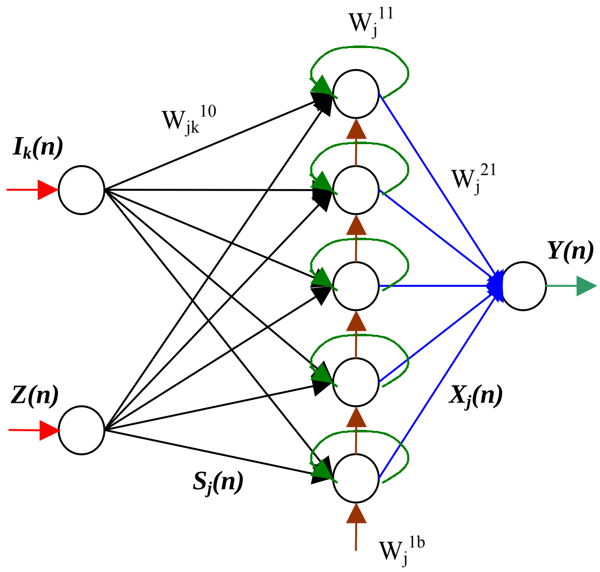


Fig. 3. Structure of the Diagonal Recurrent Neural Network *(DRNN)*

To represent the plants with nonlinear behavior, the Nonlinear Auto-Regressive with eXogenous Variable (NARX) parametric model form is used as well. In this model, the output is a nonlinear function of previous outputs and inputs of the plant. For this case, the NARX model can be represented in the form as illustrated in Fig. 4.

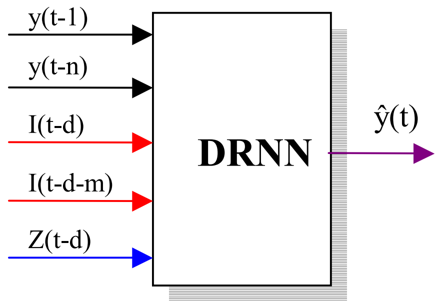


Fig. 4. NARX model

where y(t), I(t) and Z(t) the sampled plant/process output, *measureable* input and *immeasureable* input, at time instant t, respectively, ŷ(t) is output of DRNN, n is the number of input to DRNN coming from system output, d is a *delay time* of input to DRNN coming from system input, and m is the number of input to DRNN coming from system input.

5. EKF AS AN ESTIMATOR

EKF (Kalman, 1960) will perform an estimator of the state variables $(x_1(t), x_2(t))$ and the immeasurable input. The plant model of eqs. (1-3) can be written in discrete-time form as

$$S_j(t) = \sum_{k=1}^{N} W_{jk}^{10} I_k(t) + W_j^{Z} Z(t) + W_j^{11} X_j(t-1) + W_j^{1b} \quad (4)$$

$$X_j(t) = f_1(S_j(t)) \quad (5)$$

$$Y(t) = f_2\left(\sum_{j=0}^{M} W_j^{21} X_j(t)\right) \quad (6)$$

where in every discrete-time t, $I_k(t)$ is *measureable* input to k^{th} neuron in input layer, Z(t) is *immeasureable* input to neuron in input layer, $S_j(t)$ is input to j^{th} neuron in hidden layer, $X_j(t)$ is j^{th} output neuron in hidden layer, Y(t) is network output and f_1 and f_2 is activation function of the hidden and output layer, respectively, with $0 \le k \le N$, N is the number of neuron in input layer, and $0 \le j \le M$, M is the number of neuron in hidden layer.

From the above 3 equations, f_1 and f_2 is function of states (X_1, I, and Z), and the weights (W^{10}, W^{11}, W^{1Z}, W^{1b}, W^{21}). Assuming θ represents all parameters which can be changed during learning (such as weight and bias), then eqs. (4-6) can be rewritten in the following form

$$x_1(t+1) = f_1(x_1(t), Z(t+1), \theta_1(t), I(t+1)) + \xi_1(t) \quad (7)$$

$$x_2(t+1) = f_2(f_1(.), \theta_2(t)) + \xi_2(t) \quad (8)$$

$$Z(t+1) = Z(t) + \zeta(t) \quad (9)$$

$$y(t) = x_2(t) + v(t) \quad (10)$$

where the weight and bias in the hidden layer and output layer is represented as θ_1 and θ_2. Note that both vectors still have constant value during *on-line* process. $\{\xi_1(t)\}$and $\{\xi_2(t)\}$ is *Gaussian white noise* with zero mean and uncorrelated with {v(t)}, and *positive definite* variance, var[ζ(t)] = S(t). Assuming $x(t) = [x_1(t) \quad x_2(t) \quad Z(t)]^T$ then the objective of learning is to determine $\hat{x}(t) = [\hat{x}_1(t) \quad \hat{x}_2(t) \quad \hat{Z}(t)]^T$.

The overall structure of the proposed intelligent control strategy using the adaptive GPC as a controller and the virtual sensing scheme is illustrated in Fig. 5. The result (output) of the virtual sensing scheme (the lower part of the overall structure) which is the estimated immeasurable variable, is fed back to the GPC controller structure with neuro-fuzzy based model (the upper part). This controller structure follows a technique which was successfully introduced for nonlinear plant control based on neuro-fuzzy approach (Nazaruddin and Tjandrakusuma, 2001).

6. EXPERIMENTAL RESULTS AND EVALUATION

The overall adaptive-predictive controller algorithm with virtual sensing scheme has been implemented as a real-time control software developed using graphical-based programming language LabVIEW and runs on a personal computer. To see the capability and performance of the proposed intelligent control strategy, the scheme was tested in real-time environment to control the level in tanks of a process mini-plant which has strongly inherent mechanical nonlinearities.

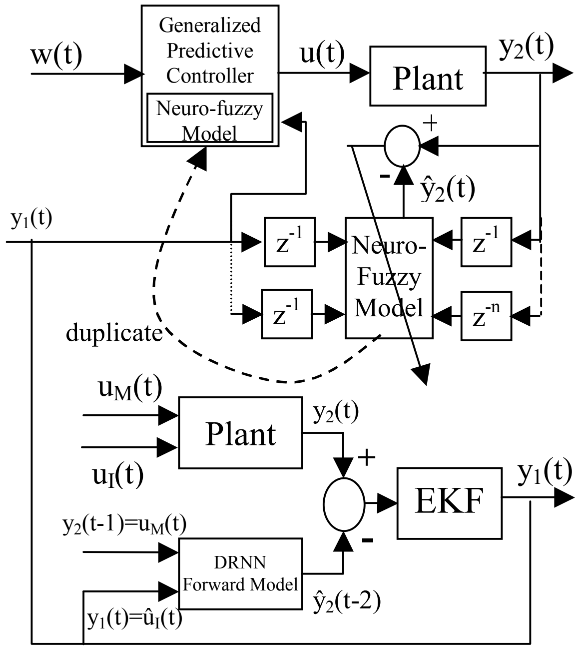


Fig. 5. The overall structure of the control scheme

6.1 Process Mini-plant Description

The process mini-plant basically consists of two tanks containing fluid which its level will be controlled, and real industrial-scaled components, such as differential pressure transmitter, control valve, I/P converter, so that it resembles almost real-plant characteristics. View of the process mini-plant is shown in Fig. 6 and the control scheme configuration in Fig. 7. The software was connected on-line to the process mini-plant through an AD/DA card and signal conditioner.

Fig. 6. View of the process mini-plant

In this investigation, $y_1(t)$ was assumed as immeasurable variable, which could be measured off-line and affected to the controlled variable $y_2(t)$. Virtual sensor was used to predict $y_1(t)$ based on variables which presumably affected it. Further, the output of virtual sensor was used as input to the GPC controller with on-line learning, as illustrated in Fig. 5. The control variable u(t) (output of the GPC) is the manipulated variable (MV), or the percentage opening of the valve LCV1.

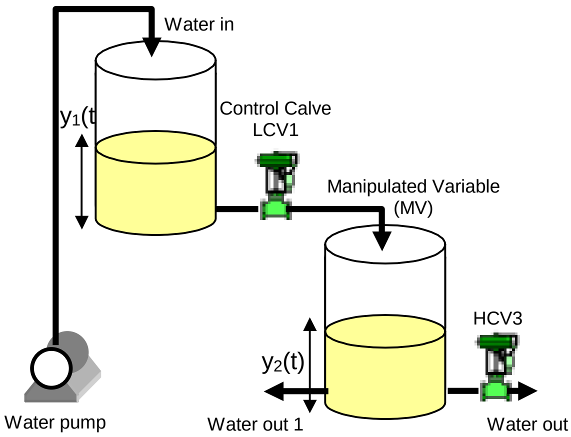


Fig. 7. Control scheme configuration

6.2 Results of Modelling and On-line Control

The control scheme will perform the predictive control mode using the model obtained from the neuro-fuzzy structure. The modelling is performed at each control steps so that the adaptive scheme is executed. In the overall control structure, the variables w(t), u(t), $y_2(t)$, $\hat{y}_2(t)$ and $y_1(t)$ were the set-point, control signal, the level of tank 2 at time t, the prediction of the level of tank 2 at time t and the level of tank 1 at time 1, respectively.

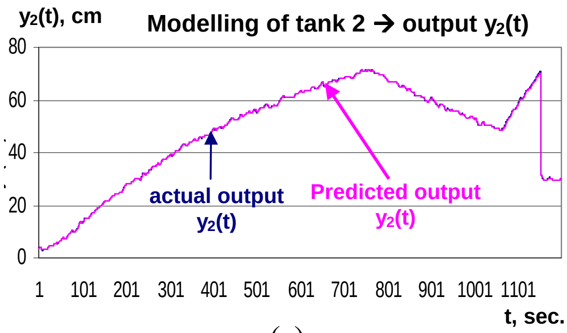
In the first step, modelling of the process of the tank 2 was conducted using the neuro-fuzzy method from the pairs of input-output data of the process mini-plant. The objective of modelling was to predict the level of tank 2 using the level of tank at t-1 and the level of tank 1 at time t. The parameters of the neuro-fuzzy methods were as follows :

- Number of training data = 3300
- Number of epoch : 3
- The forgetting factor $\gamma = 1$
- Input 1 = the level of tank 2 at (t-1) : $y_2(t-1)$
- Input 2 = the level of tank 1 at (t) : $y_1(t)$
- Input reference : the level of tank 2 at t : $y_2(t)$

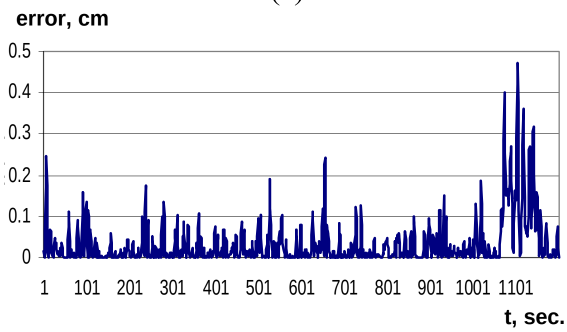
Note that as performance measure, the root means square of the error (RMSE), defined as

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N} e(k)^2}{N}} \qquad (11)$$

where $e(.)$ denotes the error at time k and N is the number of data, was used for all experimental studies. Fig. 8 shows the comparation between the measured (actual) and predicted values (based on the model) of the water level in the tank, and the error (different between measured and predicted values) for 1200 seconds of observation time. Based on the visual observation as well as from of the error (with RMSE value of 0.26), it can be seen that the process dynamics in the tank 2 is represented almost accurately by the neuro-fuzzy model



(a).



(b).

Fig. 8. The results of modelling using ANFIS
(a). measured (actual) and predicted value of the level in tank 2 (b). error

Fig. 9 shows the results of on-line control of the process mini-plant using the proposed intelligent control scheme with virtual sensing. The objective of the control is to obtain a set-point tracking. During all experiments, the set-point (level in the tank 2) was varied from 30 to 70 cm.

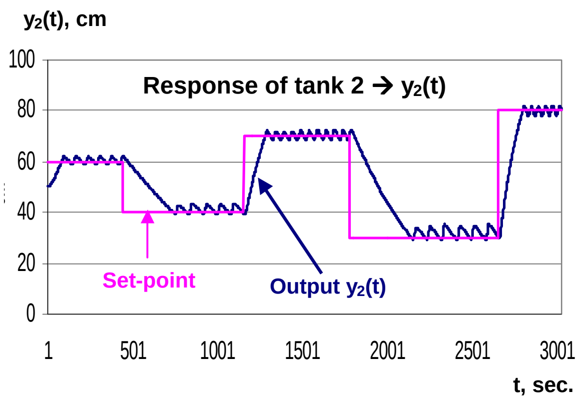
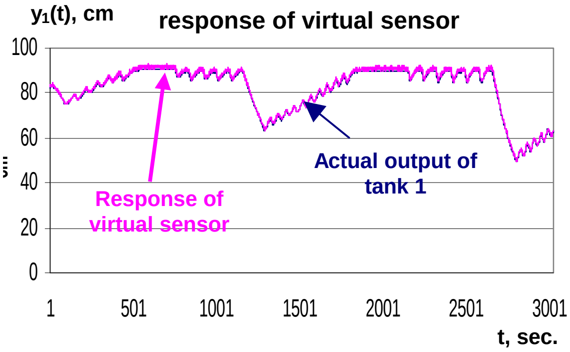


Fig. 9. Response of the level in tank 2 using the proposed intelligent control scheme with virtual sensing scheme

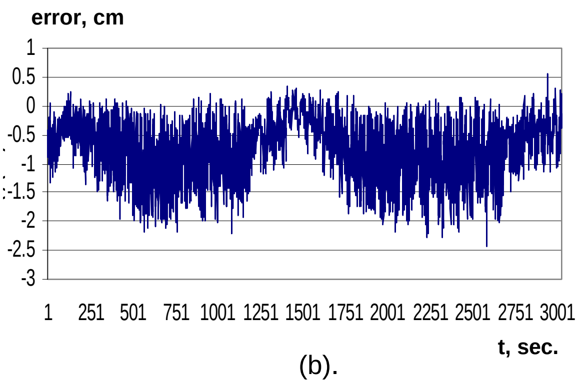
For the generalized predictive control scheme, the following setting of the horizon and weighting was used. These values were chosen based on the trial and error approach during the experimental studies.

- Minimum horizon = $N_1 = 1$
- Maximum horison = $N_2 = 10$
- Control horizon = $N_u = 1$
- Weighting of control signal = $\lambda = 0.0003$

It can be seen that satisfactory performance is obtained although the set-point was changed frequently. Acceptable results were also shown from the response of virtual sensing scheme, as demonstrated in Fig. 10.a. The immeasurable variable, $y_1(t)$, could be predicted sufficiently well by the proposed virtual sensing scheme, where it was then used for input to the adaptive predictive controller scheme. A RMSE value of 0.86 was obtained from the resulting error, as shown in Fig. 10.b.



(a).



(b).

Fig. 10. Results of virtual sensing scheme (a). response of the virtual sensor scheme (b). error between the measured (actual) and the predicted values of the sensor

6. CONCLUSIONS

An alternative intelligent control strategy, which is an integration between the Generalized Predictive Control (GPC) strategy with neuro-fuzzy based modelling and an intelligent virtual sensing elements is proposed. The virtual sensor consists of Diagonal Recurrent Neural Network (DRNN) for modelling the plant as part of the sensing algorithm and the Extended Kalman Filter (EKF) as the estimator with inputs from DRNN. The proposed strategy has been tested on a real-time environment for on-line control of a process mini-plant. In the control scheme, the modelling process will be done on-line at each control action and this will allow the control to be done adaptively.

The experimental results showed the effectiveness and the performance of the method in controlling nonlinear systems. The virtual sensing scheme predicts the immeasurable variable satisfactorily based on the information from measurable or secondary variable.

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