Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Torque Observer Modelling for Vehicle Transmission Shifting Processing Based on Neural Networks

Pingkang Li *,** **Taotao Jin** * **Xiuxia Du** *

* *Beijing Jiaotong University, Beijing, 100044, P. R. China (e-mail:pkli@bjtu.edu.cn)*
** *National Key Lab. of Vehicular Transmission , Beijing, 100072*

Abstract: To reduce shock during transmission gear shift, a Neural Network based torque observer for vehicle transmission shifting processing modelling is proposed in this paper. The problem with nonlinear model identification for an excessive number of candidate model terms or basis functions has been treated, using an Extended Kalman Filtering algorithm. The modelling of transmission input torque, which is needed by the observer for accurate clutch pressure estimation, is addressed and implemented using a Radial Basis Function Neural Network (RBFNN) based observer. A linear combination of model terms, or basis functions of the RBFNN, which are nonlinear functions of the system variables is identified as a linear-in-the-parameters model. The resulting observers are validated via off-line simulation tests, as well as experiment tests at different sampling frequencies on a test vehicle bench, for demonstration the observer performance and establishment the feasibility of the approach.

Keywords: Neural Networks; Torque Observer; Vehicle Transmission Shifting Modeling, Vehicle dynamic systems.

1. INTRODUCTION

One of the main functions of a powertrain hydraulic system is to control the automatic transmission shifting operations. Achieving a seamless shift under all operating conditions is important to meet and exceed customer expectations. A typical powertrain system consists of the torque converter, planetary gear sets, friction components, and the hydraulic control system. The operating position of the control valve dynamically changes, based upon a force balance of various hydraulic signals against a mechanical spring force or a hydraulic pressure externally controlled by a solenoid. It is known that if clutch torque and pressures are measured or otherwise estimated in real time in automatic transmissions, closed-loop control algorithms can be designed to improve shift quality (Lin, 1992) and (Masmoudi and Hedrick, 1992). However, such torque and pressure sensors are usually not used in production transmissions due to sensor cost and reliability, as well as difficulty in sensor installation and maintenance (Watechagit, 2003), (Parvateneni *et al.*, 1999). That it one of the reasons for why it is very difficult to measure friction component behaviors such as slip speed and torque in the powertrain system.

In an investigation of torque estimation for powertrain shift control, paper (Lai, 1995) concluded that an Artificial Neural Networks (ANN) approach could be feasible for off-line modelling of friction component torque dynamics. Paper (Parvateneni *et al.*, 1999) proposed a simple two layer recurrent neural network with a coupled linear-nonlinear hidden layer for frictional component dynamics modelling. While this black-box approach successfully captured the overall trend of the friction component engagement torque profiles, it failed to identify some of the important and detailed dynamic behaviors. The main drawback of the black-box model is that the known physics of the friction component is not utilized during the modelling process, which makes the network training inefficient and induces poor accuracy.

Instead of directly measuring the pressure output of a hydraulic actuator, paper of (Slotine *et al.*, 1987) and (Yi *et al.*, 2000) proposes an indirect alternative to estimate the pressure output: an observer-based approach. The main thrust of these papers are that the pressure output of a hydraulic actuator is "observable" with the slip velocity measurement of the mechanical subsystem in a vehicle power transmission control system. But the complexity of the hydraulic actuator dynamics does not allow a physical model amenable to observer design (Montanari *et al.*, 2004).

The development of a Neural Network (NN) based nonlinear observer to estimate clutch pressure and torque using speed measurements is presented, along with results from experimental implementation. The implementation results using the developed observers are presented for two sampling frequencies: a high sampling frequency to demonstrate the performance of the observer when there is less of a computational limitation imposed on the implementation, and a low sampling frequency to demonstrate the feasibility of using the observer on current production vehicles. After the brief description of the dynamic model for the transmission of interest which is presented in section 2, the development of a clutch torque observer using the NN based approach is presented in section 3, followed by the development of a turbine torque observer to enhance the accuracy of the clutch pressure estimation in section 4. The performance of the observer is evaluated by simulation and experimental tests, with the experimental results being shown in section 5. Conclusions and recommendations for future work are given in section 6.

2. TRANSMISSION MODEL OF A VEHICLE POWER TRANSMISSION CONTROL SYSTEM

A dynamic model of the transmission with a stiff drive shaft is considered here since the proposed observer uses filtered speed signals as inputs, and the effect of a high frequency oscillation from the drive shaft is suppressed. The transmission components modelled include the torque converter, the transmission mechanical system, which includes the planetary gear train, the transmission shift hydraulic system, and the driveline. The engine dynamic model is not included, experimental engine data being used instead as input to the transmission model. Note that the torque converter model used is the widely accepted static model developed by (Watechagit, 2003), and the coefficients in the model being chosen depending on measured torque converter characteristics.

The Transmission model will consider the combined mechanical system and driveline. For the simplification only the dynamic model for the transmission for operation in the 1-2 power-on up shift is supposed. In the 1st gear, two clutches, the underdrive clutch (UD) and the second clutch (2ND), are fully engaged. In the 2nd gear, the two clutches that are engaged are the UD clutch and the overdrive clutch (OD). Therefore, the 1st-2nd up shift involves releasing the 2ND clutch and simultaneously applying the OD clutch. It is known that two phases are involved during any gearshift, namely the torque phase and the inertia phase. Due to space limitations, only the dynamics of the torque phase are considered.

A vehicle power transmission control system typically consists of two subsystems, a mechanical subsystem and a hydraulic actuator. The input and output of the system under consideration are the voltage signal to the hydraulic actuator and the slip velocity between the friction elements in the mechanical subsystem, respectively. The hydraulic actuator drives the friction elements and generates the slip velocity of the mechanical subsystem according to its pressure output. Figure 1 shows a vehicle power transmission control system considered in this paper, a torque converter clutch slip control system. The mechanical subsystem consists of an engine, a torque converter, an automatic transmission with planetary gear sets, and wheels with a final reduction gear. The torque converter clutch generates friction torque acting upon the engine according to the hydraulic actuator pressure, which in turn determines the slip velocity between the engine and the turbine of the torque converter at a desired target value.

In order to derive a physical model of the mechanical subsystem, the power transmission at each stage is examined. At the very first stage, the engine torque is transmitted to the impeller and is balanced by the reaction torque of the impeller and the friction torque from the torque converter clutch. The torque converter amplifies and transmits the

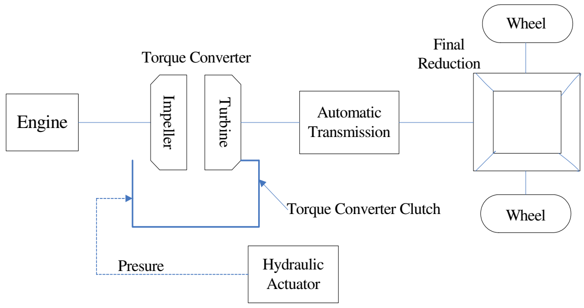

Fig. 1. A vehicle power transmission control system

impeller torque to the turbine. The turbine torque drives the automatic transmission system together with the friction torque of the torque converter clutch, while the driving load torque of the vehicle provides additional resistive force. Denoting the slip velocity between the engine and the turbine as the output of interest (y) results in

$$\begin{aligned}\frac{dy}{dt} &= -cy + \frac{1}{I_e}(T_e - T_p) - \frac{1}{I_v}\left\{(r_t r_f)^2 T_t - (r_t r_f) T_l\right\} \\ &-\frac{2}{3}\pi\mu\left(R_0^3 - R_i^3\right)\left\{\frac{1}{I_e} + \frac{1}{Iv}(r_t r_f)^2\right\} P_c \\ &= -cy + f_y(y) - g_y(y) P_c\end{aligned} \tag{1}$$

where I_e is the equivalent rotational inertia of the engine, I_v the equivalent rotational inertia of the vehicle, ω_c the angular velocity of the engine, ω_t the angular velocity the turbine, T_e the engine torque, T_p the impeller torque, T_t the turbine torque, T_c the friction torque of the torque converter clutch, T_l the driving load torque, c the equivalent damping constant of the torque converter clutch, r_t the gear ratio of the automatic transmission, r_f the gear ratio of the final reduction, m the friction coefficient of the torque converter clutch, R_o the outer radius of the torque converter clutch, R_i the inner radius of the torque converter clutch and P_c the pressure output of the hydraulic actuator.

$$f_y(y) = \frac{1}{I_e}(T_e - T_p) - \frac{1}{I_v}\left\{(r_t r_f)^2 T_t - (r_t r_f) T_l\right\} \tag{2}$$

$$g_y(y) = \frac{2}{3}\pi\mu\left(R_0^3 - R_i^3\right)\left\{\frac{1}{I_e} + \frac{1}{I_v}(r_t r_f)^2\right\} \tag{3}$$

It is worth noting that the quantities in Equation (1) are subject to errors; the damping constant is not exactly known; absence of torque sensors in a commercial vehicle entails torque estimation errors; the equivalent rotational inertia of the vehicle varies as the number of passengers changes, and only a rough bound on the friction coefficient is available.

3. MODELLING OF A HYDRAULIC ACTUATOR USING STATE SPACE FORM

A nonlinear mathematical model of the hydraulic actuator has been obtained in paper of (Watechagit, 2003) using the Newton's second law of motion. Although the nonlinear model in the paper matches the experimental results to a certain extent, it has some drawbacks when applied to the observer design problem:

1. The model order is too high (up to 10th order).

2. The governing differential equations are too stiff to numerically solve in real-time.

3. There exist numerous unknown parameters that need to be estimated or tuned in order to obtain reasonable match between experimental results and model predictions. A possible alternative is to capture the dynamics essential to the design of a nonlinear observer and to obtain a lower-order control-oriented empirical model.

Now suppose the pressure P_c is a second order process, and could be presented by (Cicci, 1999)

$$\begin{aligned} &\frac{d}{dt}\begin{bmatrix} x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} -a_1 & 1 \\ -a_0 & 0 \end{bmatrix}\begin{bmatrix} x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_0 \end{bmatrix} u \\ &P_c\left(t\right) = \left[\, 1 \;\; 0 \,\right]\begin{bmatrix} x_2 \\ x_3 \end{bmatrix} + du \end{aligned} \tag{4}$$

Combing Equation (1) into this Equation (4) by letting $y_1 = x_1$ and $y_2 = x_2$, that is

$$\begin{aligned} &\frac{d}{dt}y_1 = \frac{d}{dt}x_1 = -cx_1 + f_y\left(x_1\right) - g_y\left(x_1\right)P_c \\ &= -cx_1 + f_y\left(x_1\right) - g_y\left(x_1\right)\left(x_2 + du\right) \end{aligned} \tag{5}$$

then we have the state space form as:

$$\begin{aligned} &\frac{d}{dt}\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} -c & -g_y\left(x_1\right) & 0 \\ 0 & -a_1 & 1 \\ 0 & -a_0 & 0 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \\ &+ \begin{bmatrix} -g_y\left(x_1\right)d \\ b_1 \\ b_0 \end{bmatrix} u + \begin{bmatrix} f_y\left(x_1\right) \\ 0 \\ 0 \end{bmatrix} \\ &= Ax + Bu + F\left(x_1\right) \end{aligned} \tag{6}$$

$$y = [{}^{1\;0\;0}_{0\;1\;0}]x = Cx \tag{7}$$

where $f_y(x_1)$ and $g_y(x_1)$ are defined in Equation (2) and (3). Generally the nonlinear properties in this state space Equation (6) are difficult to dear with. Although we can use the nonlinear observer design algorithm to obtain the model as studied in the paper of (Yi *et al.*, 2000)and (Li and Du, 2006), for the nonlinear functions $f_y(x_1)$ and $g_y(x_1)$ in the state matrix A and B in Equation (2), the calculation approach should be improved and simplified. Below we introduce a Neural Network method to obtain the nonlinear observed states.

4. NEURAL NETWORK BASED OBSERVER MODELLING

Along with the approach proposed in paper (EI-Gindy and Palkovics, 1993) the Radial Based Function Neural Network (RBFNN) is introduced here to obtain the model of the transmission system, as well as the observer states. The RBFNN-based dynamic system model, such as pressure-torque or speed-torque model, directly realizes a polynomial correlation between the system input and output, and therefore could significantly improve the input-output scalability. This feature makes it a great candidate for deriving controller-design-oriented system models. This model formulates the pressure-torque correlation as a quadratic form. Therefore, by solving the 2nd-order function realized by the neural network model, the applied pressure can be easily written as a function of the torque. In other words, the RBFNN can serve as the forward and inverse system model at the same time. The RBFNN-based model could integrate the friction components with a pressure-torque model for dynamic system simulation and transmission shift controller design. These new features contribute to the improved performance and trainability over the black-box network (Parvateneni *et al.*, 1999).

The mathematical equations for the adopted RBFNN network are realized in Figure 2. It consists of the m-dimensional input x being passed directly to a hidden layer. Suppose there are c neurons in the hidden layer. Each of the c neurons in the hidden layer applies an activation function which is a function of the Euclidean distance between the input and an m-dimensional prototype vector. Each hidden neuron contains its own prototype vector as a parameter. The output of each hidden neuron is then weighted and passed to the output layer. The outputs of the network consist of sums of the weighted hidden layer neurons. The response of an RBF of the form of Figure 2 can be written as follows:

$$\hat{y} = \begin{bmatrix} w_{10} & w_{11} & \cdots & w_{1c} \\ w_{20} & w_{21} & \cdots & w_{1c} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n0} & w_{n1} & \cdots & w_{nc} \end{bmatrix}\begin{bmatrix} 1 \\ g(\|x - v_1\|^2) \\ \vdots \\ g(\|x - v_1\|^2) \end{bmatrix} \tag{8}$$

If we are given a training set of M desired input-output responses $\{xi; yi\}$ $(i = 1; \cdots; M)$, then we can augment M equations of the form of Equation (8) as follows:

$$\left[\, \hat{y}_1 \;\cdots\; \hat{y}_M \,\right] = WH \tag{9}$$

where W and H are

$$W = \begin{bmatrix} w_{10} & w_{11} & \cdots & w_{1c} \\ w_{20} & w_{21} & \cdots & w_{1c} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n0} & w_{n1} & \cdots & w_{nc} \end{bmatrix} = \begin{bmatrix} w_1^T \\ w_2^T \\ \vdots \\ w_n^T \end{bmatrix} \tag{10}$$

$$H = \begin{bmatrix} h_1^T \\ \cdots \\ h_M^T \end{bmatrix}^T = \begin{bmatrix} 1 & \cdots & 1 \\ g(\|x_1 - v_1\|^2) & \cdots & g(\|x_M - v_1\|^2) \\ \vdots & \vdots & \vdots \\ g(\|x_1 - v_c\|^2) & \cdots & g(\|x_M - v_c\|^2) \end{bmatrix} \tag{11}$$

In local support networks the approximation is generated by the neuron forming overlapping bumps which combine to give the overall mapping. The more neurons used, the greater the overlap and the smoother the approximation obtained.

Radial basis networks can be designed with the function *newrbe* in Matlab. Figure 3 is its function diagram. This function can produce a network with zero error on training samples. The usage of the function is:

$net = newrbe(P, T, Spread)$

where P - matrix of input vectors; T - target vectors; $Spread$ - a spread constant.

The function returns a network with weights and biases such that the outputs are exactly T when the inputs are P.

In this paper the output of the RBFNN model was the friction component torque. The inputs for this model included

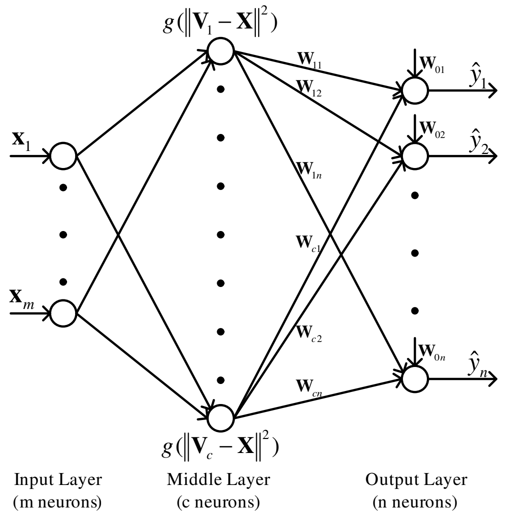

Fig. 2. RBF network with Gaussian basis functions

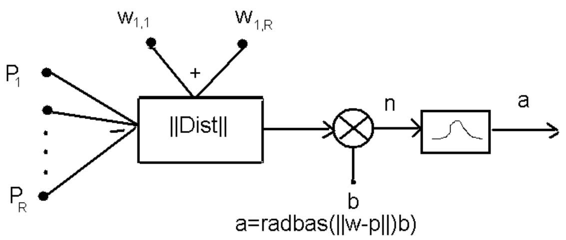

Fig. 3. Matlab expression for a neuron in RBF network

slip speed, applied pressure, as well as one-time-step and two-time-step delayed output torques. This RBFNN network configuration with feedback loop made the resultant model a dynamic system. The nonlinear neuron in the hidden layer was added to help capturing the strongly nonlinear correlation between the output torque and the applied pressure. The output neuron adopted a linear activation function. The sigmoid function could also be chosen as the activation function for the nonlinear hidden layer neurons. Because Kalman filter training provides about the same performance as gradient descent training, but with only a fraction of the computational effort (Simon, 2002), We can use Kalman filtering to minimize the training error for Equation(9). Derivations of the extended Kalman filter to train the network are widely available in the literature (Isabelle and Leon, 1998)(Yang *et al.*, 2007). The Extended Kalman Filtering algorithm used for training the Network now is adopted and listed below.

In general, we can view the optimization of the weight matrix W in (10)and the prototypes v_j in (11) as a weighted least-squares minimization problem, where the error vector is the difference between the RBF outputs and the target values for those outputs, as in Equation (9). For using the RBF network of Figure 2 with m inputs, c prototypes, and n outputs to model the system as in Equation (6), we use y to denote the target vector for the RBF outputs, and $h(\hat{\theta}_k)$ to denote the actual outputs at the kth iteration of the optimization algorithm.

$$y = [\, y_{11} \, \cdots \, y_{1M} \, \cdots \, y_{n1} \, \cdots \, y_{nM} \,]^T \tag{12}$$

Note that the y and $\hat{y}$ vectors each consist of nM elements, where n is the dimension of the RBF output and M is the number of training samples. In order to cast the optimization problem in a form suitable for Kalman filtering, we let the elements of the weight matrix W and the elements of the prototypes v_j constitute the state of a nonlinear system, and we let the output of the RBF network constitute the output of the nonlinear system to which the Kalman filter is applied. The state of the nonlinear system can then be represented as

$$\theta = \left[\, w_1^T \;\, w_2^T \cdots w_n^T \;\, v_1^T \cdots v_c^T \,\right]^T \tag{13}$$

The vector θ thus consists of all $(n(c+1)+mc)$ of the RBF parameters arranged in a linear array. The nonlinear system model to which the Kalman filter can be applied thus could be derived as a standard NARX model as follows (Li and Li, 2008).

For a general nonlinear discrete-time dynamic system

$$\begin{aligned} y(t) &= F(y(t-1),...,y(t-n_y),u(t-1),...,u(t-n_u)) \\ &= F(x(t)) \end{aligned} \tag{14}$$

where u(t) and y(t) are the system input and output variables at sample instant t , n_u and n_y are the corresponding maximal lags, $x(t) = [y(t-1),...,y(t-n_y),u(t-1),...,u(t-n_u)]^T$ represents the model 'input' vector, and $F(\bullet)$ is some unknown nonlinear function.

Suppose a linear-in-the-parameter model is used to represent system (14) such that

$$y(t) = \sum_{i=1}^{n} \theta_i \varphi_i(\mathbf{x}(t)) + \varepsilon(t), \mathrm{t} = 1, \ldots, \mathrm{N} \tag{15}$$

where $\varphi_i(\bullet), i = 1,...,n$ are all candidate model terms which are nonlinear or basis functions, and $\varepsilon(t)$ is the model residual sequence.

Suppose N data samples $\{\mathbf{x}(t), y(t)\}_{t=1}^N$ are used for model identification. Equation (15) can then be formulated as (Li and Li, 2008):

$$\mathbf{y} = \mathbf{\Phi\Theta} + \mathbf{\Xi} \tag{16}$$

where $\mathbf{\Phi} = [\varphi_1, \varphi_2, .., \varphi_n] \in \Re^{N \times n}$,

$\varphi_i = [\varphi_i(\mathbf{x}(1)), \varphi_i(\mathbf{x}(2)), ..., \varphi_i(\mathbf{x}(N))]^T \in \Re^N$, i = 1,..., n,

$\mathbf{y}^T = [y(1), \cdots, y(N)] \in \Re^N$,

$\mathbf{\Xi}^T = [\varepsilon(x_1), \varepsilon(x_2), ..., \varepsilon(x_N)] \in \Re^N$,

$\mathbf{\Theta} = [\theta_1, \theta_2, .., \theta_n]^T \in \Re^n$.

Note that $\mathbf{\Phi}$ is also called the regression or observation matrix.

Comparing with standard Kalman Filter equation (Ljung, 1999), we have

$$\begin{aligned} x_{k+1} &= F(k)x_k + w(k) \\ y_k &= H(k)x_k + v(k) \end{aligned} \tag{17}$$

by considering Equation (2) and (3), that is (Ljung, 1999):

$$\begin{aligned} &\Theta_{k+1} = \Theta_k \; (= \Theta_{true}) \\ &y_k = \varphi_k^T(x_k)\Theta_k + v(k), \mathrm{k} = 1, \ldots, \mathrm{N} \end{aligned} \tag{18}$$

then we have $F(k) \equiv I$ and $H(k) = \varphi_k^T$, with

$$\begin{aligned} Ew(k)w^T(k) &= 0 = R_1(k) \\ Ev(k)v^T(k) &= R_2(k) \end{aligned} \tag{19}$$

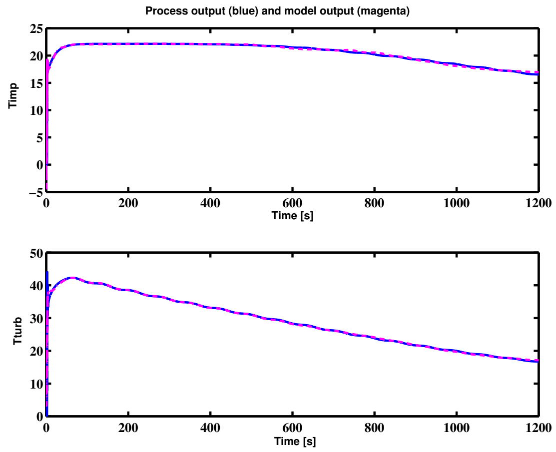

Fig. 4. Matlab Modelling for a Shifting Process

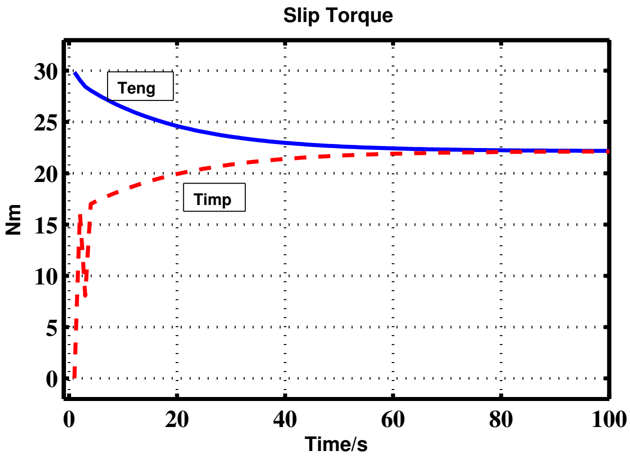

Fig. 5. Slip Torque Curves From the Simulation of the Process

The more detail about the calculation of the Kalman filter algorithm to train the Neural Network could be found as in paper (Yang *et al.*, 2007) and (Isabelle and Leon, 1998).

5. SIMULATION EXPERIMENTS AND FIELD TEST RESULTS

The simulation for the transmission system is based on the parameters from paper (Lai, 1995). The implementation results using the developed observers are presented for two sampling frequencies: a high sampling frequency $1kHz$ to demonstrate the performance of the observer when there is less of a computational limitation imposed on the implementation, and a low sampling frequency to demonstrate the feasibility of using the observer on current production vehicles.

The network begins with no hidden units, and as observations are received, new hidden units are added by taking some of the input data. The network is trained using the EKF approach. Figure 4 is the modelling result for long time shifting performance with a sample time 1 millisecond, the data coming from the simulation on T_{imp} for impeller Torque and T_{tub} for turbine Torque. Figure 5 is its slip torque process curves,where T_{eng} for Engine torque. Figure 6 is the detailed dynamic process for the demonstration. Note that for the sake of the space, only

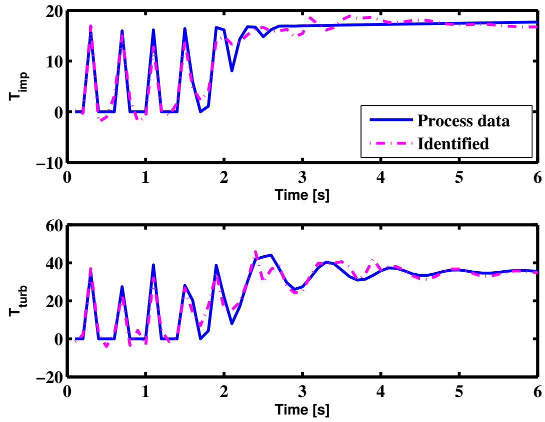

Fig. 6. Matlab Modelling for a fast sample Shifting Process

T_{imp}, the impeller torque, and T_{turb}, the turbine torque are outlined as the outputs under the inputs ω_{eng} and ω_{turb} from the simulation. The results showed that the proposed approach using a RBFNN consisting of a single hidden layer of radial basis functions and a linear output neuron can approximate arbitrarily well any bounded continuous function.

Figure 7 is the field test data curves for shifting process, where different sampling frequencies are tested on a vehicle test bench. By the same way from the simulation, the transmission system models are obtained. Figure 8 is the pressure curve from the real shifting process at high sample frequency. This process is of a second order system property. Figure 9 is the initial modelling for partially data results with slow sample frequency. The inputs there are v_{imp} and T_{imp}, and the outputs are P_c and T_{tub}. For the sake of the clarifying, only first 1000 points are selected from Figure 7. The identified observer model curves are little different from the original data curves because of the complex of the system. These implementation results show that the NN based observer is able to predict clutch pressures as well as the turbine torque with a reasonable degree of accuracy. One of the observer model for the linear part system is given as follows.

$$\hat{A} = \begin{bmatrix} .9981 & .0094 & .3394 \\ .0005 & .0015 & .0310 \\ .0014 & .0096 & .9407 \end{bmatrix}; \hat{B} = \begin{bmatrix} 0.3 & 131.9 \\ 0 & 216.1 \\ 0 & 222 \end{bmatrix};$$
$$\hat{C} = \begin{bmatrix} -.1092 & 0.2953 & -.2204 \\ -.2983 & -.1023 & -.4905 \end{bmatrix}; \hat{D} = \begin{bmatrix} 6 & 5573 \\ 3 & 5509 \end{bmatrix}$$

6. CONCLUSIONS AND FUTURE WORK

A NN-based observer for the simultaneous estimation of clutch pressure and transmission input torque with turbine torque for an automatic transmission processing is presented. The implementation results using the developed observers are presented for two sampling frequencies: a high sampling frequency to demonstrate the performance of the observer when there is less of a computational limitation imposed on the implementation, and a low sampling frequency to demonstrate the feasibility of using the observer on current production vehicles. The implementation results show that the observer is able to predict clutch pressures as well as the turbine torque with a

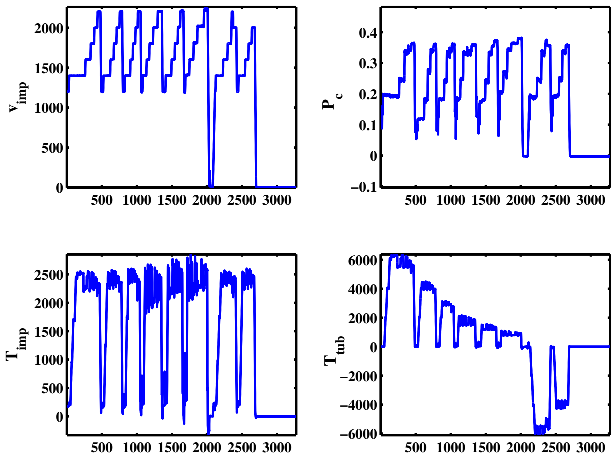

Fig. 7. Field Test Data Curves For Shifting Process

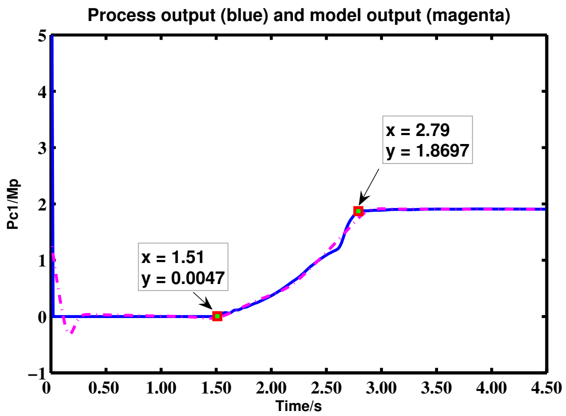

Fig. 8. Pressure Curve Modelling For Shifting Process

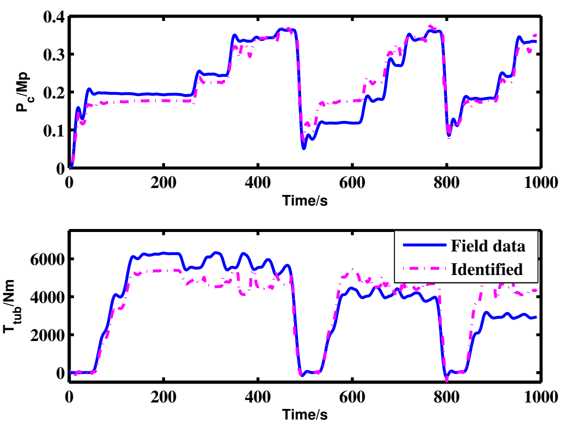

Fig. 9. Field Test Data Modelling For Shifting Process

reasonable degree of accuracy. Evaluation and refinement of the observer design for a greater variety of gear shifts and for a wider range of transmission operating conditions is warranted.

ACKNOWLEDGEMENTS

The first author would like to thank the support by Science Foundation from National Key Lab. of Vehicular Transmission (No.9140C3403010603)

REFERENCES

Cicci, D.A. (1999). Filter performance in target tracking using space-based observers. *Applied Mathematics and Computation* **99**, 275–293.

EI-Gindy, M. and L. Palkovics (1993). Possible application of artificial neural networks to vehicle dynamics and control: a literature review. *International Journal of Vehicle Design* **14**, 592–614.

Isabelle, R. and P. Leon (1998). A recursive algorithm based on the extended kalman filter for the training of feedforward neural models. *Neurocomputing* **20**, 179–294.

Lai, J. S. (1995). Intelligent robust control of clutch-to-clutch shifts in vehicle transmission systems. *Ph.D. Thesis, Penn State University*.

Li, P.K. and K. Li (2008). A recursive algorithm for nonlinear model identification. *Applied Mathematics and Computation*.

Li, P.K. and X.X. Du (2006). The observer design for nonlinear system with both input and output unknown disturbances. In: *IFAC 6th Symposium on Fault Detection, Supervision and Safety of technical Processes*. Vol. 1. Beijing, China.

Lin, W. C. (1992). Shaft-torque estimation for closed-loop transmission clutch control. *Proceedings ASME Dynamic Systems and Control Division* **44**, 293–298.

Ljung, L. (1999). *System identification: theory for the user*. 2^{nd} ed.. Prentice Hall. Upper Saddle River, N.J., U.S.A.

Masmoudi, R. A. and J. K. Hedrick (1992). Estimation of vehicle shaft torque using nonlinear observers. *ASME Journal of Dynamic Systems, Measurement, and Control* **114**, 394–400.

Montanari, M., F. Ronchi, C. Rossi, A. Tilli and A. Tonielli (2004). Control and performance evaluation of a clutch servo system with hydraulic actuation. *Contr Eng Practice* **12**(11), 1369–1379.

Parvateneni, V., M. Cao, K. W. Wang, Y. Fujii and W. E. Tobler. (1999). Hybrid neural network for modeling automotive clutches. *Proc. ASME Dynamic Systems and Control Division* **67**, 255–263.

Simon, D. (2002). Training radial basis neural networks with the extended kalman filter. *Neurocomputing* **48**, 455–475.

Slotine, J. J., J. K. Hedrick and E. A. Misawa (1987). On sliding observers for nonlinear systems. *ASME Journal of Dynamic Systems, Measurement, and Control* **109**, 245–252.

Watechagit, S. (2003). Modeling and estimation for stepped automatic transmission with cluth-to-clutch shift technology. *Ph.D. Thesis, Ohio State University*.

Yang, Huizhong, Jiang Li and Feng Ding (2007). A neural network learning algorithm of chemical process modeling based on the extended kalman filter. *Neurocomputing* **70**, 625–632.

Yi, K., B. K. Shin and K. I. Lee (2000). Estimation of turbine torque of automatic transmissions using nonlinear observers. *ASME Journal of Dynamic Systems, Measurement, and Control* **122**, 276–283.