

Engine Speed Control Using Artificial Neural Network for Vehicle Equipped with Electromechanical CVT

Sugeng Ariyono^{*}, Kamarul Baharin Tawi, Hishamuddin Jamaluddin, Bambang Supriyo^{**}

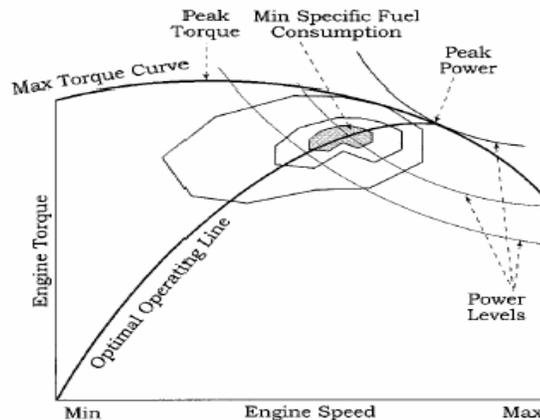
Drivetrain Research Group
Automotive Development Center
Faculty of Mechanical Engineering
Universiti Teknologi Malaysia (UTM)

Abstract: Controlling engine speed corresponding to load variations and road condition has always been a challenge to automotive engineers. However, with the introduction of electromechanical CVT, maintaining constant engine speed based on its optimum control line characteristic could be made possible. This paper describes the simulation work in this area carried out by the Drivetrain Research Group at the Automotive Development Center, Universiti Teknologi Malaysia, Skudai Johor. The developed drive train model is highly non-linear, it could not be controlled satisfactorily by common linear control strategy such as PID controller. To overcome the problem, the use of Artificial Neural Network (ANN) is employed to indirectly control the engine speed by adjusting pulley CVT ratio. Computer simulations showed that applying artificial neural network (ANN) into drive train model could select a proper transmission ratio where the engine could be maintained to run at certain desired speed.

Keyword: Artificial neural network, CVT control, electromechanical CVT

1.0 Introduction

One of the major challenges faced by car industry to day is the reduction of the fuel consumption. One alternative for achieving this goal is to increase the fuel efficiency of the engine by running the engine along its optimum operating line (OOL), Figure 1. Within the available operating range of internal combustion engine, continuously variable transmissions (CVT) is able to achieve more efficient operating levels than conventional automatic step gearbox, thus improving operational capability and fuel economy. The classical way to control CVT was the use of some information on the gear ratio or on the transmitted torque, which was then fed back by a PID type controller, [Guzzella, 1995]. He also stated that based on his experience with this approach the outcome was not very encouraging, unless reinforced with a gain scheduled controller with typically 100 difference gain points.



Masayuki Fuchino and his partner Koubei Osano, both of them came from Honda R & D Co. Ltd. They started controlling CVT with very basic control system by giving road data obtained through out their company experiment involving CVT since 1962. In 1962, the company introduced the first mass production hydraulically operated CVT into the market with the Juno, a scooter with a 0.175 liter engine generating 8.8 KW. Until the end of 1996 this company has successfully developed a new generation CVT for the 1.6 liter economy car, Civic series.

The performance of the engine and the power train takes the most important part in car's fuel efficiency and drive ability. Thus, it is very important to maintain engine being the optimal working point according to car's moving resistance by regulating the ratio and changing the throttle opening, the so-called synthesized control method can be used for this purpose, [Wang Hongyan et al. 2001]. Because the characteristic of the engine and the transmission is greatly change under different conditions, it is very difficult to control the ratio and the throttle opening to meet such demand. Fuzzy control strategy was investigated to solve this problem, the simulation done by Wang Hongyan et al shows that the synthesized controller realized by the fuzzy strategy can maintain engine operating at the maximum efficiency point at any power demand level.

2.0 Drive train Model.

To model the desired engine speed based on modelling, it is necessary to determine the drive train parameter. The dynamic vehicle is divided into three parts, engine, CVT, and wheel, Figure 2. It is assumed that there is no wheel slip; those vehicle speed is equivalent to wheel speed. The analysis begins with the engine speed dynamics, modelled as a single inertia system, given as:

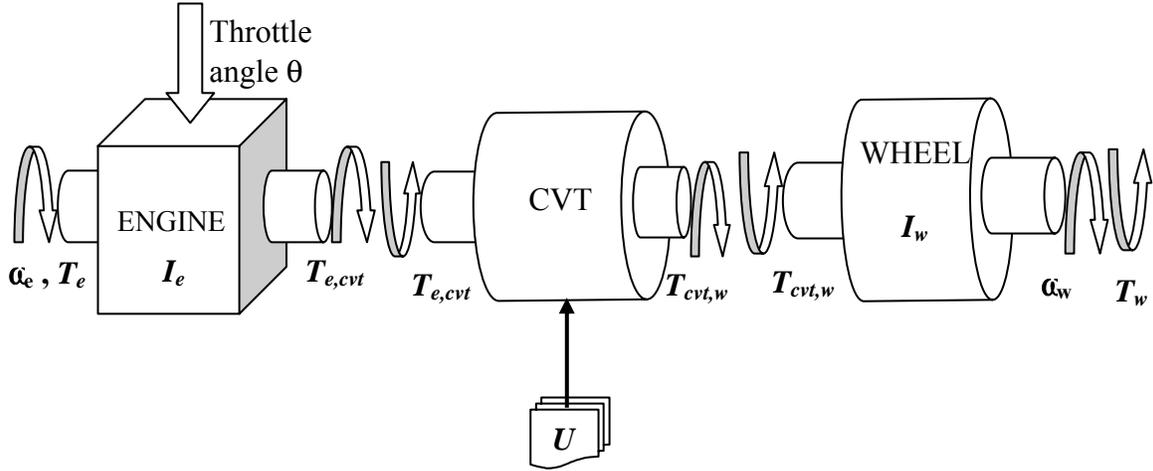


Figure 2. Drivetrain model

$$\alpha_e^{\mathbf{p}} = \frac{1}{I_e} [T_e - T_{e,CVT}] \tag{1}$$

where $T_e(t)$ is the torque generated by the engine and $T_{e,CVT}(t)$ denotes the torque applied to CVT by the engine. Secondly for the CVT, it is modelled as single integrator with a lumped inertia placed on the engine side of the CVT.

The wheel side of the vehicle was modelled as single inertia with

$$\alpha_w^{\mathbf{p}} = \frac{1}{I_w} [T_{CVT,w} - T_w] \tag{2}$$

Using kinematics relation

$$v\alpha_w = a_e \tag{3}$$

and the power balance in the CVT

$$a_w T_{CVT,w} = \eta_e T_{e,CVT} \tag{4}$$

The above equations can be represented into a single equation:

$$\omega_e^{\text{eff}} = \frac{vT_e - (\omega_w^{\text{eff}} I_w + T_w)}{I_e v} \quad 5$$

Where T_e is the engine torque, which is a function of, throttle angle, θ_{throttle} , and engine speed, ω and can be represented as:

$$T_e = f(a_e, \theta_{\text{throttle}}) \quad 6$$

I_w and I_e are Vehicle inertia and engine inertia respectively, where as, ω_w is the vehicle speed with the torque on wheel T_w is function of drag force, rolling resistance, gradient resistance as well as acceleration resistance.

The external torque could be modelled as

$$T_w = (Ra + Rr + Rg + Ri) * r \quad 7$$

Where the first term on the right hand side represent the drag, which is equal

$$\frac{1}{2} \rho C_d A v^2 \quad 8$$

R_r is rolling resistance, where the type of tyre will influence its value, but there is a standard equation of rolling resistance and represented as follow.

$$R_r = (a + b v) mg \cos \theta \quad 9$$

The drag resistance, R_g , represent road gradient in the form of

$$R_g = mg \sin \theta \quad 10$$

And the last term is acceleration resistant which equal to

$$R_i = m \frac{dv}{dt} \quad 11$$

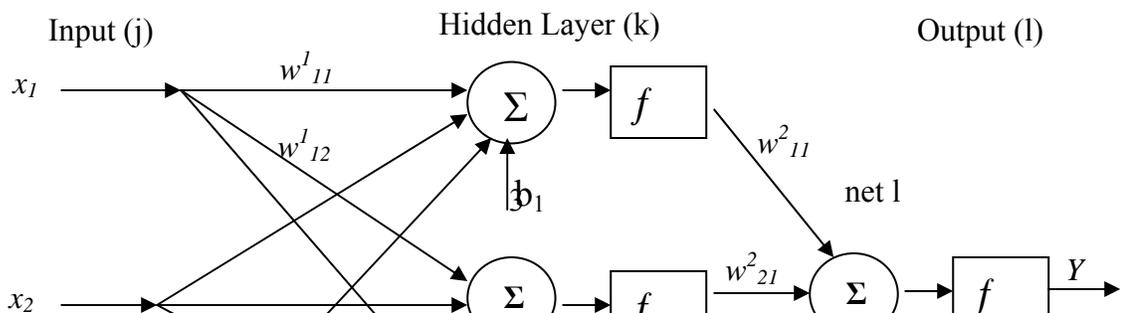
4.0 Neural Network Architecture

An artificial neural network consists of a number of very simple and highly interconnected processors, also called neurons, which are analogous to the biological neurons in the brain. The neurons are connected by weighted links passing signals from one neuron to another. Each neuron receives a number of input signals through its connections: however, it never produces more than a single output signal. The output signal is transmitted through the neuron's outgoing connection, which in turn, splits into a number of branches that transmit the same signal.

The single unit of the neural network (also called a neuron, or perceptron) is just a function applied to the weighted sum of inputs. The perceptron shown in Figure 7, implements the function:

$$Y = f\left(\sum_{i=0}^n w_i x_i + b\right) \quad 12$$

where f is the activation function, w_0 is the constant threshold value (called weighting factor), and b is a bias. Even a specific network structure and the activation function for each unit are given, the expressive power of the neural network would be meaningless, unless can figure out the correct weights for the connection. Fortunately, there is an algorithm called back-propagation that allows the network to learn the weights [Rumelhart, 1986]. Usually, the neuron in the back-propagation network uses a sigmoid activation function, which is simple equation. The sigmoid activation function is expressed as:



$$Y^{sigmoid} = \frac{1}{1 + e^{-x}} \quad 13$$

The learning in the neural network works by back-propagating [Bryson and Ho, 1969] the error that occurs at the output units. At each step, an input is presented to the network and the output is compared to the correct target value. The weights of the units and bias are then readjusted so as to minimise the error they have made. The error is defined as the sum of square errors over all output units and it is expressed as:

$$E_t = \frac{1}{2} \sum_{t \in \text{outputs}} (r_t - o_t)^2 \quad 14$$

where k is the number of iteration. Consider to above neural network architecture, Figure 7, the following algorithm is top adapt the weights between the output (l) and hidden (k) layers:

$$w_{lk}(t+1) = w_{lk}(t) + \Delta w_{lk}(t+1) \quad 15$$

$$\text{where } \Delta w_{lk}(t+1) = \alpha \Delta w_{lk}(t) \quad 16$$

$$\text{and } \Delta w_{lk} = \frac{\partial E}{\partial w_{lk}} \quad 17$$

Expanding the expression by chain rule, equation 17 become

$$\frac{\partial E}{\partial w_{lk}} = \frac{\partial E}{\partial net_l} \frac{\partial net_l}{\partial w_{lk}} \quad 18$$

Let $\frac{\partial E}{\partial net_l}$ be δ_l , which is the error signal

Since $net_l = \sum_k w_{lk} O_k + b_l$, where O_k is the output of hidden layer m,

$$\cdot \frac{\partial E}{\partial w_{lk}} = \delta_l O_k \quad 19$$

Here δ_0 is the error signal from the neural network output to the hidden layer. By chain rule again:

$$\delta_l = \frac{\partial E}{\partial net_l} = \frac{\partial E}{\partial O_l} \frac{\partial O_l}{\partial net_l} \quad 20$$

Since $O_l = f(net_l) = \frac{1}{1 + e^{-net_l}}$

Thus $\frac{\partial O_l}{\partial net_l} = \frac{\partial}{\partial net_l} \left\{ (1 + e^{-net_l})^{-1} \right\} = -(1 + e^{-net_l})^{-2} [-e^{-net_l}]$ 21

Substituting $e^{-net_l} = \frac{1 - O_l}{O_l}$ into equation 21 to get

$$\frac{\partial O_l}{\partial net_l} = \frac{1}{(1 + e^{-net_l})^2} \frac{1 - O_l}{O_l} = O_l^2 \frac{1 - O_l}{O_l} = O_l(1 - O_l)$$
 22

Since $E = \frac{1}{2}(r_l - O_l)^2$

therefore $\frac{\partial E}{\partial O_l} = -(r_l - O_l)$ 23

Equation 20, δ_l which is the error signal between layer k and l becomes:

$$\delta_l = -(r_l - O_l)O_l(1 - O_l)$$
 24

Thus equation 17 becomes

$$\Delta w_{lk} = (r_l - O_l)O_l(1 - O_l)O_k$$
 25

Similar rule to the hidden layer and output layer, the adaptation of weights between hidden (k) and input (j) layers have the value of:

$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj}(t+1)$$
 26

where $\Delta w_{kj}(t+1) = \alpha \Delta w_{kj}(t)$ 27

and $\Delta w_{kj} = \delta_l w_{lk} O_k (1 - O_k) O_j$ 28

Substitute with equation 24, equation 28 becomes

$$\Delta w_{kj} = -w_{lk} (r_l - O_l) O_l (1 - O_l) O_k (1 - O_k) O_j$$
 29

By adapting the weights and bias, the error between the threshold and the output can be minimised. In this paper, the NN will be applied to the vehicle plant to control the CVT ratio so that the actual engine speed will follow the engine reference. The equation 5, for vehicle model with dynamic motion, is used to develop control strategy which will be explained in the next sub-chapter.

3.0 Proposed Control Scheme

Simulink tools were used to simulate the above equation. The drive train plant could be modelled as follows:

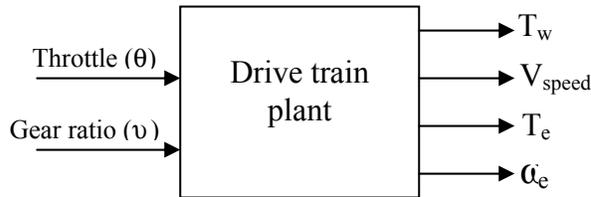


Figure 4. Vehicle dynamic plant

Based on the equation 3 where $\nu \alpha_w = \alpha_e$ and T_e was function of ω and throttle opening, $\theta_{throttle}$, it could be understood that behavior of the engine speed depend on gear ratio as throttle opening remain constant.

When the throttle opening was kept at constant value:

- The engine speed ω would increase while the gear ratio ν increases
- The engine speed ω would decrease while the gear ratio ν decreases

The basic control scheme the author proposed is described in the following Figure.

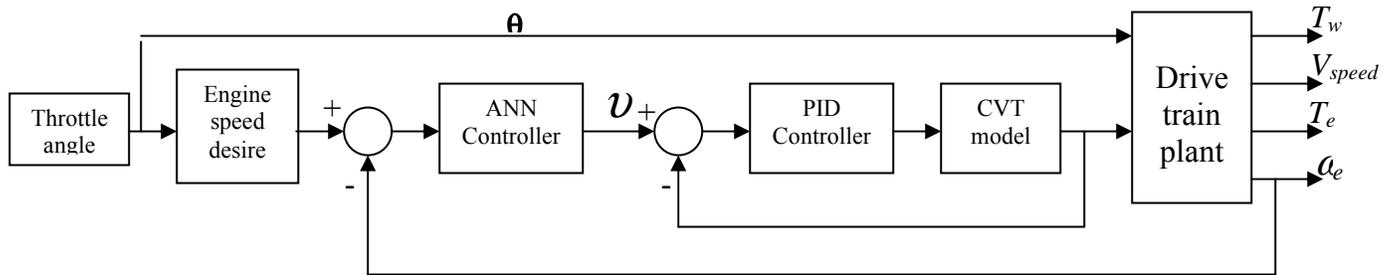
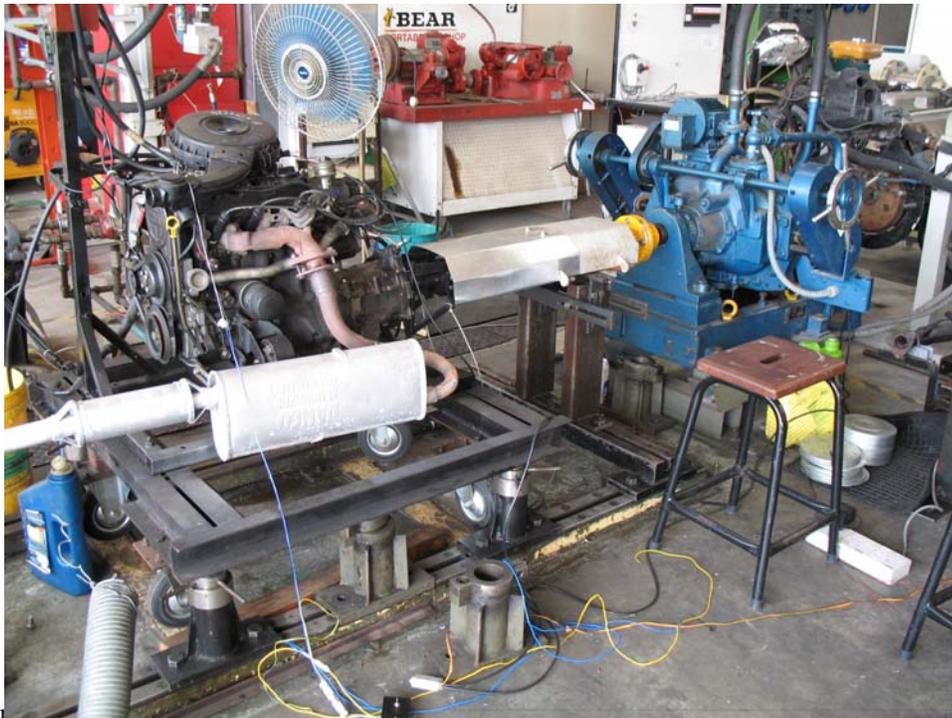


Figure 5. Proposed control scheme

The engine speed desired could be plotted based on optimum control line or engine speed at maximum power or maximum torque in engine power map. Engine power map could be carried out experimentally as shown in Figure 6. The engine 660 cc Daihatsu was coupled with hydro water break dyno as load variator. The opening throttle angle, $\theta_{throttle}$ was set at constant angle and hydro water break dyno was loaded, hence the engine torque could be plotted by using data acquisition system. Figure 7 shows the experimental results of engine torque uses 660 cc Daihatsu engine. Every line in the graph represents torque of engine for certain throttle opening and start from very small throttle angle, 3%, up to 99.9%. This graph was applied to the model plant by equation 6 and equation 5 became drivetrain plant with gear ratio, ν , throttle angle, $\theta_{throttles}$, and engine speed, ω , as input. By controlling gear ratio, ν , the engine speed can be maintain constant on its trajectory.



The online control system will then be sent back to adjust the weights and bias by back propagation rule. The result of controller is the ratio desired and will be sent to CVT inner controller as desired ratio. This ratio then compensates a torque delivered by the engine to the wheel so that the engine runs closed to engine speed desired.

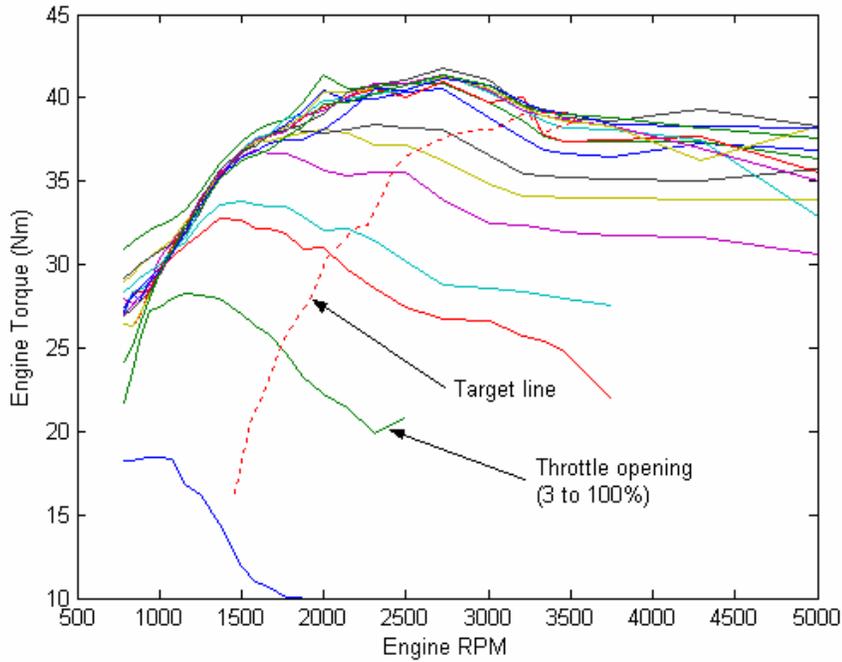


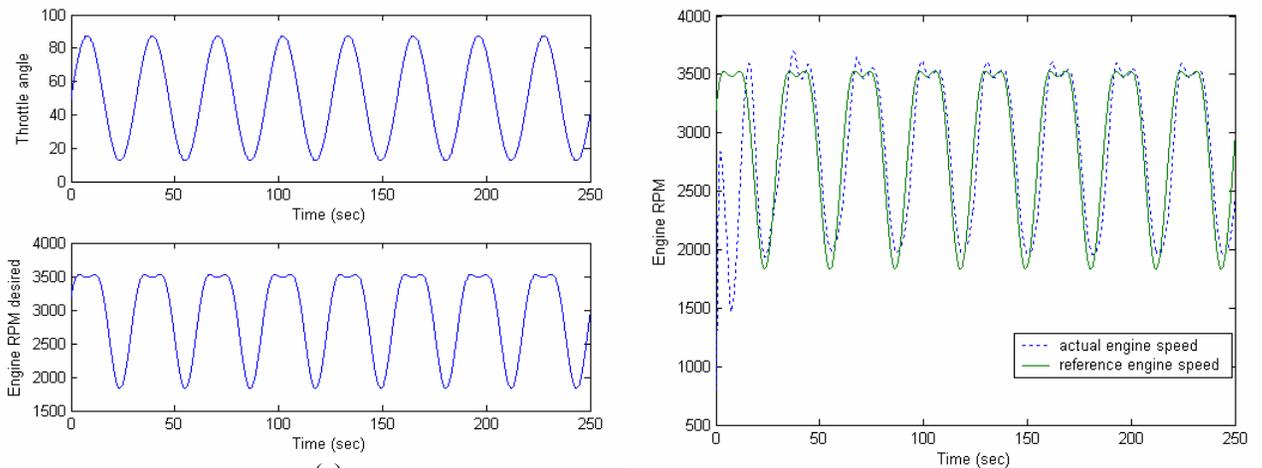
Figure 7. Engine 660 cc Daihatsu torque performance

5.0 Results and Discussion

The engine output torque is the function of engine throttle opening, $\theta_{throttle}$, and its speed n_e , which is modelled as numerical table through the calibrated experimental at certain condition, Figure 6b. In this simulation, the target line is represented with 3rd order polynomial:

$$n_e = c_1 \theta_{throttle}^3 + c_2 \theta_{throttle}^2 + c_3 \theta_{throttle} + c_4 \quad 30$$

where $c_1 = -0.00000098825264$, $c_2 = -0.00023266280965$, $c_3 = 0.05409118539876$ and $c_4 = 1.19385322086360$



The design criterion for the ANN controller is to maintain engine speed at desired engine speed (b) target line based on the opening throttle angle, $\theta_{throttle}$. To evaluate the performance of the ANN controller, the engine speed was adjusted by setting throttle angle, $\theta_{throttle}$ at certain value or plot the $\theta_{throttle}$ according to sinusoidal line, Figure 8 (a) top, equation 30, which would calculate the engine speed desired, had value such as plotted in Figure 8 (a) bottom.

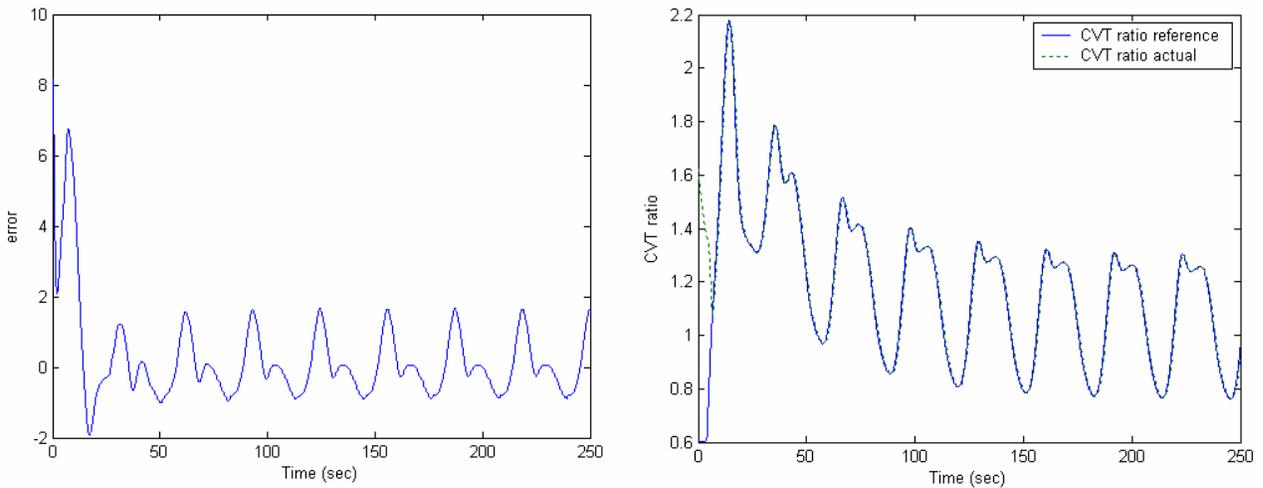


Figure 9. (a) Error system (b) Response of inner CVT controller using PID

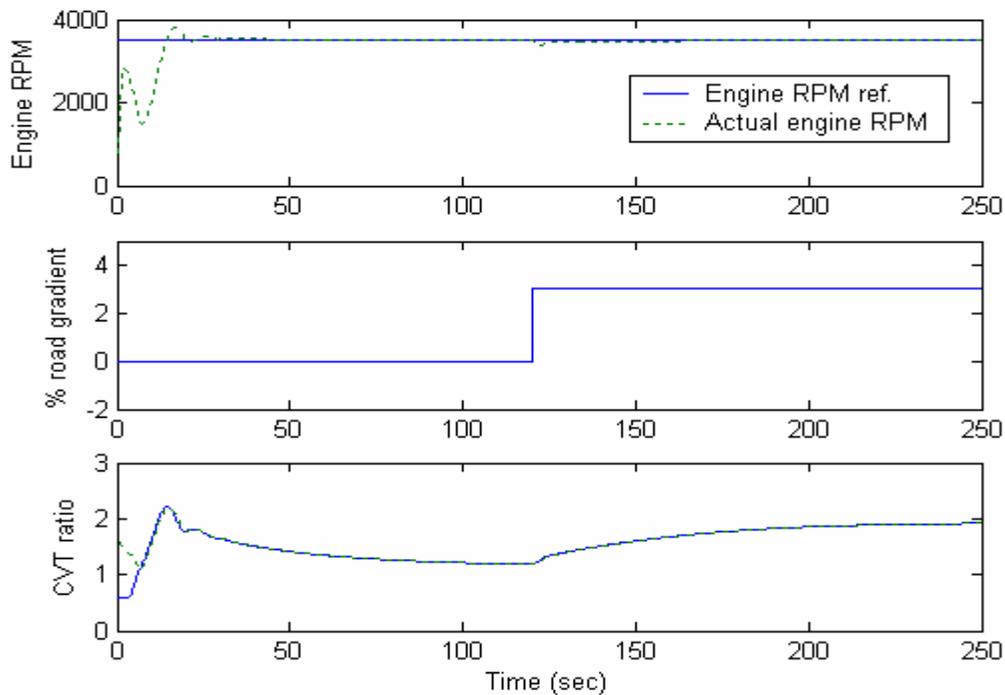


Figure 9. Response of online ANN with different road gradient

In order to explore the working of the back propagation, which was applied, to online ANN, the author adjusted various learning parameters until a number of learning rates had obtained. To find the exact learning rate, which can be used in difference set point, the author had try to applied in 2 difference situation. Firstly, the set point of engine speed was based on the sinusoidal line between 15% to 90% throttle opening then calculate with 3rd order polynomial, equation 30, the engine speed was obtained as engine speed referent, Figure 8(a). With learning rate, α , of 0.0000000875 the results shown that the actual engine speed can follow the referent after 20 sec, Figure 8(b).

The responses of the starting vehicle to move was slow almost 20 sec before steady state. In the reality, starting the vehicle to move will use another controller and will not be discussed in this work. Figure 8(b) shows that when the engine speed is in the top of graph before slowing down or in the bottom graph before it is speed-up, the error is high as seen in Figure 9(a). This phenomenon caused by the changing direction of DC motor in the inner CVT controller as seen in Figure 9(b). Because the gear ratio between motor to the power screw used in the CVT is high (1:128.57), the response of power screw to return is slow.

Secondly, throttle angle, $\theta_{throttle}$, was kept in constant value, hence the engine speed reference remain in constant value, and then the road gradient in the simulation was set based on the highway road condition that average road gradient between 3-5%, Figure 10. With learning rate, α , of 0.0000000875, the result of the simulation shown that the controller was able to keep the engine speed in its reference condition.

6.0 Conclusion

The control strategy for CVT ratio control to maintain engine speed follow a desired engine speed has been developed. Online ANN is used to control behaviour between the engine and vehicle dynamic due to road condition, whereas the PID is used to control inner CVT ratio by controlling two DC motor synchronously to achieve its ratio desired. The control model is implemented in Matlab/Simulink environment and is capable of simulating ratio and engine speed during ratio change due to external disturbance such as road gradient. This serial control is working well and it is clear that online ANN is able to maintain engine speed to its referent by changing the ratio of the CVT.

7.0 References

- Guzzella L. & Schmid A, (1995), "Feedback Linearisation on Spark-Ignition Engines with Continuously Variable Transmission.", IEEE, Swiss Federal Institute Of Technology (ETH), Zurich, Switzerland, P 54-60
- Rumelhart, D.E., Hilton, G.E., and Williams, R.J. (1986). "Learning Internal Representations by Error Propagation. In Rumelhart, D.E., and McClelland, J.L. (editor), Parallel Distribution Processing: Explorations in the Microstructure of Cognition", chapter 8. MIT Press, Cambridge, MA, and London, England.
- Fuchino M., Ohsono K. (1996), "Development of Fully Electronic Control Metal Belt CVT", SAE Technical Paper Series 9636286
- Sharon Liu and Anna G. Stefanopoulou (2002), "Effects of Control Structure on Performance for an Automotive Powertrain With a Continuously Variable Transmission", IEEE Transactions on Control Systems Technology, vol. 10, no. 5, September
- Bryson, A.E. and Ho, Y.C. (2001) "Applied Optimal Control", Blaisdel, New York.
- Wang Hongyan, Zhou Yunshan, Zhang Boying, Qiau Xiding (1999). " Research on Integrated Control Strategy of CVT for passenger cars", Proceedings of the American Control Conference, Arlington, VA June.