Adaptive Neural Network Optimisation Control of ICE For Vehicle With Continuously Variable Transmission

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Abstract-**Continuously variable transmissions (CVT) have received great interest as viable alternative to discrete ratio transmission in passenger vehicle. It is generally accepted that CVTs have the potential to provide such desirable attributes as: a wider range ratio, good fuel economy, shifting ratio continuously and smoothly and good driveability. With the introduction of Continuously Variable Transmission (CVT), maintaining constant engine speed based on either its optimum control line or maximum engine power characteristic could be made possible. This paper describes the simulation work in drivetrain area carried out by the Drivetrain Research Group (DRG) at the Automotive Development Centre (ADC), Universiti Teknologi Malaysia, Skudai Johor. The drivetrain model is highly non-linear; and it could not be controlled satisfactorily by common linear control strategy such as PID controller. To overcome the problem, the use of Adaptive Neural Network Optimisation Control (ANNOC) is employed to indirectly control the engine speed by adjusting pulley CVT ratio. In this work, the simulation results of ANNOC into drivetrain model showed that this highly non-linear behaviour could be controlled satisfactorily.**

Keyword: Adaptive neural network, CVT control, electromechanical CVT, engine speed control.

I. INTRODUCTION

One of the major challenges faced by car industry to day is the reduction of the fuel consumption of automobiles. For this task to be accomplished a combination of the following three approaches has to be employed

- reduction of car mass
- reduction of dissipative losses, such as drag, rolling resistance, etc
- increase of fuel efficiency of the engine

In this paper we will focus on the aspect. As seen in Fig. 1, the typical engine map shows torque curve, fuel consumption and its power for every throttle opening. Increase of fuel efficiency of the engine can be done by running the engine along its optimum control operating line (OCL). It is almost impossible to maintain engine speed on its OCL by using fix gear transmission. Continuously variable transmission (CVT) enables the engine to run at either its fuel-efficient operating

point or its maximum power for any vehicle load, due to its wide range coverage of transmission ratio, hence improving the engine optimisation. Although well known for quite a long time this technology never gained much attention because of its limited power range and due to reliability problem. Since in both respects remarkable progress has been made CVT's have become a very interesting preposition.
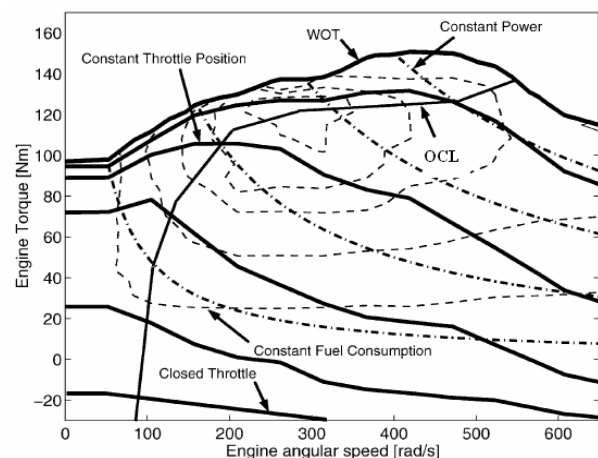

Figure 1. Typical engine map with optimum control line (OCL)

Many researchers have done in controlling the CVT by many different approach such as: Guzzella stated that based on his experience with classical control such as PID approach the outcome was not very encouraging, unless reinforced with a gain scheduled controller with typically 100 difference gain points [1]. Masayuki Fuchino and his partner Kouhei Ohsono, both of them came from Honda R & D Co. Ltd. They started controlling CVT with very basic control system by giving read data obtained through out their company experiment involving CVT since 1962, [2]. 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.

Fuchino M., Ohsono K. (1996) introduce synthesized control method that can be used for maintaining engine being the optimal working point according to road load by regulating the transmission ratio and throttle opening, [3,4]. Because the characteristic of the engine and the transmission varies greatly under different road conditions, it is very difficult to control the transmission ratio and throttle opening to meet such demand.

II. DRIVETRAIN MODEL

A vehicular drivetrain is depicted in Fig. 2. It consists of engine, clutch, EMDAP-CVT transmission, final drive, drive shaft and wheels. In this section basic equation for the drivetrain will be derived including some basic equation regarding the force acting on the wheels are obtained.
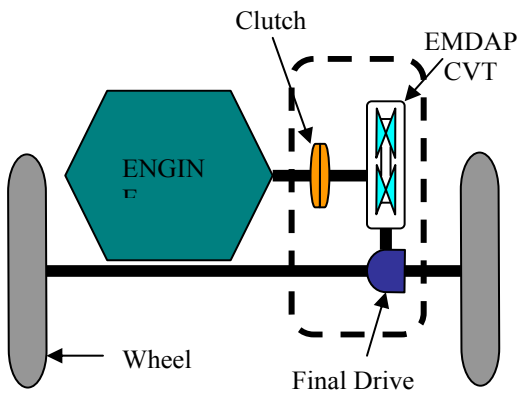

Fig. 2. A vehicular drivetrain

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 3. So, assuming that there is no wheel slip; the vehicle speed is equivalent to linear wheel speed. Most researchers use Euler equation as the basic equation for vehicle dynamic shown on Figure 3 [1,5,6,7,8,9]. The analysis begins with the engine speed dynamics given as:
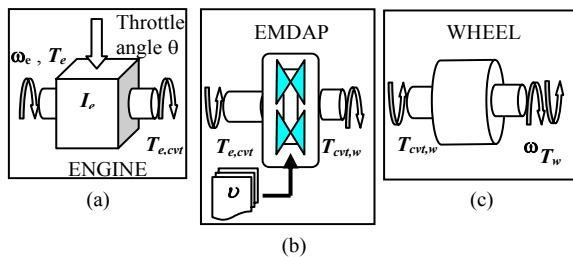

Fig. 3 Drivetrain model

$$\dot{\omega}_e = \frac{1}{I_e}\left[T_e - T_{e,CVT}\right] \qquad (1)$$

Similarly, the vehicle wheel was modelled as

$$\dot{\omega}_w = \frac{1}{I_w}\left[T_{CVT,w} - T_w\right] \qquad (2)$$

Since the function of EMDAP-CVT is to transfer torque from the engine to the wheels, $T_{e,CVT}$ denotes the torque applied to CVT by the engine. By modelling the EMDAP-CVT as single integrator (refer Figure 2b.) [1,9], the equation of torque relation can be given as:

$$T_{CVT,w} = \upsilon T_{e,CVT} \qquad (3)$$

$$\dot{\upsilon}(t) = u(t) \qquad (4)$$

The kinematics relationship of the shaft speed on either side of the EMDAP-CVT is given by:

$$\upsilon\omega_w = \omega_e \qquad (5)$$

Simplifying equations (1)-(5), the vehicle engine angular acceleration will be given as:

$$\dot{\omega}_e = \frac{\upsilon T_e - (\dot{\omega}_w I_w + T_w)}{I_e \upsilon} \qquad (6)$$

and the vehicle engine torque, T_e, will be given by:

$$T_e = f(\omega_e, \theta_{throttle}) \qquad (7)$$

Most of the current researches [1,5,6,7,8,9], the engine torque was approximated by second order polynomial, but actually the engine torque map is very complicated and almost impossible to develop the model by second order polynomial. Thus the author tries to develop the engine map model using look-up table based on data experiment.

The external torque in the equation (6) is equal to sum of total resistance multiplied by effective radius of tyre.

$$T_w = (Ra + Rr + Rg + Ri)*r \qquad (8)$$

The external resistance of drag resistance, *Ra*, rolling resistance, *Rr*, and acceleration resistance, *Ri*, are the function of vehicle speed. Whereas gradient resistance is the function of road slope.

Both of the vehicle speed and road gradient are the external disturbance in the vehicle controller. When the throttle opening remain constant, transformation of the road gradient will have an in with transformation of the engine speed. Therefore to keep engine speed constant, the transmission ratio needs to be adjusted throughout the controller. This external vehicle load is unpredictable throughout road condition resulting highly non-linear problem.

A linear control system with invariant plant parameters can be designed easily with the classical design techniques, such as Nyquist and Bode plots. However in drivetrain applications, where the parameters of external disturbance hardly remain constant, the performance of a conventional feedback controller is difficult to maintain. Actually, in the plant parameters variation requires adaptation of the controller parameters in real-time called as adaptive control technique. Fig. 4 shows the proposed macroscopic controller,

where the different between the output of the plant and the target value is used to adjust the ANN in a real time.
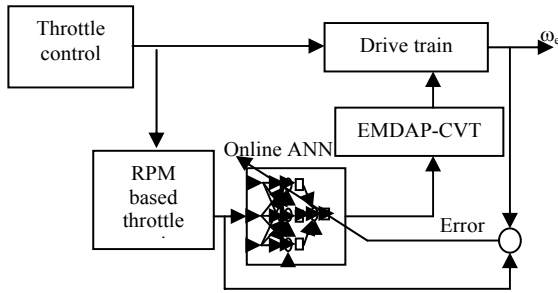

Fig. 4 Proposed control for drivetrain model with online ANN

III. DEVELOPMENT OF ANNOC

Inspired by the successful function of the human brains, the artificial neural network (ANN) was developed for solving many large scale and complex problems [5]. Based on ability to process some information and also to analyze the input and output simultaneously, it makes ANN suitable for dynamic, nonlinear and variable parameters system. Based on the Efficiency Optimization Control concept, the structure and learning algorithm of the ANNOC is developed.

A. Development of Adaptive Neural Network Efficiency Optimization Controller

The principle of searching efficiency driving control is described in Fig. 1. to achieve the minimum axis, the target line in the Fig. 8 is used to supervise the neural network controller during learning process. The output of the adaptive neural network is used to adjust the ratio desired.

B. Structure of Adaptive Neural Network Controller (ANN)

The controller consists of input layer, hidden layer and output layer. Based on number of the neuron in the layers, the ANN is defined as a 2-3-1 network structure. The perceptron shown in Figure 4, implements the function:
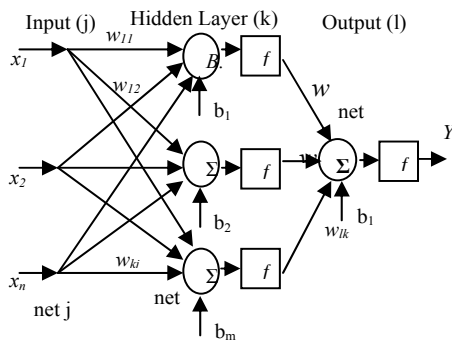

Fig. 5. A layered structure of perceptons

$$Y = f\left(\sum_{i=0}^{n} w_i x_i + b\right) \qquad (9)$$

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 [10]. Usually, the neuron in the back-propagation network uses a sigmoid activation function, which is simple equation. The activation function for the output layer is linear and for the hidden layer is a tangent hyperbolic function given by:

$$Y^{sigmoid} = \frac{2}{1+e^{-2x}} - 1 \qquad (10)$$

The learning in the neural network works by back-propagating the error that occurs at the output units [11]. 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:

$$E_t = \frac{1}{2} \sum_{t \in outputs} (r_t - o_t)^2 \qquad (11)$$

where t is the number of iteration. Consider to above neural network architecture, Figure 4, the following algorithm is to adapt the weights between the output (l) and hidden (k) layers:

$$w_{lk}(t+1) = w_{lk}(t) + \Delta w_{lk}(t+1) \qquad (12)$$

where $\quad \Delta w_{lk}(t+1) = \alpha \Delta w_{lk}(t) \qquad (13)$

and $\quad \Delta w_{lk} = \dfrac{\partial E}{\partial w_{lk}} \qquad (14)$

Expanding the expression by chain rule, equation 14 become

$$\frac{\partial E}{\partial w_{lk}} = \frac{\partial E}{\partial net_l} \frac{\partial net_l}{\partial w_{lk}} \qquad (15)$$

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

Since $net_l = \sum_l w_{lk} O_k + b_l$, where O_k is the output of

hidden layer k,

$$\therefore \frac{\partial E}{\partial w_{lk}} = \delta_l O_k \qquad (16)$$

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

$$\delta_l = \frac{\partial E}{\partial net_l} = \frac{\partial E}{\partial O_l} \frac{\partial O_l}{\partial net_l} \qquad (17)$$

Since $O_l = f(net_l) = \dfrac{2}{1+e^{-2net_l}} - 1$

Thus $\dfrac{\partial O_l}{\partial net_l} = \dfrac{\partial}{\partial net_l}\left\{\dfrac{2}{1+e^{-2net_l}} - 1\right\} = 1 - \left(\dfrac{2}{1+e^{-2net_l}} - 1\right)^2 \quad (18)$

Hence, $\dfrac{\partial O_l}{\partial net_l} = 1 - O_l^2$ (19)

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

Therefore $\dfrac{\partial E}{\partial O_l} = -(r_l - O_l)$ (20)

Equation 17, δ_l, which is the error signal between layer k and l becomes:

$$\delta_l = -(r_l - O_l)(1 - O_l^2)$$ (21)

Thus equation 13 becomes

$$\Delta w_{lk} = (r_l - O_l)(1 - O_l^2)O_k$$ (22)

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

$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj}(t+1)$$ (23)

where $\Delta w_{kj}(t+1) = \alpha \Delta w_{kj}(t)$ (24)

and $\Delta w_{kj} = \delta_l w_{lk}(1 - O_k^2)O_j$ (25)

Substitute with equation 20, equation 24 becomes

$$\Delta w_{kj} = -w_{lk}(r_l - O_l)(1 - O_l^2)(1 - O_k^2)O_j$$ (26)

By adapting the weights and bias, the error between the threshold and the output can be minimised. In this paper, the ANN 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 (6), for vehicle model with dynamic motion, is used to develop control strategy, which will be explained in the next sub-chapter.

IV. PROPOSED CONTROL SCHEME

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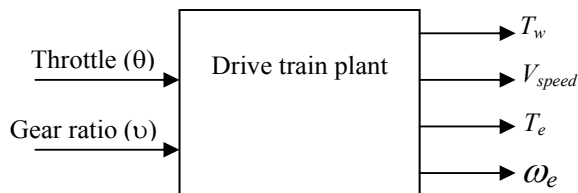

Fig. 6. Vehicle dynamic plant

The above figure shows that the model plant is similar to the real vehicle where the speed of the vehicle, engine speed, and torque deliver to wheel are depend on throttle opening and gear ratio as control input. Based on the equation 3 where $\upsilon\omega_w = \omega_e$ and T_e was function of ω_e and throttle opening, $\theta_{throttle}$, it could be understood that performance of the engine speed depend on gear ratio when throttle opening remain constant.

When the throttle opening was kept at constant value:

The engine speed ω_e would increase while the gear ratio υ increases

The engine speed ω_e would decrease while the gear ratio υ decreases

The basic control scheme the author proposed is described in the Fig. 6. The control scheme must take by necessity both a macroscopic view by examining the interaction of the engine-EMDAP-CVT-load dynamics as well as the driver intentions and road condition, and microscopic view of individual EMDAP-CVT subsystems and subassembly with respect to ratio control. For this project, the macroscopic controller is suitable to use intelligent controller rather than classical controller. Because in this section interaction between vehicle, engine and road gradient have highly non linear.
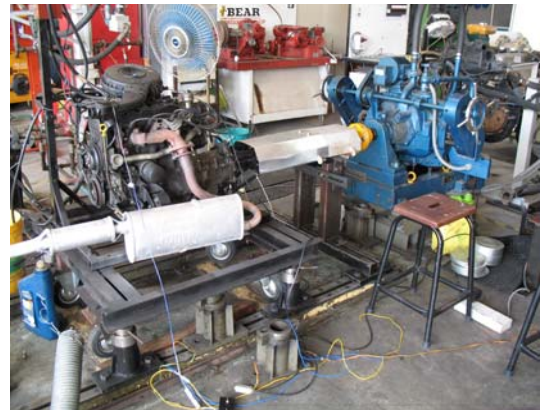

Fig. 7: Experimental rig of 660 cc Daihatsu engine with Hydro water break dyno as load factor

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 Fig. 7. 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.

Fig. 8 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, υ, throttle angle, $\theta_{throttle}$, and engine speed, ω_e, as input. By controlling gear ratio, υ, the engine speed can be maintain constant on its trajectory.

The online adaptive neural network is applied to find out the suitable CVT ratio. The error between the output and the reference will then be sent back to adjust the weights and bias by back-propagation rule. The

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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.
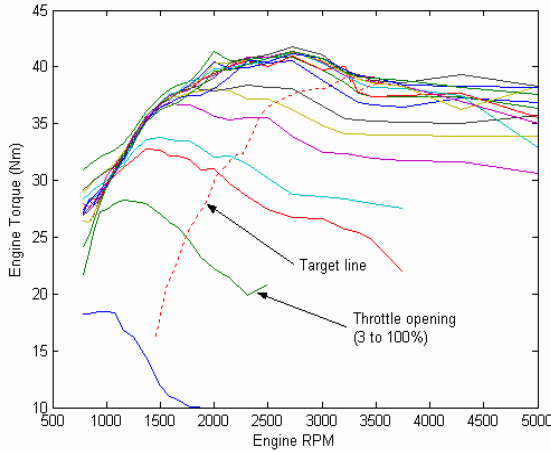

Fig. 8. Engine 660 cc Daihatsu torque performance

V. 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 8. In this simulation, the target line is represented with 3rd order polynomial:

$$n_e = c_1\theta_{throttle}^3 + c_2\theta_{throttle}^2 + c_3\theta_{throttle} + c_4 \qquad (27)$$

where c_1= -0.00000098825264,

c_2=-0.00023266280965,
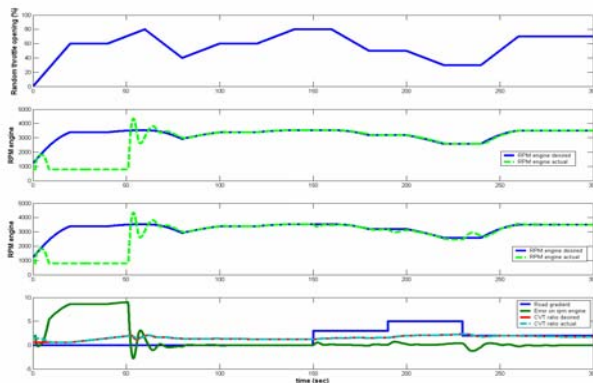
c_3=0.05409118539876

and c_4=1.19385322086360

Fig. 9. Simulation result of randomise throttle opening with the external disturbance

The control strategy for CVT ratio control to maintain engine speed follow a desired engine speed has been developed. The simulation result of ANNOC controller shows very good result where the engine load can be maintain at its optimum control line even the throttle opening was set at random value. The simulation describes in the real situation, where the road gradient is also randomise. The randomise throttle opening was set, meaning that the engine rpm was exactly similar as seen in the second graph of Fig. 9. When the road slop was changed (blue line in the bottom graph at 150 seconds), the actual engine rpm was slightly lower than the target engine rpm (3rd graph). The online ANN then re-adjusts the EMDAP-CVT ratio to achieve target engine rpm. As soon as the road slop keeps in the constant value, the actual engine rpm is set back to the target engine rpm. Repeated as before, the road slop suddenly increased to 5% as represented with blue line in the bottom graph. Again the online ANN was able to re-adjusts the EMDAP-CVT so that the error was almost zero (green line in the bottom graph).

Experemental result shows that the ANNEOC was able to control the engine speed on its optimum control line, Fig. 10.
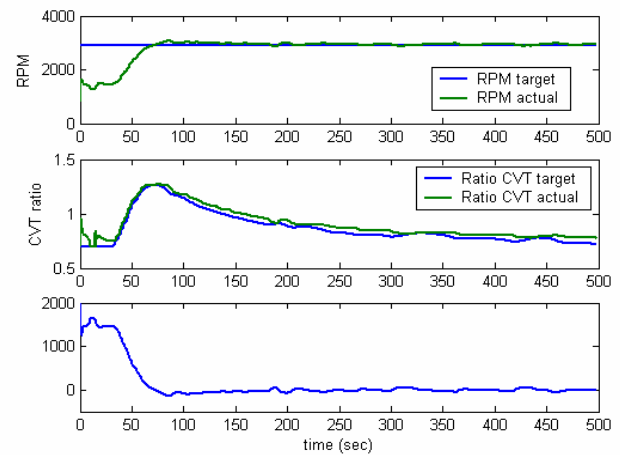

Fig. 10 Experimental result of EMDAP-CVT controller using ANNEOC.

With constant throttle opening of 40 % and desired engine speed 3000 rpm, Fig. 10 shows that actual engine speed meet the desired engine speed almost 80 second. It assumed that the fist 60 second is used to control clutch pedal.

The microscopic controller using PID to control two synchronize DC motor was also work well, where the target ratio can be closely followed by actual ratio. The error mostly due to mechanical losses.

VI. CONCLUSION

The group has successfully developed a CVT controller using on-line ANNEOC to maintain vehicle angine speed of a vehicle that travel on various road gradients. Online ANNEOC is used to control the behaviour between the engine and vehicle dynamic due to road condition, while the PID is used to control inner CVT ratio by controlling two DC motor simultaneously to achieve the desired ratio. 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 proves that online ANNEOC is able to maintain engine speed to its referent by changing the ratio of the CVT.

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