Intelligent control system for high efficiency Electric Vehicles

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Abstract. Brush-less Direct Current (BLDC) motor drive systems are widely used in electric vehicles (EV). However, most EV control strategies only focus on BLDC motors without considering changes in different driving conditions. This paper proposes an intelligent control strategy based on an intelligent neural network that can change control parameters based on changing driving conditions. This system has the ability to self-learning and adapt based on driving conditions. The simulation is carried out using the Electric Vehicle Drive Train model and run on the MATLAB-SIMULINK platform. The simulation results show that the smart control strategy designed shows very good efficiency with minimal errors and quickly adapts to different driving conditions.

1. Introduction
The electric vehicle (EV) market is increasing at a level of 22-23 percent per year and is projected to reach $567 billion by 2025. This is driven by the problem of air pollution and energy problems in internal combustion engine (ICE) vehicles. As a primary means of transportation, ICE generates greenhouse gas emissions and contributes to global warming of around 21% [1]. On the other hand, the depletion of fossil fuels significantly changes interest from ICE to EV [2].

Meanwhile, the main problem faced by electric vehicles is the efficient use of power which impacts on mileage and battery management. This has become a serious challenge for researchers. It was proposed that a hybrid EV with a battery could be charged even when the EV was in motion because it contained an ICE engine and an electric generator [3,4]. However, this proposal has problems related to the complexity of internal systems and high prices. It is proposed the use of renewable energy sources such as solar energy [5], while in Shetty [6] proposes a regenerative braking system that will produce energy during the deceleration phase. This solution is quite good, but the amount of energy produced is not enough, especially when used on urban highways.

In addition, Flah [7] and Gaoua [8] propose the use of intelligent techniques for power optimization using fuzzy techniques. This technique requires tuning based on personal experience and requires a long time to get the optimal value of control and unable to adapt if there are changes in parameters. To overcome this problem, this paper has proposed the use of artificial neural networks as intelligent control techniques that can adapt to changes in road terrain and EV parameters. Proof is done through simulations by comparing the performance based on manual controls that have been widely used, namely conventional PID and the control techniques proposed in this paper with changes in road terrain and randomly changing parameters [9].
2. Method

2.1. Electric vehicle modelling

To validate and verify the performance of the initial design of the subsystem or component, a Model Based Design method has been developed. Integration of simulations in the design process is believed to reduce costs and time. In this paper, the EV model used is based on the EV drive train as shown in Figure 1 [10]. The EV drive train model consists of six components namely electric motors, power electronics, batteries, motor controllers, battery controllers, and vehicle interfaces.

The vehicle interface provides an interface for sensors and controls that communicate with the motor controller and battery controller. The motor controller usually controls the power supplied to the motor, while the battery controller controls the power from the battery. Batteries for energy storage, usually lithium-ion cells that provide more than 200 V and high currents to power electronics. Power electronics manipulate the voltage, current, and frequency provided to meet motor requirements [11].

![Figure 1. EV drive train.](image)

Each block in the EV model as shown in Figure 1 represents a mathematical equation according to each component. Mathematical equations for Motor, battery, motor controller, and regional proportional controller (P-I) use the equation in [11] and are implemented using the MATLAB-Simulink platform.

2.2. Intelligent control

Intelligent control in this paper is used to adjust the motor or in figure 1 representing the motor controller block. The intelligent control used is single neuron adaptive (SNA)-PID [12, 13]. Block diagram of the SNA-PID controller system is shown in Figure 2. The inputs of the state convertor are the difference between the reference input r(k) and the actual output y(k) of the plant. While the outputs of state convertor can be written as follows:

\[ x_1(k) = e(k) - e(k-1) \]  \hspace{1cm} (1)
\[ x_2(k) = e(k) \]  \hspace{1cm} (2)
\[ x_3(k) = e(k) - 2e(k-1) + e(k-2) \]  \hspace{1cm} (3)

with the error at time k is \( e(k) = r(k) - y(k) \), the error at time \( k-1 \) is \( e (k-1) \), and for \( k-2 \) is \( e (k-2) \), respectively.
The outputs of the state convertor are then inputted to the single neuron acting like a PID, with the weights matrix of the neuron is defined as \( W = (w_1, w_2, w_3)^T \). The output of the neuron, with the gain \( K \) can be written as:

\[
\Delta u(k) = K(w_1 x_1(k) + w_2 x_2(k) + w_3 x_3(k))
\]  

Using the gradient descent algorithm and the chain rule, the single neuron connection weights are updated by:

\[
\Delta w_i(k) = w_i(k+1) - w_i(k) = -\alpha_i \frac{\partial P(k)}{\partial w_i(k)}
\]  

\[
= \alpha_i K e(k) \frac{\partial y(k+1)}{\partial u(k)} x_i(k), \quad i = 1, 2, 3
\]

Where the learning rate for each weight updating. As for the unknown system, the term \( \frac{\partial y(k+1)}{\partial u(k)} \) is unknown, thus a function sign[ \( \frac{\partial y(k+1)}{\partial u(k)} / \frac{\partial u(k)}{\partial u(k)} \) ] can be used instead.

The control signal is then calculated through:

\[
u(k) = u(k - 1) + \Delta u(k)
\]  

With

\[
\Delta u(k) = K \sum_{i=1}^{3} \bar{w}_i(k) x_i(k)
\]

And

\[
\bar{w}_i(k) = w_i(k) / \sum_{i=1}^{3} |w_i(k)|, \quad i = 1, 2, 3
\]

The structure of single neuron adaptive PID control algorithm is the same as that of incremental PID algorithm. And the three connection weight values have the same function as that of the three coefficients of incremental PID algorithm. The difference is that the three coefficients of incremental PID algorithm will not change after having been set, while the three connection weight values of single neuron adaptive PID control can be adjusted on-line according to the optimal value of the objective function. So, the single neuron auto-tuning PID control is a self-adaptive control method.

3. Results and discussion

The model block diagram is presented in Figure 3 which has two inputs namely Road Speed and Road Torque, as well as the Motor Model block, Controller Model, Battery Model, PI Controller Model, and feedback from the PI Controller to the main power controller. Meanwhile, two outputs were set to determine performance and EV efficiency, namely (1) Battery error; and (2) Gain value.
The performance and efficiency of the drive system model is proven by providing input in the form of a Speed and Torque data set to see the performance and efficiency of the drive system. The input provided consists of a set of speed and torque as shown in Figure 4.

![Figure 3. EV drive simulation model.](image)

![Figure 4. Speed and torque values for the simulation.](image)

The battery voltage error during the 100 s simulation time is calculated from the input road speed and road torque data from the driving cycle and is plotted in Figure 5. The battery voltage error is the difference between the actual battery internal voltage and the one calculated from the motor voltage and current.

Figure 5 shows the comparison of results between using the PID controller (blue line) and using SNA-PID (red line). It seems that SNA-PID is better with smaller maximum errors and excellent error accuracy. MSE value at 100 seconds of simulation obtained that PID has MSE 3744.67 while SNA-PID has MSE 121.24. Also, in the enlarged image, there is still an error on the PID, around 3V while the SNA-PID with an error of 0 volts. With smaller errors, it is certain that SNA-PID has a higher efficiency...
than PID. This happens because SNA-PID can adapt to change control parameters in accordance with changes in driving conditions that occur.

![Battery Voltage Error](image)

**Figure 5.** Battery voltage error.

Figure 6 shows the comparison of controller gain values (K) using PID and SNA-PID during the simulation. SNA-PID can adapt to changes in input that occur (changes in speed and torque) and performs faster when compared to PID. This can be seen with the SNA-PID rise time (red line) always faster than the PID (blue line). SNA-PID has a rise-time of 3.6561 seconds while PID has a rise-time of 6.0830 seconds or slower 2.4269 seconds (47.75%).

![Controller Gain K Value](image)

**Figure 6.** Controller gain K value.

4. Conclusion
This research has implemented an intelligent controller to produce an optimal controller gain so that the error is even smaller and even zero. Based on simulation trials it is believed that the proposed intelligent controller SNA-PID is more effective and efficient than conventional PID controllers in controlling BLDC motors in an electric vehicle with different driving conditions.
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