Regenerative brake controller based on vehicle behavior prediction

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ABSTRACT: The braking function of an electric vehicle can be implemented with both friction brakes and electric motors, which require a suitable control strategy for their coordinated operation. Many previous studies on this topic have focused on conventional serial or parallel brake control strategies. In this paper, we present a different approach to brake torque blending control based on a motor efficiency map and an improved single pedal control strategy based on vehicle behavior prediction. In this strategy, the regenerative braking is prepared for activation when the controller predicts a deceleration mode. The motor efficiency map of the test model was analyzed and optimized in this way. An artificial neural network was selected to implement an advanced braking strategy. Standardized driving cycles with three different driver profiles were used to train and evaluate the neural network. The results show that this approach significantly improves the vehicle's efficiency. For the WLTP cycle, the proposed strategy can reduce the average energy consumption by 4%, at which the energy recovered has been increased by 9%. For the HWFET cycle, the recovered energy could be increased up to 24%.

KEY WORDS: electric vehicle, regenerative braking, artificial neural network, electric motor.

1. INTRODUCTION

Although electric motors are capable of regenerating energy during braking, conventional friction brakes are still installed in electric vehicles to ensure braking performance and fault-tolerant operation. (1,2) This requires appropriate control strategies for coordinated operation of both braking systems.

Currently, serial and parallel architectures exist for most regenerative braking control strategies. (3) The main difference between parallel and serial approaches is that in the parallel architecture a specific braking torque ratio between the friction braking system and the electric motor is specified. In the serial strategy, the maximum possible braking torque of the electric motor is used as a constant, and the friction braking system is activated only when needed. (4)

Some previous studies have shown that both strategies work differently depending on the maneuvering conditions. For example, the article (5) shows 6-12% better results for the serial control. However, in the article (6) the parallel strategy shows better performance under certain maneuvers and operating conditions. This can be explained by the fact that the efficiency of the electric motor is not constant under different load conditions. (7)

In this paper, a different strategy is proposed based on floating mixing ratio control, which realizes separate management of the two braking systems depending on the motor efficiency map. This strategy will later be referred to as "floating".

It should also be mentioned that some strategies aim to improve the braking efficiency not only by regeneration, but also by reconfiguring the propulsion system or adjusting its parameters to the maneuvering conditions (8), which can lead to a reduction in the total power consumption of the electric vehicle. For example, in work (9), the powertrain configuration is adapted to the driving conditions based on the prediction of the vehicle behavior using Markov chains. Another example is the work (10), which deals with the prediction of the speed profile using neural networks.

In this work, advanced regenerative braking control based on vehicle behavior prediction is also proposed.

2. Controller Design

2.1. Target vehicle

The experimentally verified vehicle model used in this study is based on an all-wheel drive sport utility vehicle (SUV) with a total mass of 2857 kg. The powertrain is implemented with in-wheel motors (IWM). The IWM parameters are given in Table 1. The vehicle systems were first tested on the appropriate dynamometric and component test rigs to produce highly realistic models, including the electrohydraulic decoupled braking system model, vehicle body inertia model, suspension kinematics model, vehicle aerodynamic model, IWM and electric powertrain models, and tire dynamics model. The models were then implemented in a co-simulation environment consisting of the Simcenter Amesim and MATLAB/Simulink software. The regenerative controller was designed in MATLAB/Simulink.

Table 1 Motor Specifications

Nominal supply voltage	370 V DC
Max. Torque (velocity, current)	1200 Nm (300 rpm, 390 A)
Max. Power (torque, velocity)	110 kW (1500 Nm, 700 rpm)
Max. speed (no-load) 425 V DC	1516 rpm
Max. electric motor efficiency	94%

2.2. Proposed controller architecture

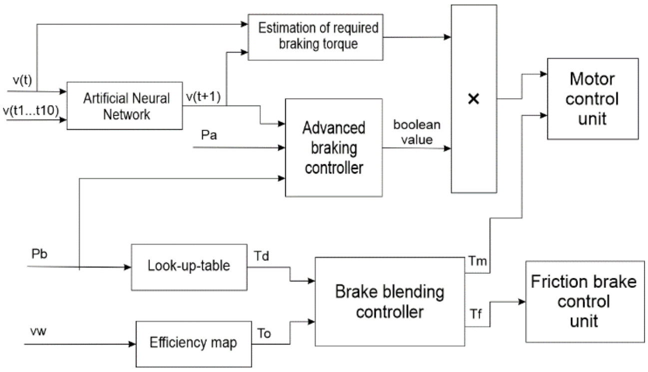

Fig. 1 Controller flowchart.

The control unit is constructed according to Fig. 1 with the following parameters: Pb - brake pedal position, Pa - accelerator pedal position, Tm - motor torque, v(t) - current velocity of the model, v(t+1) - predicted velocity of the model in 1 second, v(t1...t10) - an array of data on the previous behavior of the vehicle, Td - required torque, To - optimal regenerative torque, Tm - torque exerted by motor, Tf - torque generated by the friction brake system, vw - wheel velocity. The amount of energy recovered depends mainly on two parameters: the torque on the wheel and the speed of the IWM rotor. However, this parameter is also affected by the efficiency of the motor, which is different for negative torque (i.e. braking torque). Therefore, it is necessary to use the efficiency map of the motor as a function of the motor efficiency at certain rotor velocities and torques, Fig. 2.

It is also necessary to find a condition for using the maximum motor efficiency. For the proposed strategy, the efficiency map was optimized using the Gradient descent method.

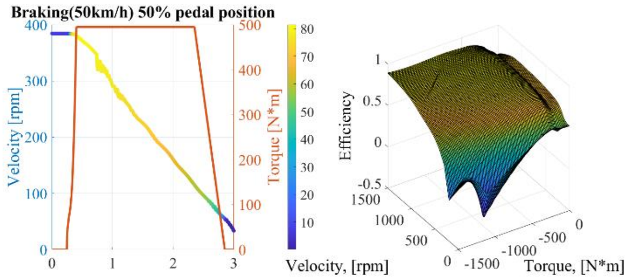

Fig. 2 Motor efficiency when braking a vehicle model.

Thus the optimization task is defined as follows.

$$MAX_{demand,v_x}\,(Energy[Torque, velocity, efficiency])$$

For the driver's current deceleration demand, the optimization looks for the maximum energy recovered as a function of three variables: torque, wheel speed, and electric motor efficiency under current conditions.

2.3. Formulation of the braking control

According to the proposed strategy, regenerative braking is applied only when the vehicle would continue to decelerate. When the driver is about to release the pedal and maintain the previous velocity, the regenerative brake should not be activated. To implement this method, it was decided to predict the speed of the vehicle. In this study, it is proposed to predict the velocity using an artificial neural network based on the previous velocity profile of the vehicle.

The forward prediction time should be several times faster than the response time of the braking system, in which it is possible to request the required braking torque. An average value of 1 second was chosen to predict the behavior of the vehicle.

The data available to create the neural network prediction may also be limited. For this reason, it was decided to set the length of the maneuver between 4 and 20 seconds. This means that the data set consists of samples recorded at a rate of 1 per second, and each sample contains between 4 and 20 values, depending on the case.

Since the number of available artificial neural network architectures is very large, different types have been studied and tested. Recurrent neural networks (RNNs) are designed to process sequential data and are used for time series prediction. They use information from the sequence and are therefore better able to work with patterns. The task described does not require the analysis of very long sequences, so it is possible to use a simpler cell type. However, a simple RNN is more sensitive to the vanishing gradient problem, which negatively affects what is known as short-term memory. The advantage of Gated Recurrent

Units (GRUs) and Long Short-Term Memory (LSTM) cells over a simple RNN architecture is that they reduce the probability of the vanishing gradient problem. When choosing between GRU and LSTM, it should be noted that due to the structural characteristics of GRU, it is possible to achieve faster prediction compared to LSTM by reducing the number of computations, which is crucial when using the predicted information in a complex system such as an ECU in a vehicle. Considering this, the GRU architecture has been shown to be the most suitable for vehicle behavior prediction. [(10)]

In this study, an artificial neural network is used to implement vehicle braking before the driver presses the brake pedal.

Embedded Keras libraries with a number of 2 to 28 neurons on two layers and three different architectures were used to implement the neural network. Training was performed by backpropagation, specifically Levenberg-Marquardt training. Performance measures were compared over 163 training trials with different numbers of neurons.

3. Experimental results

3.1. Motor efficiency optimization

The torque optimization experiments were performed using the real-time cosimulation with the high-fidelity models created as a result of testing the relevant hardware components. The controller was implemented on the real-time vehicle model according to the algorithm (Figure 1). Three types of braking tests were performed: parallel regeneration mode, serial regeneration mode, and braking with a variable blending factor (based on the efficiency map). In this test, the vehicle accelerates to a velocity of 50 km/h, maintains this velocity for 10 seconds, and then brakes at a specific brake pedal position. In the study, the brake tests were conducted at four pedal positions: 20%, 40%, 50%, and 70% of full pedal travel. The results of the tests are shown in Figure 3.

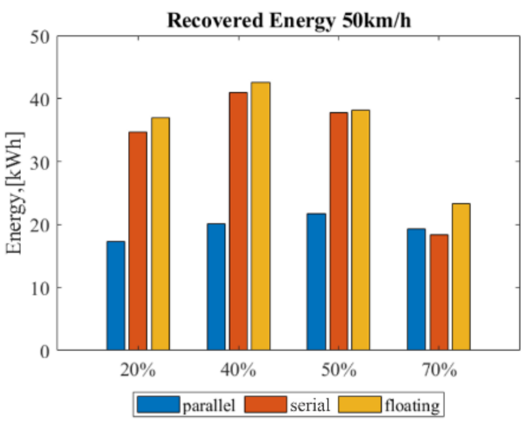

Fig. 3 Comparison of regenerated energy with three different strategies at different brake pedal positions.

Comparing the experimental results at different brake pedal positions for the proposed strategy with a floating blending factor for the parallel and serial strategies, we can see that the amount of energy recovered was increased by more than 2% for the proposed floating strategy.

3.2. Neural Network prediction optimization

The next step was to develop an advanced braking strategy. A GRU architecture showed the smallest errors in predicting vehicle velocity. Experiments were performed with different sizes of input data windows: from 4 seconds to 20 seconds with 2-second increments and different numbers of neurons.

The results presented in Fig. 4 show that the lowest prediction error was achieved with a 12-second window and a total of 45 neurons. The network was trained for a specific driving style of each driver, since it was decided to test the prediction accuracy with different drivers. All three drivers had different driving styles and were described using real tests with different vehicle dynamics. The predicted and actual speeds were estimated, and a mean absolute error (MAE), root mean square error (RMSE), and a scatter index (SI) were calculated. The driving cycle included both highway and city driving. The total distance traveled by the drivers was approximately 150 km. The results are shown in Table 2.

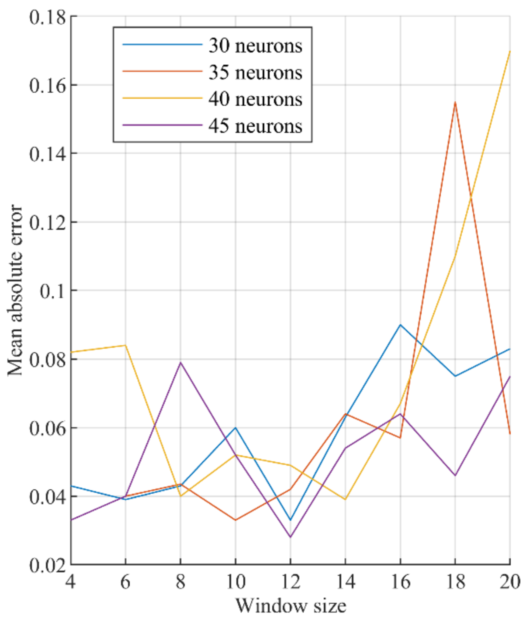

Fig. 4 Mean absolute error as a function of window size for different neural network architectures. The window size refers to the number of samples recorded at one second intervals.

Table 2 Error outcomes predicting vehicle behavior for a local cycle for three different drivers

Driver profile	MAE	RMSE	SI
1	1,128	1,062	5,76
2	0,149	0,387	2,68
3	0,513	0,717	4,26

As it can be seen from the results, the maximum error is not more than 6% and the minimum error for driver 2 is 2.68%. These errors are acceptable, especially since the predicted velocity is only an indication of the algorithm to be used in the future.

3.3. Experimental validation and results

To test the proposed controller, it was decided to use three standardized driving cycles: the Worldwide Harmonized Light Vehicles Test Procedure (WLTP), the Highway Fuel Economy Test (HWFET) and the EPA Federal Test Procedure (FTP-75, defined by the US Environmental Protection Agency (EPA). These cycles were chosen as common driving standards on different continents, so that the WLTP simulates driving on European urban roads, while the HWFET reflects U.S. highway speeds. The FTP-75 is a mixed city/highway cycle.

To evaluate the proposed algorithms, four experiments were conducted for each cycle:

1. Without regeneration;
2. With regeneration. A serial blending strategy was used;
3. Efficiency map. In this test, the strategy based on the algorithm described in Section 2.2 was used.
4. Advance braking. In this test, the regeneration strategy of the efficiency map was used in conjunction with the algorithm defined in Section 2.3, which is based on the Artificial Neural Network.

Table 3 shows the simulation results for the experiments performed.

Table 3 Experimental total energy consumption results, [kW/100km]

	WLTP	HWFET	FTP-75
Without Regeneration	20.449	13.3527	19.0094
With Regeneration	14.9744	11.46660	12.57320
Efficiency map	14.8764	11.46210	12.31490
Advance braking	14.2129	10.87450	11.78810

The result of the comparison of the proposed algorithms can be seen in the pie chart (Fig. 4). This diagram shows how much braking energy is recovered into electrical energy with the different strategies.

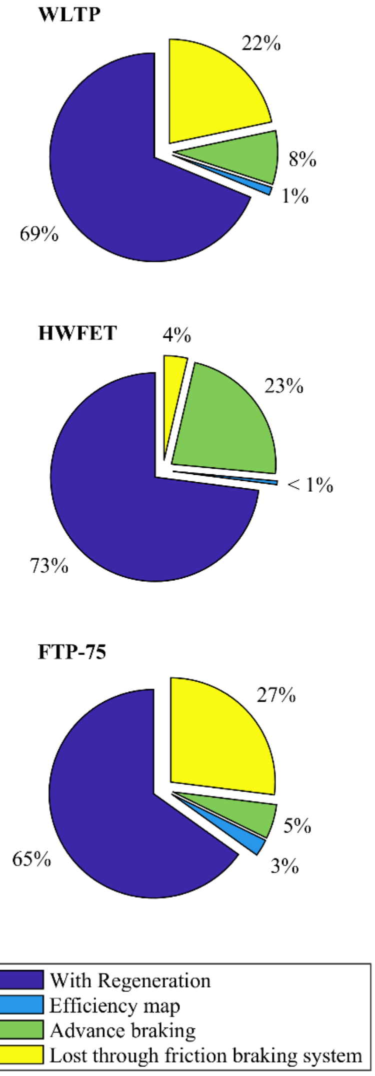

Fig. 5 Percentage of brake energy dissipation for different cycles, where 100% is the whole kinetic braking energy.

For the WLTP cycle, 69% of the kinetic energy is recovered with the series strategy. If the strategy based on the engine efficiency map is used, the recovered energy can be increased by 1%. On the other hand, the predictive braking strategy, i.e., using information about the predicted speed, increases the recovered energy by another 8%. The remaining 22% is lost due to heat from the brake discs and pads.

For the HWFET cycle, the series strategy recovers 73% of the kinetic energy. With the strategy based on the engine efficiency map, the recovered energy can be increased by less than 1%. In addition, early braking, i.e., using predicted speed information, increases the recovered energy by another 23%. The remaining 4% is lost due to heat from the brake disks and pads.

For the FTP-75 cycle, only 65% of the kinetic energy is recovered with the standard strategy. With the strategy based on the engine efficiency map, the recovered energy can be increased by 3%. When using advance braking, i.e., using information about the predicted speed, the recovered energy increases by another 5%. The remaining 27% is lost due to heat from the brake disks and pads.

In summary, the use of the Efficiency Map and Advance Braking strategy has a positive effect in all three driving cycles. The effect was most pronounced in the HWFET cycle, where a total of 24% more energy was recovered, while only 4% was lost due to heat generated. The smallest effect, 8% more energy recovered, was in the FTP-75 cycle. However, the standard system was also able to store the least amount of energy. This is due to the higher number of full stops compared to the HWFET and WLTP cycles and the type of recovery in the motors used.

4. CONCLUSION

This study has shown that the proposed regenerative braking strategy can be improved based on the optimization of the motor efficiency map and advanced braking with vehicle behavior prediction. For this controller, experimental validation with different cycles was conducted, which confirmed its efficiency.

With the efficiency map and advanced braking strategies proposed in this article, up to 24% more braking kinetic energy can be recovered depending on the driving cycle.

REFERENCES

(1) Itani, K., De Bernardinis, A., Khatir, Z., Jammal, A. and Oueidat, M., 2016. Regenerative braking modeling, control, and simulation of a hybrid energy storage system for an electric vehicle in extreme conditions. *IEEE Transactions on Transportation Electrification*, 2(4), pp.465-479.

(2) Ko, J., Ko, S., Son, H., Yoo, B., Cheon, J. and Kim, H., 2014. Development of brake system and regenerative braking cooperative control algorithm for automatic-transmission-based hybrid electric vehicles. *IEEE Transactions on Vehicular Technology*, 64(2), pp.431-440.

(3) Sangtarash, F., Esfahanian, V., Nehzati, H., Haddadi, S., Bavanpour, M.A. and Haghpanah, B., 2009. Effect of different regenerative braking strategies on braking performance and fuel economy in a hybrid electric bus employing CRUISE vehicle simulation. *SAE International Journal of Fuels and Lubricants*, 1(1), pp.828-837.

(4) Zhang, J., Lu, X., Xue, J. and Li, B., 2008. Regenerative braking system for series hybrid electric city bus. *World Electric Vehicle Journal*, 2(4), pp.363-369.

(5) Varocky, B.J., Nijmeijer, H., Jansen, S., Besselink, I.J. and Mansvelder, R., 2011. Benchmarking of regenerative braking for a fully electric car. *TNO Automotive, Helmond & Technische Universiteit Eindhoven (TU/e)*.

(6) Xiao, B., Lu, H., Wang, H., Ruan, J. and Zhang, N., 2017. Enhanced regenerative braking strategies for electric vehicles: Dynamic performance and potential analysis. *Energies*, 10(11), p.1875.

(7) Boisvert, M., Mammosser, D., Micheau, P. and Desrochers, A., 2013. Comparison of two strategies for optimal regenerative braking, with their sensitivity to variations in mass, slope and road condition. *IFAC Proceedings Volumes*, 46(21), pp.626-630.

(8) Kim, D., Eo, J.S. and Kim, K.K.K., 2021. Service-oriented real-time energy-optimal regenerative braking strategy for connected and autonomous electrified vehicles. *IEEE Transactions on Intelligent Transportation Systems*.

(9) Lin, X., Zhang, G. and Wei, S., 2021. Velocity prediction using Markov Chain combined with driving pattern recognition and applied to Dual-Motor Electric Vehicle energy consumption evaluation. *Applied Soft Computing*, 101, p.106998.

(10) Fedorova, A.A., Beliautsou, V.A. and Anikin, I.V., 2020, September. Prediction vehicle's speed with using artificial neural networks. In *2020 International Russian Automation Conference (RusAutoCon)* (pp. 11-15). IEEE.