20th International Conference on Renewable Energies and Power Quality (ICREPQ'22)
Vigo (Spain), 27th to 29th July 2022
Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, Volume No.20, September 2022

Comparative Analysis of Intelligent Braking Controllers for Electric Vehicles

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Abstract. Contemporary society benefits multiple advantages from electric cars. However, there exist still many obstacles to common adoption of the electrically-fed vehicles related mostly to the battery-based energy sources. This analysis addresses the energy recovery in battery and hybrid electric vehicles during their gradual deceleration and emergency stop. Using the proposed classification of braking controllers, several solutions are considered related to the growth on energy saving. Here, intelligent braking systems with fuzzy logic and neural network controllers are compared and evaluated based on data collected in different institutions and by the authors themselves from real vehicles and laboratory test benches.

Key words. Intelligent control, energy recovery, electric vehicles, brakes, fuzzy logic, neural network controllers.

1. Introduction

Electric vehicles (EV) bring multiple benefits to modern society [1 – 4]. Thanks to high efficiency of electrical machines and drives, EVs decrease fuel costs, guarantee tailpipe absence on the move, ensure easier servicing, provide fast acceleration and deceleration, and mitigate audio noise typical for petrol/diesel cars. However, significant hurdles remain that prevent broad adoption of EVs [5 – 7]. Researchers commonly note such battery negative features as quick discharge resulting in a low life span and insufficiently high energy density, long-lasting charging period, weak charging infrastructure, as well as carbon emissions from the production and fallen battery dismantling, and also from the fossil fuels used to generate electricity for charging.

Most of the energy can be saved while the car is slowing down [8 – 10]. Therefore, solving the problem of braking energy recycling now looks very important, because it could help enlarge the driving range, increase mileage, and boost the EV efficiency throughout the vehicle braking or downhill running. Due to energy regeneration upon electrical braking (EB), an electrical machine acts as a generator, and the energy flows back to the hybrid energy storage (HES). Commonly, the HES combines two parts, namely the battery of high energy density and ultracapacitors or flywheels of high power density. Regeneration capability is one of the most significant advantages of EB over the traditional friction brake (FB) systems, in which unwanted braking kinetic energy is wasted to heat due to friction. Usually, EB and FB are aggregated together in a common blended braking system (BBS). A specific torque allocation (TA) block built into the braking controller estimates, which part of the BBS has to be running in various braking modes. This type of a controller, capable of choosing the optimal braking mode depending of the driving situation and the restrictions of the HES state of charge (SOC), is called an intelligent controller in this analysis. Figure 1 demonstrates an approximate scheme of a braking system based on the intelligent controller.

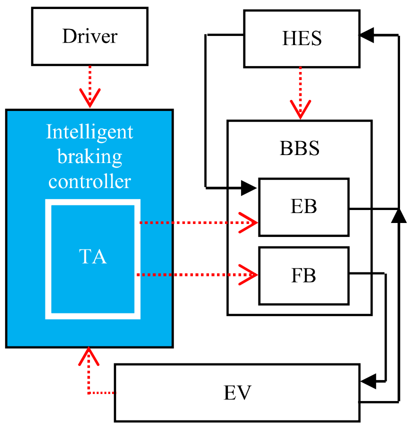

Fig.1. Scheme of a braking system built on the intelligent controller: solid lines – energy flow, dotted lines – sensing and control signals.

The goal of the offered analysis is to evaluate the benefits and drawbacks, challenges and prospects of various intelligent braking controllers that are already in used or can be applied in EVs. The paper focuses primarily on the energy recovery during the gradual and emergency deceleration.

Based on the classification developed by the authors, several braking controllers tested on real vehicles or in the laboratory are considered here. Various categories of intelligent controllers are compared and discussed relying on the data obtained experimentally in many studies.

2. Intelligent Braking Controllers

In a braking system, a braking controller is the main part, which runs the EB, FB, or both in the BBS frame aiming to realize the required braking mode, decrease vehicle velocity, and absorb braking energy. All controllers in this research are divided into those that are able to manage energy regeneration based on EB and those that do not have such an ability. The former are further divided into conventional (road- and HES-independent) and intelligent (road- and HES-dependent). This classification is shown in Fig. 2.

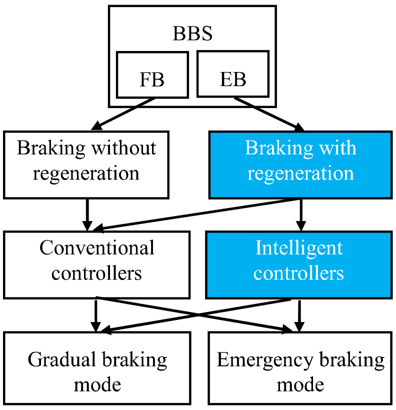

Fig.2. Classification of braking controllers by energy recovery abilities.

Conventional braking controllers can serve both gradual and emergency braking modes. They identify neither the road surface under the tires nor the HES state and, therefore, usually ignore all instabilities of the driving situation. Different types of conventional controllers are known, including the proportional-integral-differential controllers (PIDC) and their versions, such as PI, PD, etc., as well as the sliding mode controllers, the threshold controllers, and some others.

The class of intelligent systems involves fuzzy logic controllers (FLC), neural networks (NN) based on the appropriate neural network controllers (NNC), and the model-reference controllers (MRC), as well as their numerous compositions, such as fuzzy PIDC, neuro-fuzzy controllers, NN-PIDC, etc. Application of intelligent braking controllers promises such benefits as optimal management of vehicle deceleration on changing road surfaces, slopes, and wind conditions that are usually not supported by conventional controllers. It is remarkable that the intelligent controllers can carry out both the gradual and emergency braking for the sake of energy efficiency boosting, whereas the conventional controllers are commonly designed for either gradual or emergency braking.

As follows from the recent publications, by now intelligent controllers are becoming to be an effective tool primarily as emergency braking equipment, since the antilock braking systems (ABS) managed by the conventional controllers act unsuccessfully in volatile and unknown road conditions [11], [12]. At the same time, the intelligent controllers are known as a promising instrument for significant improvement of energy efficiency in gradual braking as well [13]. The two most notable reasons for their introduction are, firstly, the exact fulfilment of the driver's targets due to their smart road recognition capabilities and, secondly, the accurate sharing of the desired braking torque among the front and rear wheels, as well as its allocation between EB and FB. Both of these benefits are very important in terms of maximizing regenerative energy due to their ability to control the braking process along with energy recovery management. The most advanced of such systems, for example [14 – 16], successfully detect a priori unknown changes in driving conditions, correctly identify environment variations, and solve many issues of vehicle dynamics.

3. Fuzzy Logic

Numerous advantages of FLCs are presented in [17] and [18]. In these and similar papers devoted to fuzzy braking control, various FLC features are analysed, including fuzzy logic control of the braking torque and fuzzy distribution of the actuated torque. Both of them are aimed at energy recovery growth.

In the first group of publications, specifically in [19], an advanced braking FLC is developed and integrated into the series regenerative braking system. In [20], fuzzy control provides stabilization of a moving vehicle under unknown disturbances. To increase efficiency, a double-level supervisory controller is used here. In [21], a fuzzy algorithm is proposed aiming at deriving the required control vector that ensures the stabilization of an oscillating continuous-time plant. The techniques suggested and verified in [17] and [22] are based on the hardware-in-the-loop test benches and a multi-input, single-output (MISO) FLC for the ABS management. In this process, the vehicle speed and the longitudinal wheel slip signals are fed to the FLC inputs, and the actuating torque appears at the FLC output.

Fuzzy distribution of the actuating torque is described, in particular, in [12] and [23], where the FLC allocates the braking torque between EB and FB. This control approach takes into account the vehicle speed level, position of the brake pedal, and the HES SOC. These signals are sent to the FLC, which generates the ratio of the EB actuating torque to the total braking torque at the output. Another torque distribution method is designed in [24]. It is also based on a multi-input FLC that minds the effects of the HES SOC, braking torque, and vehicle speed.

In all the noted fuzzy logic systems, the FLC is tuned based on expert skills, experience and qualifications, without systematic construction. Since tuning specialists use a case-by-case trial-and-error approach, fuzzy methods usually fail in continuously unstable processes. One of such processes is the gradual EV deceleration, at which it is necessary to take into account numerous variables to develop reliable control actions. This makes many driving situations incompatible with the fuzzy logic approach. Definition of a great number of tuning parameters, identifying multiple scaling factors and linguistic rules, and configuring the fuzzy sets cause many serious troubles related to the classical FLCs due to the complexity of the nonlinear input-output surface [25], [26]. Moreover, many conventional FLCs produce steady-state errors and fail in dynamics, in contrast to the PIDC that can easily prevent static errors and provide nice dynamic robustness being accurately tuned.

These conflicting issues are often resolved with the help of fuzzy PIDCs. In this class of intelligent controllers, two groups of parameters are periodically generated, namely, the scaling factors and the fuzzy rule base [27 – 29]. They have the same structure as the conventional PIDCs, but ensure smart settings. As follows from the comprehensive review on the fuzzy PIDC approach [27], such controllers provide better handling capabilities than both the PIDC and the FLC.

However, the analytic complexity of the multi-input, multi-output (MIMO) composition remains the negative side of the fuzzy PIDC. This drawback constrains fuzzy PIDC design and autotuning, which makes the configuration of the rule base and MIMO inferencing quite problematic [30]. As a result, there are rather few publications devoted to the MIMO fuzzy PIDCs for automotive applications that could convert several inputs, at least the speed error and its rate, directly into three PIDC parameters. As an example, the dual-input three-output fuzzy PIDC in a vehicle braking system can be considered as successfully designed and co-simulated in MATLAB/Simulink™ and AMESim™ [31].

The paper [32] is also devoted to the fuzzy PIDC operation under changing driving modes and road conditions. Unlike the above studies, it lays emphasis on providing not so much the best always, but some optimal braking dynamics in terms of the speed overshoot and the response time. Here, the authors address two issues, namely, the precision following the standard dynamics, and the fastest achievement of the desired vehicle velocity or stop. The first task is focused on a variety of non-autonomous and semi-autonomous EVs acted in more or less stable conditions at moderate velocities, such as industrial cars, loaders, forklift trucks, carriers, etc. The second refers to conventional road vehicles. The research is devoted to the PIDC autotuning procedure based on two inputs, namely, the slope error and the peak error, with the help of MIMO fuzzy controllers. The NI LabVIEW™ toolkit is used in this study as an intelligent modelling instrument with an intuitive graphics-based user interface suitable for collecting and analysing data from vehicles with PIDC, FLC, and fuzzy PIDC.

4. Neural Networking

To optimize energy recovery in EVs, NNCs are being successfully implemented. Today, various NN approaches are applied in braking controllers of vehicles. Several reviews [33 – 36] describe intelligent NNCs that, unlike the FLCs, do not require human experts since their performance is based on the sets of accurately collected experimental data.

A robust NNC discussed in [37] ensures stability upon unknown disturbances at urgent braking on a variable-surface road by tracking the wheel slip in different driving modes. In other paper [38], an effective engineering solution is proposed aimed at enhancing the ABS control. Here, the friction coefficient is estimated with the help of video equipment. An emerging deep learning method is applied in [39] to differentiate six types of road surfaces met in driving: wet and dry gravel, wet and dry cobblestone, and wet and dry asphalt. At this, an experimental study of the convolutional NN was produced for the tire model parametrization. To recognize the driving cycle and configure the NNC, a recurrent NN is proposed in [40]. This NN tracks the portion of collected data, such as average, maximum, and minimum velocity and acceleration, and use them as the driving cycle characteristics. The NN has six input neurons, ten hidden neurons with a sigmoid function, and a single-neural output layer.

Using the torque gradient control method offered in [41], the maximal energy can be returned to the HES at braking, despite the absence of tire-road models. The developed algorithm of torque sharing allocates the driver's request between the FB and EB, thereby enabling regeneration in all braking scenarios, while the SOC and voltage levels of the HES are unsaturated.

Another example of an NN-fed BBS is presented in [42], where an optimal policy is sought in the Markov decision-making process. To this end, the braking space is divided between actions such as no braking, gradual braking, average braking, and urgent braking, upon which deep reinforcement learning is applied. One more NNC shown in [43] analyses two braking operations, namely releasing the accelerator pedal and pressing the brake pedal, and trains the NN using the multi-correlation coefficient method.

In [44], a convolutional NN is applied to evaluate energy and power consumption in EVs. To transfer braking energy to the HES devices, a regenerative EB is offered in [45] based on the multilayer feedforward NNC able to comprise EV velocity and HES SOC in different braking modes. The authors of [46] apply collected data of power consumption, trip time, and SOC as training inputs to the NN, whereas the NN output specifies the optimal driving mode. At this, typical peak and off-peak loads, human behaviour, seasonal and weather conditions are taken into account. Deep learning proposed in [47] for energy demand estimation is based on the driving cycle data converted into maps that serve as an NN input. Several feedforward NN architectures are considered for this application. The HES-based braking system offered in [48] ensures automatic control of the EV, providing both driver comfort and energy efficiency. It is based on accurate prediction of vehicle driving mode and deep NN, consisting of a sequential recurrent network with long-short-term memory and a two-layer conventional network model.

Many NNCs are designed for use in driving scenarios other than braking, for example [49], [50]. A system proposed in [51] can employ both the gradual and the urgent braking modes. During the training, random sampling was used here with the equal numbers of urgent and gradual samples in every batch. Since emergency braking is a rare event, urgent samples were collected five times more often than the gradual ones to construct a balanced testing dataset.

One of the directions of the on-board NNC implementation is focused on finding the optimal parameters of a conventional PIDC to optimize energy recovery. For example, to adjust parameters of the PIDC with NN using a particle-swarm optimization algorithm, the adaptive self-tuning technique was created in [52], in which the number of dimensions in swarm optimization is equal to the number of PIDC gains and the least mean squared error function is chosen as a quality criterion.

An approach offered in [53] merges the PIDC with a single-layer NN, which tunes online its P, I, and D gains. To minimize an error, an adaptive linear NN is applied here, in which the error tracking algorithm adjusts the weights and biases. In [54], the PIDC is managed by an NN with three types of neurons: P, I, and D. In [55], an adaptive NN-PIDC is designed to manage the MIMO nonlinear vehicle system. In [56], the NNC provides twice less transition time comparing to the conventional PIDC along with a reduction of both the energy loss and the EV velocity overshoot. This controller provides economic gradual braking due to its ability to define optimal PIDC gains and predict their influence on the energy distribution. The NN proposed in [57] also enhances PIDC operation since its energy management strategy is robust with respect to the load and mass uncertainties.

Examples of fuzzy NNs integrated into the EVs can also be found in literature. The fuzzy NN designed in [58] considers velocity and the speed range as input constraints. The system consisting of ten hidden layers with one neuron each is evaluated using 110 different cases. An example of a hybrid intelligent controller composed of the FLC and NNC can be found in [59]. An NN-based FLC presented in [60] provides torque distribution for regeneration in the braking hybrid bus. An algorithm described in this study processes the bus velocity, wheel speed, and the brake pedal stroke in the associated FLC and backpropagation NNC.

Very successful combination of the NNC, sliding-mode controller, and PIDC is displayed in [61]. To match the nonlinear time-varying dynamics, the NNC is designed based on a sliding-mode controller and a single-neuron PIDC, which provides urgent braking. In a neuro-fuzzy PIDC developed in [62], the proportional, integral and derivate gains can be self-tuned online. Three control advantages were reached in this system, namely reduced deceleration time, restricted slip, and increased energy efficiency.

An intelligent control module like MRC generates control signals that minimize some fitness function, which is the difference between the braking signals of a real car and its model [63]. The MRC involves a reference model and an adaptive mechanism, wherein the controller and the vehicle constitute an inner loop, and the reference model and the adaptive mechanism form an outer loop [64 – 67]. Compared with conventional closed-loop feedback controllers [68], like PIDC, this topology ensures that the system output closely tracks the output of the reference model. As an example of the MRC application, in [143] the receding horizon NN control strategy [69] is described, suitable for managing gradual braking. Here, the observer predicts the response of the vehicle over a certain time interval in the future. The prediction of motor current, voltage, and EV velocity is based on the previous transients and the real system robustness.

An MRC created in [41] is able to meet the conflicting needs of urgent and gradual braking scenarios upon the volatile road surfaces. Two stages of the MRC design were produced in this research, namely identification of the EV NN model and training the NNC based on the identified model. During the identification of the NN EV model, the model parameters were estimated that reflect the behaviour of an unknown vehicle. This model uses a feedforward topology, while the NNC applies a recurrent one. In both NNs, a double-layer architecture is applied.

5. Conclusions

Given that the focus of this analysis is on the energy saving situation, different intelligent controllers have been ranged and compared in terms of the gradual and emergency braking efficiency, their suitability for road surface estimation and torque allocation, as well as simulation toolboxes and model verification tools used by different authors. As a result, all controllers are divided into those that are able to save energy and those that do not have this ability. The former ones are additionally divided into conventional (road-independent) and intelligent (road-dependent). The best energy efficiency are shown by such intelligent controllers as FLC, NNC, MMC, and their numerous associations. It is especially important that the most advanced of their representatives successfully recover braking energy both during gradual and emergency braking.

Acknowledgement

This work was supported by the Estonian Research Council grant PRG 658 and by the MDPI Travel grant.

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