Improving Regenerative Braking Strategy using Genetic Algorithm for Electric Vehicles

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ABSTRACT

The regenerative braking system is one of the most fundamental advantages of electric vehicles compared with internal combustion vehicles. With a proper regenerative braking strategy, a fraction of vehicle's kinetic energy is harvested by the electric motor, which is configured as a generator during braking. The strategy distributes the required braking force between friction brakes of both axles and regenerative breaks. This study presents a genetic algorithm brake force distribution strategy to increase energy recovery, considering the Economic Commission for Europe (ECE) regulations. The performance of the proposed regenerative braking control algorithm is evaluated by the ADVISOR which is based on MATLAB/Simulink environment. The results indicate that the driving range has maximum increased to 25 percent with regards to the drive cycle.

Keywords: *Regenerative Braking, Genetic Algorithm, Electric Vehicles, Braking Force Distribution Strategy*

Introduction

Regenerative braking is a crucial technology that improves the fuel efficiency of an electric vehicle (EV); it also compensates for battery capacity limitation of an EV with an onboard energy storage system (ESS). With this technology, kinetic energy is converted to electricity, so that it can be stored in an ESS to be reused. The regenerative braking strategy goal is to optimally distribute required braking torque between friction and regenerative brakes so that the

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harvested energy is maximized while maintaining vehicle stability. Hence, this problem can be considered as an optimization problem. In articles [1]–[3], authors suggest using fuzzy logic as a braking force distribution strategy. This article [4] uses particle swarm optimization (PSO) to optimize the membership functions (MFs) and rules of the regenerative braking force distribution fuzzy controller regenerating braking energy under the conditions of the braking stability. Compared to the proposed genetic algorithm (GA) that can solve the problem, fuzzy logic is heavily depended on the membership functions one chooses to model. Paper [9] suggests using a multi objective GA to distribute braking force, they have put energy harvesting as their main priority. This approach may cause the vehicle to be unstable. When the vehicle become unstable, the safety features of vehicle are activated while deactivating regenerative braking system; in order to stabilize the vehicle. Thus, decreasing the total harvested regenerative braking energy. In this study, GA is implemented to optimize the braking force distribution under required constraints. Simulations are performed using advanced vehicle simulator (ADVISOR) in MATLAB/Simulink environment.

Braking Dynamics

Considering the Economic Commission for Europe (ECE) braking regulations (ECE, 2014), the algorithm choose the braking force distribution coefficient (β) in a reasonable range in order to avoid braking instability. The ECE regulation prescribes “in all load status of the vehicle, the adhesive utilization coefficient curve of the rear axle can't be above that of the front axle when the braking intensity is between 0.15 and 0.8; while the coefficient of adhesion k is between 0.2 and 0.8, the braking intensity must fulfil: $z \geq 0.1+0.7\ (k-0.2)$”. This regulation is shown in Figure 1. The ECE regulation is abstracted as below:

$$\begin{cases} k_f \geq k_r & (\mathrm{z} = 0.15 \sim 0.80) \\ k_f \leq \dfrac{z-0.1}{0.7} + 0.2 & (\mathrm{z} = 0.10 \sim 0.52) \\ k_r \leq \dfrac{z-0.1}{0.7} + 0.2 & (\mathrm{z} = 0.10 \sim 0.52) \end{cases} \tag{1}$$

where, k_f and k_r are the adhesive utilization coefficients of the front and rear axles. The definition of adhesion coefficient utilization is:

$$\begin{cases} k_f = \dfrac{F_{bf}}{F_{zf}} = \dfrac{\beta\, z\, L}{b + z\, h_g} \\ k_r = \dfrac{F_{br}}{F_{zr}} = \dfrac{(1-\beta)\, z\, L}{a - z\, h_g} \end{cases} \tag{2}$$

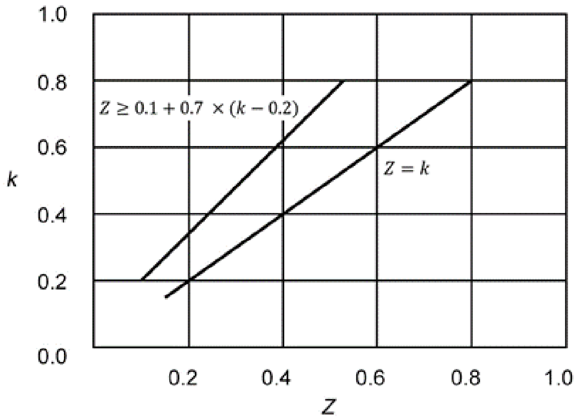

Figure 1: The ECE regulation about braking force distribution [5]

where, F_{bf} and F_{br} are front and rear axle surface braking forces, F_{zf} and Fzr are the vertical load of the front and rear axle respectively, β is defined as the front axle braking force to the total braking force. L is the distance between the front and the rear axle, a is the distance from the center of the vehicle to the front axle, b is the distance from the center of the vehicle to the rear axle, h_g is the gravity center's height of the vehicle. Considering the definition of β, equations (1) and (2) are expressed further as below:

$$\beta \geq \frac{b + z\, h_g}{L} \qquad (z = 0.15\sim 0.8) \tag{3}$$

$$\beta \leq \frac{(z + 0.04)(b + z\, h_g)}{0.7\, z\, L} \qquad (z = 0.1\sim 0.52) \tag{4}$$

$$\beta \geq 1 - \frac{(z + 0.04)(a - z\, h_g)}{0.7\, z\, L} \qquad (z = 0.1\sim 0.52) \tag{5}$$

when $z < 0.1$, all the required braking force can be provided using only regenerative braking. If $z > 0.80$ then the braking should be done by using only friction brakes due to emergency braking requirements [6].

System Modeling

The GA needs to evaluate each solution; a mathematical system model is required. In this study ADVISOR's models are used in order to keep the consistency of the algorithm with the simulation environment.

Energy storage system model

ADVISOR has two main battery models: 1) The RC model (resistive-capacitive). 2) The Rint Model (internal resistance) characterizes the battery with a voltage source and internal resistance. RC model which includes transient effects in the battery, is developed over Rint model; it gives a better state of charge (SOC) estimation over a simulation period. On the other hand, since Rint model is simpler and also provides acceptable voltage predictions within 3% error limit over fifteen US06 drive cycles [7], Rint model is used for the EV simulation. Internal resistance (R) of battery and its open circuit voltage (V_{OC}) is estimated using lookup tables provided by the battery manufacturer; While, R and V_{OC} are functions of SOC and temperature. In order to determine the maximum power that the battery is able to deliver, the battery operating voltage (V_{bus}) is compared with battery's minimum voltage, motor's minimum voltage or $V_{OC} / 2$ value. If the operating voltage drops, the maximum power available to the system is constrained by either of these limitations. The power delivered to the system is obtained using equation (6).

$$P = V_{bus} * \frac{V_{OC} - V_{bus}}{R} \tag{6}$$

The current of the equivalent circuit (I) is determined by using V_{OC}, R and power values using the equation (7).

$$P + R\, I^2 - (V_{OC} * I) = 0 \tag{7}$$

Finally, the effective SOC of the battery is computed by using the equation (8).

$$SOC = \frac{Ah_{max} - Ah_{used}(\eta_{coulomb})}{Ah_{max}} \tag{8}$$

Where,

$$Ah_{used} = \begin{cases} \int_0^t A\, dt & for\ A > 0\ discharge \\ \int_0^t \eta_{coulomb}\, A\, dt & for\ A < 0\ charge \end{cases} \tag{9}$$

Where, Ah_{max} is battery's capacity in terms or ampere per hours, A is the current that the battery is charging/discharging with. $\eta_{coulomb}$ is battery's Coulombic efficiency. Above all, the thermal model of the battery calculates the impact of temperature on battery's performance parameters, efficiencies also maximum capacity value. The thermal model utilizes lookup tables indexed by the operating temperature. For detailed information about battery and its thermal model refer to [8].

Motor model

Using lookup tables indexed by motor speed, the motor model is able to compute the available torque and speed at the operating point. Moreover, these lookup tables also contain the loss, which is indexed by torque, speed and also inertia effects. Lastly, the model uses another lookup table indexed by the current speed in order to calculate the maximum torque. The output power calculation is abstracted as equations below:

$$P_{m,req} = P_{m,out} + P_{m,loss}(\tau_{m,out}\ , \omega_m) \tag{10}$$

$$P_{m,req} = \left(\tau_{m,req} + \tau_{m,inertia}\right) * \omega_m \tag{11}$$

$$\tau_{m,inertia} = I_{m,inertia} * \frac{d\omega_m}{dt} \tag{12}$$

where, $P_{m,req}$ is electrical power required by motor, $P_{m,out}$ is motor power output, $P_{m,loss}$ $\left(\tau_{m,req} + \tau_{m,inertia}\right)$ is motor power loss which is a function of motor torque and its angular speed (ω_m), $\tau_{m,out}$ is motor torque output, $\tau_{m,req}$ is motor torque required, $\tau_{m,inertia}$ is motor torque needed due to inertial effect, $I_{m,inertia}$ is motor inertia.

Genetic Algorithm

The problem in this study can be formulated as an optimization problem [9]. The flowchart of the developed GA-based braking force distribution strategy is illustrated in Figure 2. Each individual in GA is a solution to the problem, in this study each chromosome can be coded and presented as below:

$$i_n = [F_{dr}, F_f] \tag{13}$$

where, F_f is braking force provided by front axle. F_{dr} is defined as the ratio of braking force provided by drivetrain to the total braking force of front axle, i_n is one individual in the population. In order to build the initial population, the chromosomes are made randomly while their feasibility is checked using ECE regulation equations. If a chromosome is feasible, the algorithm puts it into the initial population. This process is continued until the number of chromosomes in the initial population equals to the population size.

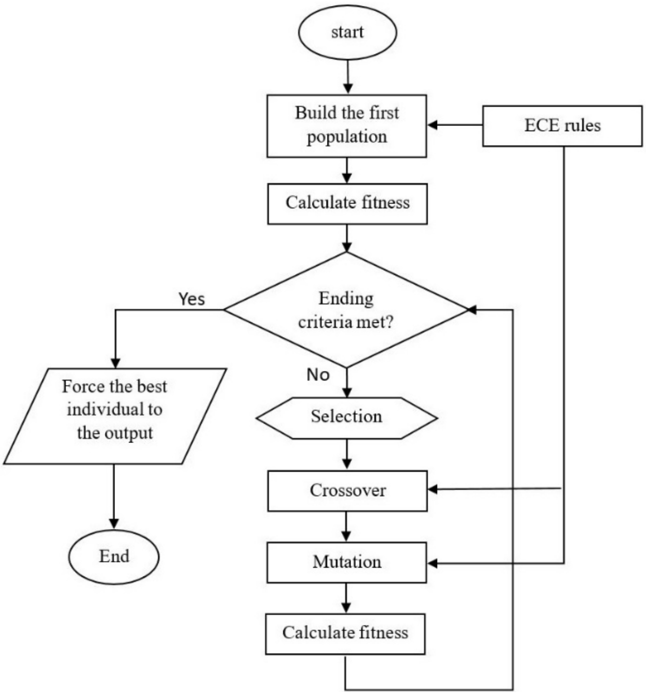

Figure 2: The flowchart of the GA based regenerative braking force distribution strategy

The proposed EV has an electric motor propelling the front wheels. As illustrated in Figure 3, when the driver requests a brake, the required braking force is distributed between driveline and friction brakes. The regenerative braking energy is transferred to the motor; which is working as an inverter, this mechanical energy is converted to electrical form, stored in the ESS. Motor input torque ($\tau_{m,input}$) is calculated from equation below:

$$\tau_{m,input} = F_d \cdot \frac{r}{i} \cdot \eta_{drive} \cdot \eta_{axle} \tag{14}$$

where, r is the rolling radius of the wheels, i is the transmission ratio, η_{drive} and η_{axle} are the drivetrain and axle efficiencies respectively. Motor delivered power ($P_{m,out}$) to ESS is obtained from equation (15).

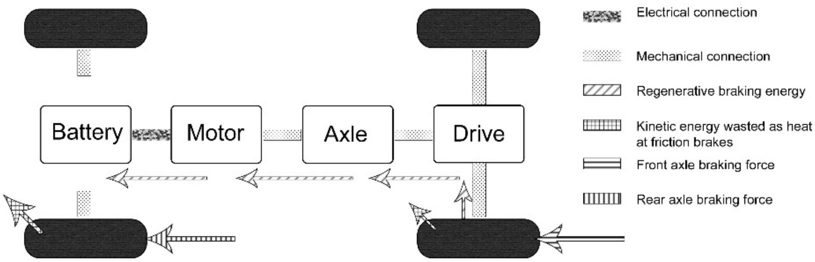

Figure 3: The energy flow of the proposed EV with regenerative braking

$$P_{m,out} = \tau_{m,input} \cdot \omega_m \cdot \eta_m \tag{15}$$

Having $\tau_{m,input}$ and motor's angular speed (ω_m), Motor's efficiency η_m is obtained using motor's efficiency 2D-table. The output power of motor which is working as an inverter during regenerative braking, is applied to the ESS, recharging batteries. According to the equation (7) the current delivered to the battery can be calculated using equation (16).

$$I = \frac{V_{oc} - \sqrt{{V_{oc}}^2 - 4 * P_{m,out} * R}}{2R} \tag{16}$$

However, during charge, the maximum voltage must not be exceeded. This maximum charge current is found from equation (17).

$$I_{max} = \frac{V_{oc} - V_{max}}{R} \tag{17}$$

SOC can be calculated using equations (8) and (9). *ΔSOC* is defined as the fitness (ϕ) of each individual.

$$\phi_i = \Delta SOC_i = SOC_i - SOC_0 \tag{18}$$

Where, SOC_0 is the SOC in the beginning of the time step and SOC_i is the SOC according to the regenerative braking provided by the individual *i*.

The selection is carried out using the roulette method. By merging parts of information from two separate individuals from the population, this operator forms two new individuals called offspring. The crossover operator utilizes a combination of blending method with extrapolation technique [10]. The offspring obtained from crossover operator are placed in the new population.

Then, mutation operator randomly selects an individual in the new population and changes one of the parameters based on a non-uniform probability distribution. The algorithm checks the offspring and mutated individual feasibility using ECE regulations and rejects non-feasible individuals. One way to stop the algorithm is to use the relative error between maximum and minimum fitness value. The smaller the relative error is, the more convergent the current population is. If this situation continuous for a certain generation, a threshold is used to stop the algorithm. However, If the generation number reaches the predefined maximum generation, the algorithm stops.

Simulation and Analysis

Simulations are performed using ADVISOR. Using Simulink blocks the EV is modeled graphically in order to express the connections between different components. The Simulink model of the EV inputs the required data from the MATLAB Workspace. Then, outputs the simulation results to the Workspace to be presented in the results interface of ADVISOR. Table 1 shows the main simulation parameters used.

Table 1: Simulation parameters

	Parameter	**Value**
GA	Max generation	100
	Population size	20
	Crossover probability	0.7
	Mutation probability	0.01
Vehicle	Mass (kg)	1082
	Wheel base (m)	2.6
	Wheel rolling radius (m)	0.282
	Height of center of gravity (m)	0.5
Motor	Peak power (kW)	58
	Peak torque (N m)	400
	Peak speed (r/min)	4000
Battery	Nominal voltage (V)	436
	Capacity (A h)	28

In order to evaluate the proposed algorithm, two regenerative braking strategies are compared with an EV configuration that does not utilize regenerative braking (NR). The first braking strategy is ADVISOR's embedded braking strategy (AES), the second strategy is the GA proposed in this study. To compare these braking strategies, these five typical drive cycles are used: US06, UDDS, 1015, FTP and HWFET. Table 2 shows driving distance in each driving cycle using different braking strategies. Total Harvested Energy (THE) shows how much energy is harvested in each particular driving cycle. The GA based braking strategy shows better performance in compared with AES, it can harvest more energy from braking situations. The amount of harvested energy is highly depended on driving situation and driver's habits. In driving cycle 1015 which is the Japanese 10-15 mode driving cycle, the harvested energy using GA is significantly more than what AES could harvest. However, in driving cycles similar to HWFET which is The Highway Fuel Economy Test, the difference is not significant.

Table 2: Simulation results

Driving cycle	**Braking strategy**	**Driving distance, (km)**	**THE, (kJ)**	**Driving distance improvement, (%)**	**THE improvement, (%)**
1015	NR	77	0	-	-
	AES	87.9	2355	14.16	-
	GA	96.3	6711	25.06	184.97
FTP	NR	76.4	0	-	-
	AES	86.1	3244	12.70	-
	GA	90.9	5752	18.98	77.31
HWFET	NR	84.7	0	-	-
	AES	87.6	805	3.42	-
	GA	88.8	1383	4.84	71.80
UDDS	NR	77.1	0	-	-
	AES	87	3254	12.84	-
	GA	92.8	5913	20.36	81.71
US06	NR	55	0	-	-
	AES	60.5	3225	10.00	-
	GA	62.2	4388	13.09	36.06

Conclusions

The simulation results show that an effective braking strategy is able to harvest additional energy and extend the driving range of the EV. The amount of energy being harvested varies for different driving cycles. For example, in UDDS driving cycle which represents city driving conditions, the total harvested energy using GA is 81.71% more than what AES could harvest, but in US06 which represents an aggressive, high speed and/or high acceleration driving behaviour, the improvement is only 36.06% compared with an EV without regenerative braking.

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