Genetic Algorithm Optimization of an Energy Storage System Design and Fuzzy Logic Supervision for Battery Electric Vehicles

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Additional information is available at the end of the chapter

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Abstract

This chapter presents a methodology to optimize the capacity and power of the ultracapacitor (UC) energy storage device and also the fuzzy logic supervision strategy for a battery electric vehicle (BEV) equipped with electrochemical battery (EB). The aim of the optimization was to prolong the EB life and consequently to permit financial economies for the end-user of the BEV. Eight variables were used in the optimization process: two variables that control the energy storage capacity and power of the UC device and six variables that change the membership functions of the fuzzy logic supervisor. The results of the optimization, using a genetic algorithm from MATLAB®, are showing an increase of the financial economy of 16%.

Keywords: Genetic algorithm optimization, battery electric vehicle, fuzzy logic, ultracapacitor, electrochemical battery

1. Introduction

The humanity has to act on two major directions in order to reduce the pollution and the greenhouse effect of carbon dioxide released into atmosphere: on the one hand to increase the exploitation of renewable energy in the detriment of fossil fuel and on the other hand to increase the energy conversion efficiency in all the sectors of activity. Electrification of transportation sector will help reduce the pollution, mainly in the cities as there are mostly affected by this problem and will help reduce the greenhouse effect if the energy that powers the electric vehicles comes from renewable sources. The main advantages of electric vehicles compared to those equipped with combustion engine are as follows: greater efficiency, increased reliability, better dynamics, and sometimes smaller costs [1].

Pure electric vehicles can be classified into non-autonomous vehicles and autonomous vehicles. The non-autonomous vehicles, represented by tramways, trolleybuses, metros, electric locomotives, and trains, depend on an external electric energy supply system: catenary lines or feeding rail. These types of vehicles are very clean and efficient solution to move people and goods on an established trail or route. In the future, these types of vehicles will be further improved and their use extended. The autonomous electric vehicles are needed where the routes are variated, for example, for personal small vehicles. These vehicles are usually depending on an electrochemical battery (EB) to be feed. The EBs are nowadays the most expensive part of the battery electric vehicles (BEVs), and thus, actions to optimize their operation and increase their lifespan should be taken. In [2], the authors are stating that for some LiFePO4 batteries, "the cycle depth of discharge and relative fraction of low-rate galvanostatic cycling vs. acceleration/regenerative braking current pulses are not important even over thousands of driving days"; in conclusion, the only important factor in battery ageing is the energy processed. In this study, the authors are estimating an approximate capacity lost per normalized Wh of about $-6 \times 10^{-3}\%$ for plug-in hybrid vehicle use and $-2.7 \times 10^{-3}\%$ for vehicle to grid use, due to more rapid cycling found in driving conditions. In order to reduce the energy processed by the EB, a very well-known solution is to complement it with an ultracapacitor (UC) energy storage device that has opposite characteristics compared to EB, high-power and low energy density. Many papers are treating this combined energy storage system. The UC has usually the role to reduce the stress on the EB, by power peak shaving and braking energy recovering. In reference [3], a comparison between "current/voltage/power profiles of the batteries with and without UCs indicated the peak currents and thus the stress on the batteries were reduced by about a factor of three using UCs. This reduction is expected to lead to a large increase in battery cycle life". The authors of reference [4] are proposing a strategy to design and supervise the battery and UC on a fuel-cell hybrid electric vehicle. The proposed strategy uses low-pass filters and some logical operations. In reference [5], a fuzzy logic strategy is presented, aiming at the reduction of power peaks on the EB with the help of a UC. In [6], a fuzzy logic control method is utilized to design an energy management strategy that enhances the fuel economy and increases the mileage of a vehicle by means of a hybrid energy storage power system consisting of fuel cell, EB, and UC. The authors of reference [7] are proposing a new battery/UC configuration that allows a reduced-size power converter. The braking energy is completely stored in the UC, having an important capacity of almost 1200 kJ.

Compared to state of the art, this chapter presents a methodology to optimize altogether the capacity and power of the UC energy storage device and also the fuzzy logic supervision strategy for a BEV equipped with EB. In Section 2, the power system architecture will be presented, in Section 3, the fuzzy logic supervision strategy, in Section 4, the BEV simulation, and in Section 5, the optimization using genetic algorithm.

2. Power system architecture

Figure 1 presents the simplified diagram of the on-board power system [8] considered. The main power source consists of an EB that can be connected to the loads directly or by means of a power converter. The UC usually is connected through a buck–boost (DC/DC) converter to the DC link, due to low-voltage operation. The electric motors are supplied through power inverters (DC/AC converter).

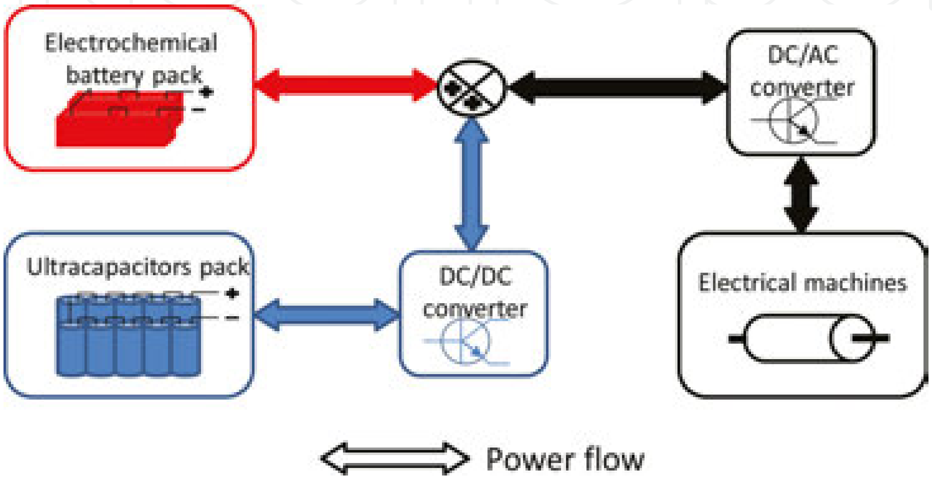

Figure 1. Schematic of the BEV power system.

The EB used should be a rechargeable type. Li-based battery technology is nowadays the most used type of battery in electric vehicles due to its high energy-to-weight ratio, no memory effect, and low self-discharge, compared to other solutions like Ni/Cd or Ni/MH. Another important candidate that does not use toxic elements (like Lithium) is the EB with molten salts. This technology is maybe not as mature as Lithium technology but has similar energy density. The most important drawback of molten salt batteries is that they work at high temperature, around 300°C; thus, the thermal insulation of the battery should be very good in order to increase its efficiency.

UCs work in much the same way as conventional capacitors, in that there is no ionic or electronic transfer resulting in a chemical reaction, that is energy is stored in the electrochemical capacitor by simple charge separation. The main advantage of the UCs is the high-power capability that makes them highly suitable to be used in conjunction with the EBs. The energy stored (E) in UCs varies linearly with the equivalent capacity (C) and with the square of the voltage (U):

$$E = \frac{1}{2} * C * U^2 \quad (1)$$

3. Fuzzy logic supervision strategy

The fuzzy logic supervision strategy is considered appropriate to create an overall energy flow management between electrical machines or equipment and energy storage devices. The main idea behind this supervision strategy is to vary the UCs level of charge considering the BEV operation point. Thus, it has been considered that when the BEV is at stop, the UC should have a high state of charge (SoC), to be able to provide power when BEV starts moving. During the increase of speed, the UCs should reduce their energy storage and when arriving at high speeds should be discharged to be able to recover the most or all of the energy generated when braking. More details are given in Breban and Radulescu [8].

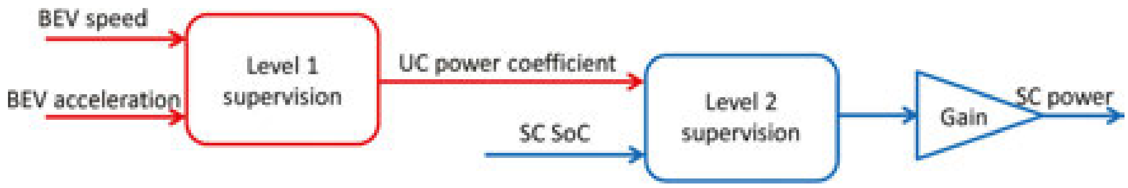

Figure 2. Fuzzy logic supervision strategy methodology.

The fuzzy logic supervision strategy is divided into two levels. Each level of supervision has two inputs and one output. The input variables of the first supervision level are the BEV speed and acceleration. The output is a power coefficient of the UC (**Figure 2**). The second level of supervision has also two inputs, that is the output of the level one and the SoC of the UC, and one output, the UC power. All variables are expressed in p.u. values. These are representing the ratio of each considered parameter to its nominal value. The *Gain* multiplier makes the passing from p.u. to real power system values. This multiplier can also be used to increase or decrease the dynamics of the supervision strategy.

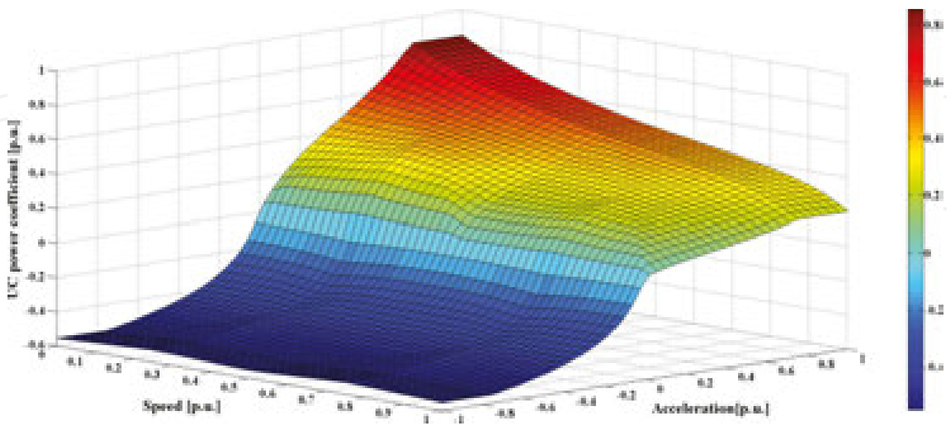

Figure 3. First level fuzzy logic supervision response surface.

For each level of supervision, a 3D response surface can be plotted (**Figures 3** and **4**). The outputs have a variation between −0.55 and 0.85 p.u for the first level and between −0.8 and

0.8 p.u. for the second level. This is due to the centroid defuzzyfication method. Thus, the UC power coefficient input of second-level supervision was developed with a variation between −0.5 and 0.8 p.u. to increase the supervisor dynamic response at the limits of variation. More details are presented in Breban and Radulescu [8].

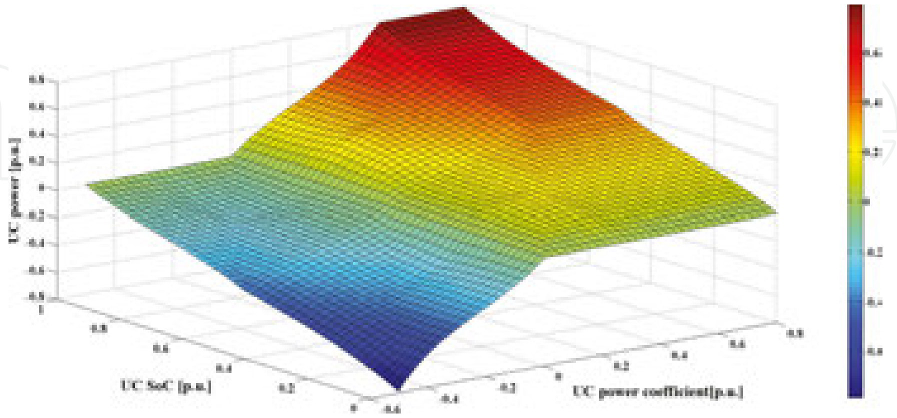

Figure 4. Second level fuzzy logic supervision response surface.

4. BEV simulation

In order to obtain the power absorbed or produced by the BEV, three different simulations for two driving cycles were considered: the New European Driving Cycle (NEDC) that consists of four ECE-15 cycles followed by one EUDC cycle (**Figure 5**), and the Urban Dynamometer Driving Schedule (UDDS) as presented in **Figure 6**. The first two simulations are considering the EUDC and UDDS cycles with slopes (**Figures 7** and **8**) and in the third simulation, the UDDS cycle without slopes. The simulated BEV has a total mass of 1400 kg, the equivalent frontal area is 2.2 m^2, and the aerodynamic drag coefficient is 0.25. The air density was considered 1.2 kg/m^3 and the air mass speed, zero. The BEV is equipped with a 16 kWh EB.

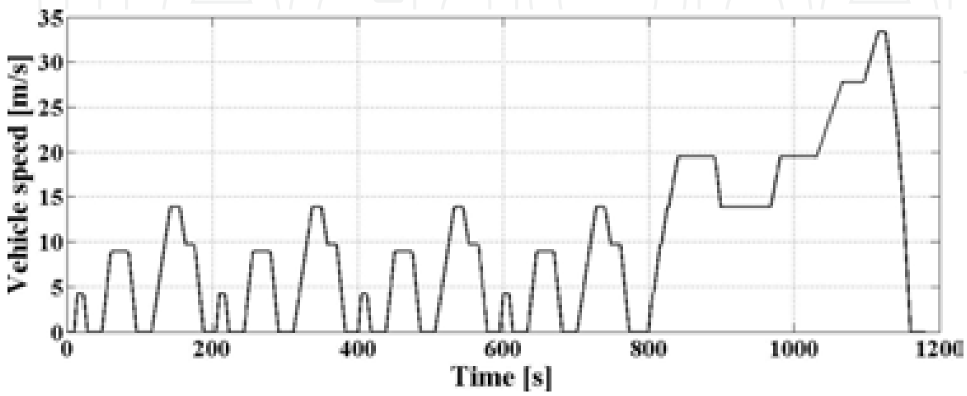

Figure 5. BEV speed (NEDC cycle).

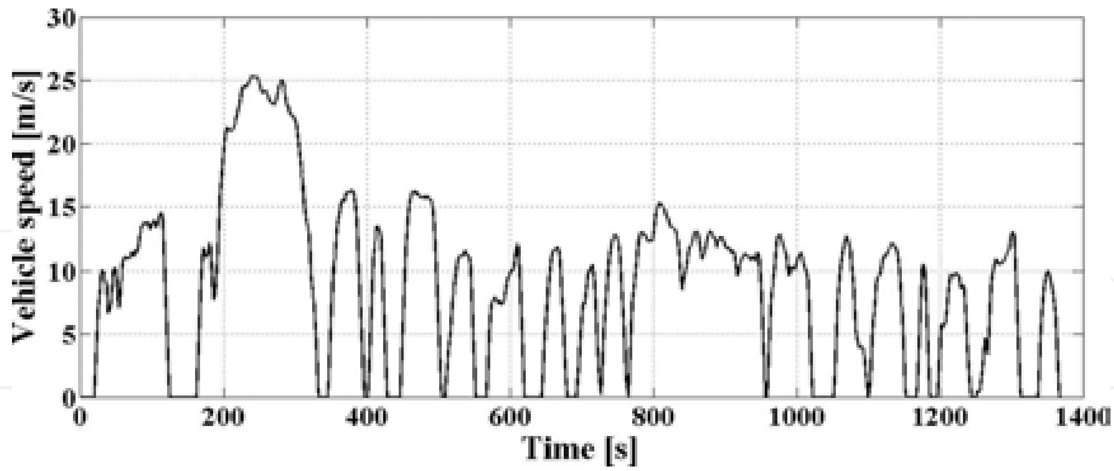

Figure 6. BEV speed (UDDS cycle).

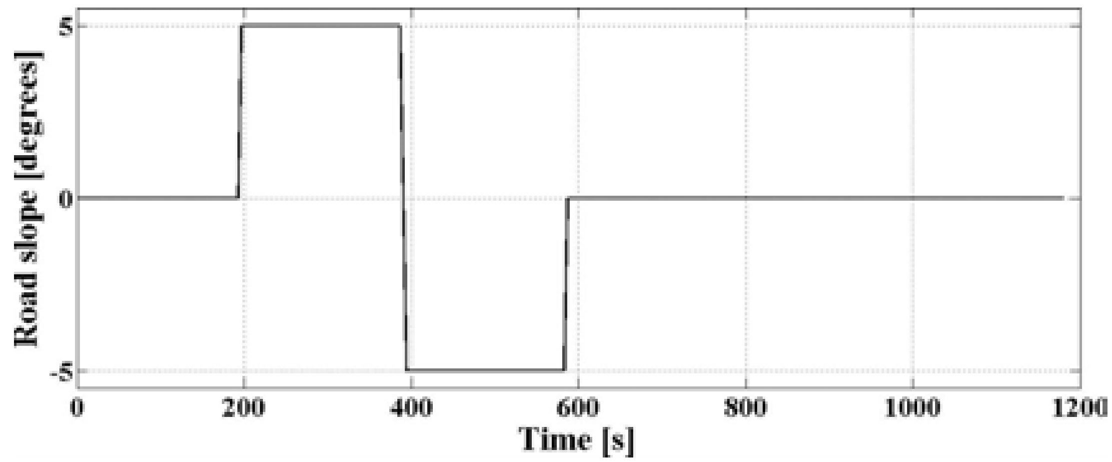

Figure 7. Road gradients (NEDC cycle).

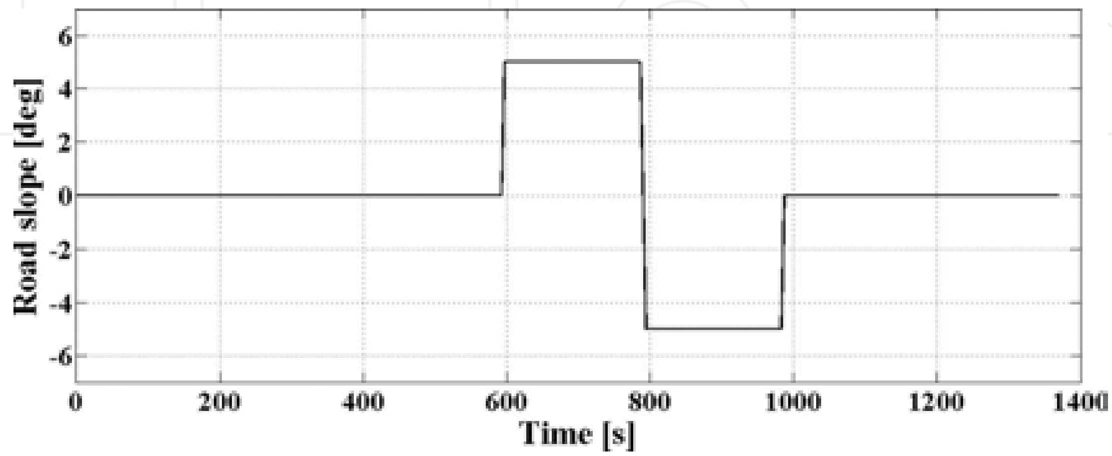

Figure 8. Road gradients (UDDS cycle).

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5. Optimization using genetic algorithm

The optimization was made using Global Optimization toolbox and Optimization tool interface from Matlab®. Eight variables were used in the optimization process: The UC capacity (kJ), the *Gain* that passes the UC power to real values (kW) and six variables that change the membership functions of the fuzzy logic supervisor, that is the membership functions of the two inputs and one output for each level of supervision. The limits of variation for the eight variables are presented in **Table 1**. In the third line of **Table 1**, the empiric choice of variables is presented, which is used in the first phase of development of the fuzzy logic supervision strategy, with the results presented in Breban and Radulescu [8].

Variables	Gain (kW)	UC capacity (kJ)	First input; first level	Second input; first level	Output; first level	First input; second level	Second input; second level	Output; second level
Limits of variation	1÷100	1÷1000	0÷0.25	0÷0.375	0÷0.1	0÷0.25	0÷0.25	0÷0.2
Empiric choice	25	250	0	0	0	0	0	0

Table 1. Variables and limits of variation during optimization and empiric choice of variables.

The number of individuals used in the optimization algorithm is 800. This number was empirically chosen considering the fact that eight optimization variables were used and in order to allow a good initial spreading of individuals in the eight dimensions domain of search. In other words, 100 individuals were consider for each optimization variable. The number of generations was set to 25 as it was observed that the optimization function was converging. Two individuals are guaranteed to survive to each next generation, 80% of the individuals are generated by crossover and the remaining by mutation. The crossover function creates a random binary vector in order to select the genes from two parents and from a child. The mutation randomly generates new individuals considering that the limits of variation (presented in **Table 1**) are satisfied. At every five generations, 20% of the individuals of n^{th} subpopulation are migrating toward the $(n + 1)^{th}$ subpopulation. This percent is calculated considering the smaller of the two subpopulations that moves.

The optimization function Eq. (3) to be minimized is the difference between the cost of the UC and the financial economy due to the increase in the lifespan of the EB. This financial economy Eq. (2) is calculated considering the product between the EB cost and the reduction of the energy processed by the EB, with the optimum UC capacity and control variables, compared to the case when no UCs are used, expressed in percentage.

$$\mathrm{Economy}_{\mathrm{EB\,life\,increase}} = \mathrm{EB}_{\mathrm{cost}} \times E_{\mathrm{reduction}} \tag{2}$$

$$f = \mathrm{SC}_{\mathrm{cost}} - \mathrm{Economy}_{\mathrm{EB\,life\,increase}} \tag{3}$$

The EB considered cost is 500 dollars/kWh, and the UC cost is 2.85 dollars/Wh. The empiric choice of the variables gives for f = 1942 dollars of economies and the optimized variables f = 2256.4 dollars (**Figure 9**), thus an increase of around 16% is achieved.

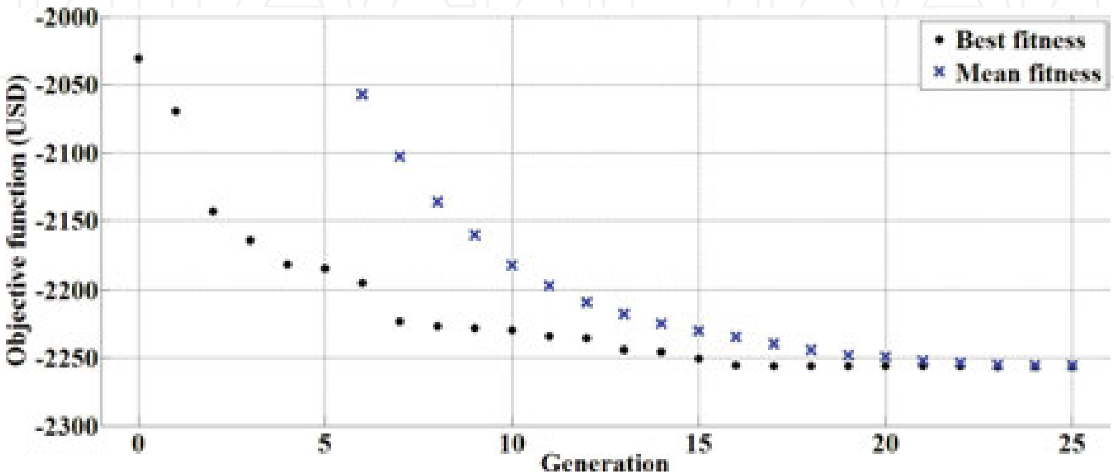

Figure 9. Best and mean fitness for the optimization function.

The optimum values for the eight variables used in the optimization algorithm are given in **Table 2**. As can be seen, the first two variables and the outputs of each level of supervision variables are changing considerable from the empiric choices, and the other four variables have only slight modifications or none. Also, the *Gain* value increases from 25 to reach almost the maximum permissible value, that is an increase of UC power from 20 to 80 kW. UC capacity increases from 250 kJ to more than 600 kJ. It should be noted that the mass of the BEV was considered constant whatever the value of the UC was used.

Variables	Gain (kW)	UC capacity (kJ)	First input; first level	Second input; first level	Output; first level	First input; second level	Second input; second level	Output; second level
Optimum	99.544	614.247	0.001	0.001	0.095	0	0	0.168

Table 2. Optimum values for the optimization variables.

As an example of membership function modifications with the change of an optimization variable, in **Figures 10** and **11**, the membership functions are presented for the output of the first level of supervision in the case of empiric choice of variable, respectively, optimum variable.

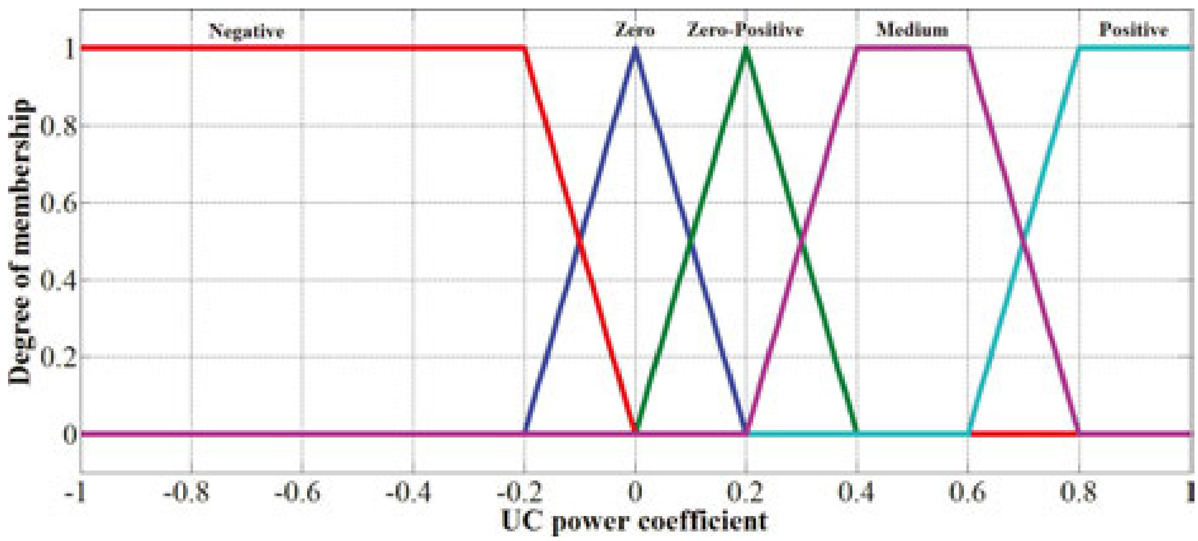

Figure 10. Membership functions for empiric choice of variable.

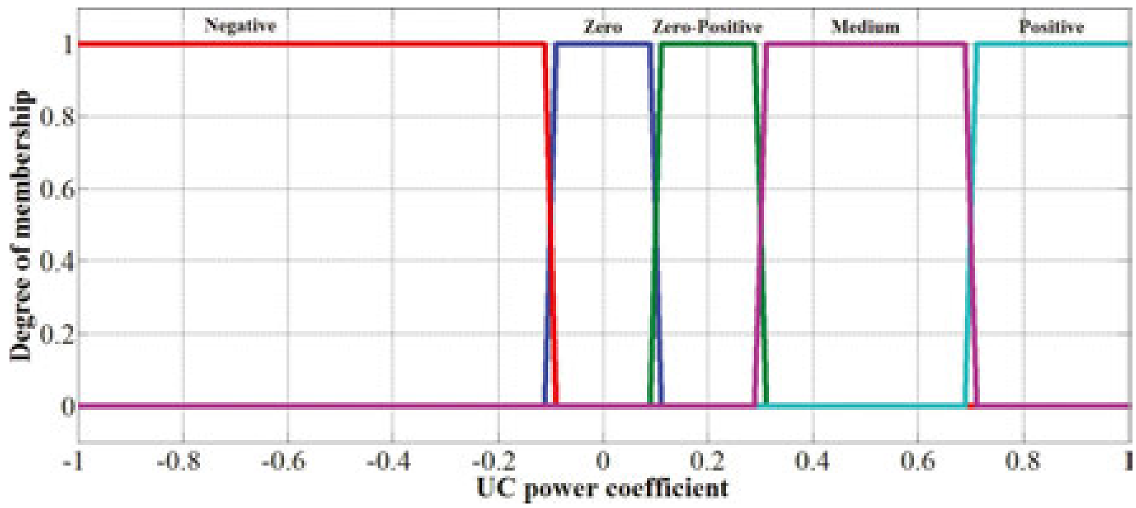

Figure 11. Membership functions for optimum variable.

From the point of view of BEV operation, the EB power and the UC power for each of the three road simulation conditions are presented as follows. **Figures 12** and **13** present the EB and UC powers for NEDC having the characteristics presented in **Figures 5** and **7**. **Figures 14** and **15** present the EB and UC powers for UDDS cycle having the characteristics presented in **Figures 6** and **8** from 500 to 1200 s in order to better view the power variations during BEV operation on a road with slopes. **Figures 16** and **17** present the EB and UC powers for UDDS cycle having the characteristics presented in **Figure 6** (no slopes) for the first 500 s.

As expected, the EB power, when optimum variables are used, decreases in certain periods of BEV operation, compared to the cases where the empiric variables were used, thus the energy processed by the EB reduces, as the SC power increases. Finally, this would lead to a lifespan extension for the EB and financial economies for the end-user.

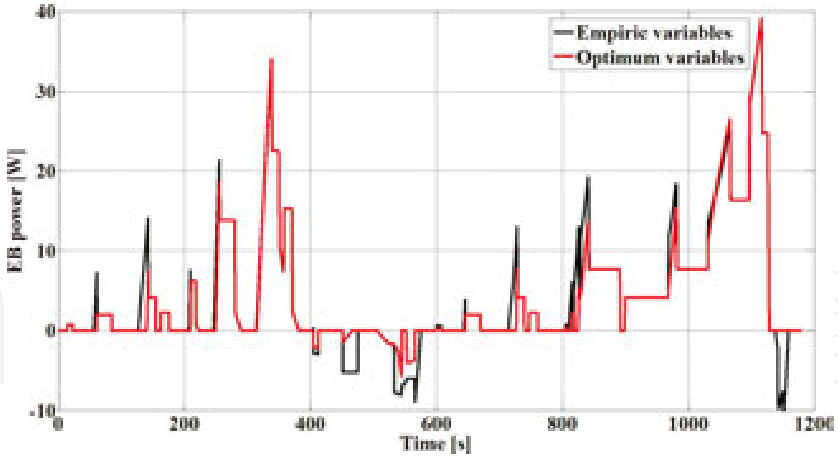

Figure 12. EB power for EUDC cycle.

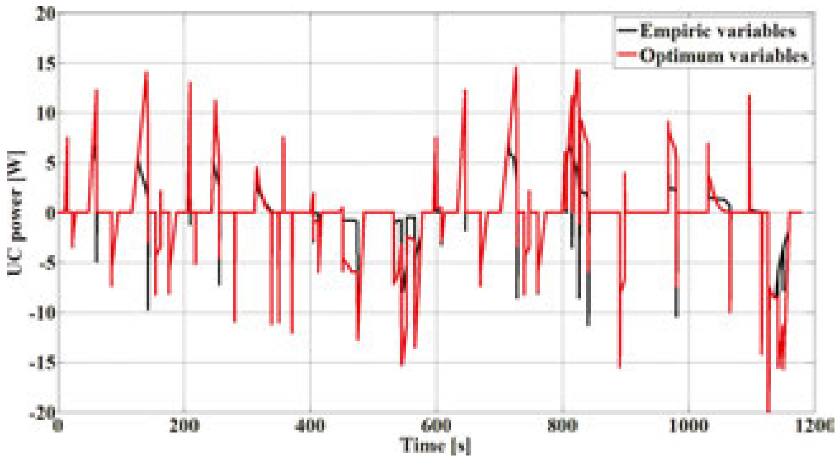

Figure 13. UC power for EUDC cycle.

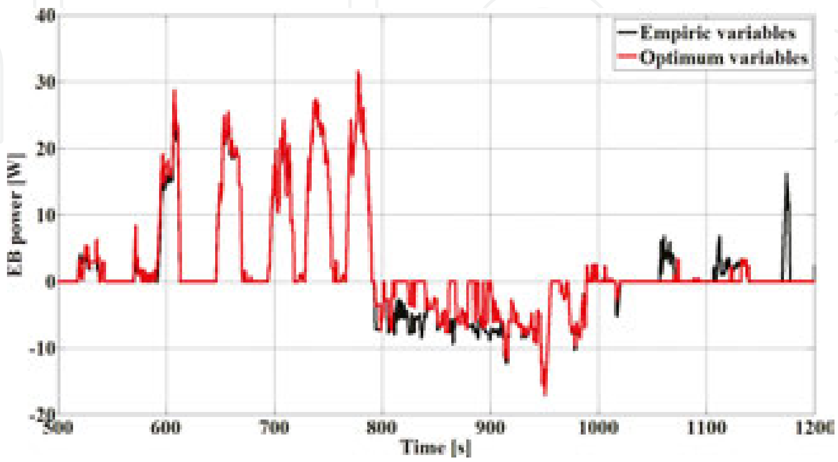

Figure 14. EB power for UDDS cycle with road gradients.

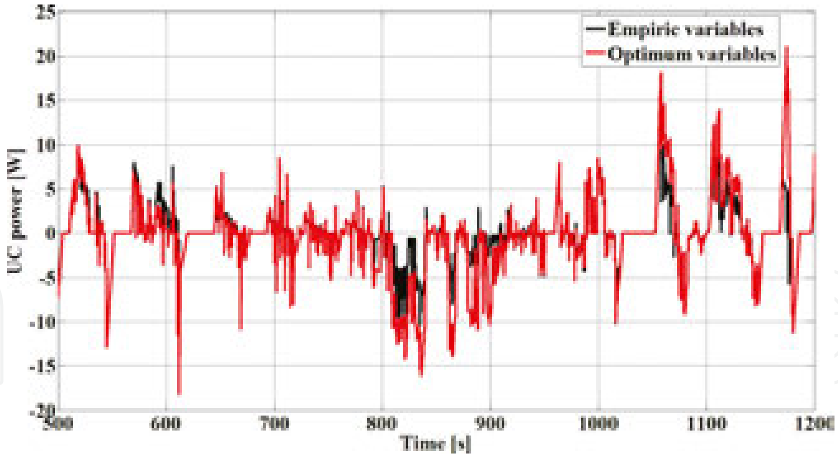

Figure 15. UC power for UDDS cycle with road gradients.

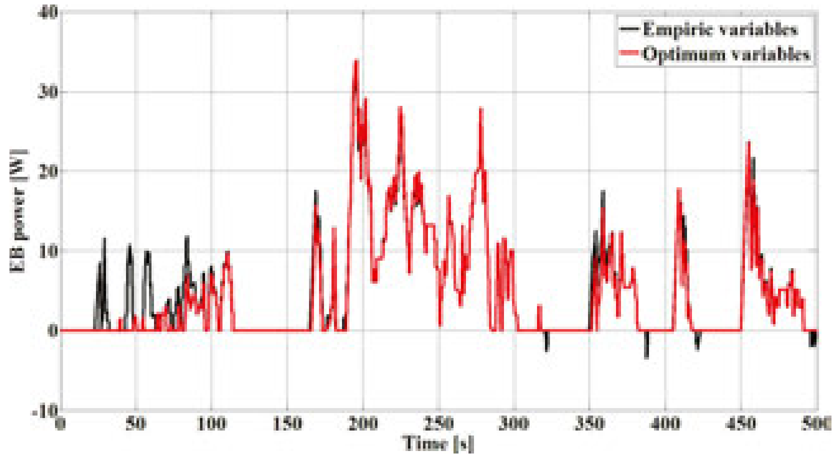

Figure 16. EB power for UDDS cycle without road gradients.

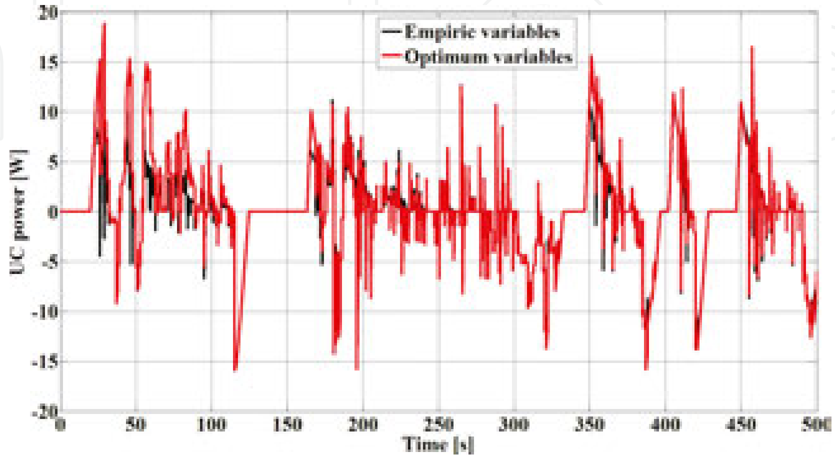

Figure 17. UC power for UDDS cycle without road gradients.

6. Conclusion

A methodology to optimize the capacity and power of the UC energy storage device and also the fuzzy logic supervision strategy for a BEV equipped with EB was presented. The results are showing that important financial economies could be made if an UC energy storage device is used with the aim to reduce the energy processed by the EB. The optimization algorithm maximizes these economies, in this study, an increase of around 16% is achieved, proving that optimization is an essential part of any product and system development.

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References

[1] Zhang H, Saudemont C, Robyns B, Petit M. Electrical features comparison between more electric aircrafts and hybrid electric vehicles. Electromotion 2009;16(3):111-120.

[2] Peterson SB, Apt J, Whitacre JF. Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization. Journal of Power Sources 2010;195:2385–2392. doi:10.1016/j.jpowsour.2009.10.010

[3] Burke H, Miller M, Zhao H. Lithium batteries and ultracapacitors alone and in combination in hybrid vehicles: Fuel economy and battery stress reduction advantages. In: 25th World Battery, Hybrid and Fuel Cell Electric Vehicle Symposium & Exhibition; 5–9 Nov. 2010; Shenzen, China. 2010.

[4] Schaltz E, Khaligh A, Rasmussen PO. Influence of battery/ultracapacitor energy-storage sizing on battery lifetime in a fuel cell hybrid electric vehicle. IEEE Transactions on Vehicular Technology 2009;58(8):3882–3891. doi:10.1109/TVT.2009.2027909

[5] Wang G, Yang P, Zhang J. Fuzzy optimal control and simulation of battery-ultracapacitor dual-energy source storage system for pure electric vehicle. In: International Conference on Intelligent Control and Information Processing; 13–15 Aug. 2010; Dalian, China. 2010. doi:10.1109/ICICIP.2010.5564185

[6] Li Q, Chen W, Li Y, Liu S, Huang J. Energy management strategy for fuel cell/battery/ultracapacitor hybrid vehicle based on fuzzy logic. International Journal of Electrical Power & Energy Systems 2012;43(1):514–525. doi:10.1016/j.ijepes.2012.06.026

[7] Cao J, Emadi A. A new battery/ultracapacitor hybrid energy storage system for electric, hybrid, and plug-in hybrid electric vehicles. IEEE Transactions on Power Electronics 2012;27(1):122–132. doi:10.1109/TPEL.2011.2151206

[8] Breban S, Radulescu MM. Fuzzy-logic supervision strategy for battery-powered electric vehicles. UPB Scientific Bulletin, Series C: Electrical Engineering and Computer Science 2014;76(2):187–196.