Real time energy management strategy for a fast charging electric urban bus powered by hybrid energy storage system

Huilong Yu [a], Davide Tarsitano [a], Xiaosong Hu [b], Federico Cheli [a, *]

[a] Department of Mechanical Engineering, Politecnico di Milano, Milan, 20156, Italy
[b] The State Key Laboratory of Mechanical Transmissions, Chongqing University, Chongqing 400044, China

In this paper, an innovative real time energy management strategy design approach is proposed for a fast charging electric urban bus with hybrid energy storage system composed of conventional batteries and supercapacitors. After modeling, a multi-objective optimization problem taking into account cycle life of the battery, total energy consumption and specific requirement that minimizing the use of battery is formulated. A quantifiable evaluation model is firstly derived to evaluate different kinds of strategies. Then a conventional fuzzy logic control based energy management strategy with features of intelligence and adaptability is proposed, but the simulation result shows that even after long time tuning it can not achieve the desired result with the manual set membership functions. Thereafter, an optimal energy management strategy based on dynamic programming is developed as a benchmark to see the room for improvement. Finally, an innovative model in the loop optimization approach based on genetic algorithm is proposed to optimize the membership functions of the conventional fuzzy logic based energy man-agement strategy. Simulation results demonstrate that the overall performance of optimized fuzzy logic based energy management strategy can be improved significantly and can even approach the optimal results of dynamic programming.

Keywords: Energy management strategy, Hybrid energy storage system, Fuzzy logic controller, Genetic algorithm, Model in the loop

1. Introduction

To face the challenge of air pollution, dependence on petroleum, and greenhouse gas emissions, research on improving the performance of Electric Vehicles (EVs) to promote the wide range public and private use of them has been conducted for decades [1]. However, high cost and short cycle life of batteries have always been the problem hindering the developing process and penetration of EVs [2]. Conventional batteries which are the most common energy storage systems of EVs can have high energy density [3], but may accelerate the degradation when there is high and surge discharging or charging power demand during acceleration and deceleration process [4]. In recent years, Hybrid Energy Storage System (HESS) was proposed to stimulate keen interest of many researchers to optimize it as a solution to solve the foregoing problems entrenched in battery-only option [5]. Supercapacitors with the features of high power density, long cycle life, easy and accurate modelling, wide range of operating temperature and high efficiency can be complementary with conventional battery [6], in order to reduce the high peak power impact on battery and to absorb more regenerative braking power [7]. HESS thus can assist in prolonging the cycle life of battery and overall system efficiency. Comparison performed in Ref. [8] showed that the battery's rate of cycle-related capacity degradation decreased by a factor of 2 and rate of cycle-related impedance degradation, by a factor of 5.9 when the supercapacitors were implemented, while Ref. [9] further demonstrated the benefits of optimized HESS in terms of battery life, system efficiency and size. Besides, well sized HESS can achieve smaller weight and volume compared with battery-only energy storage in high power EVs [10], and the dynamic performance of EVs can also be improved.

Design of Energy Management Strategy (EMS) to achieve the optimal power distribution is especially important to expand the battery cycle life and improve the overall efficiency. Many researchers have been exploring the EMS of HESS in recent years, which can be mainly divided into two broad classes, the rule based approach and the optimization approach [11].

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* Corresponding author. Department of Mechanical Engineering, Politecnico di Milano, Via G. La Masa 1, 20156, Milano, Italy.
E-mail addresses: huilong.yu@polimi.it (H. Yu), davide.tarsitano@polimi.it (D. Tarsitano), xiaosonghu@ieee.org (X. Hu), federico.cheli@polimi.it (F. Cheli).

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Rule based EMS is generally devised according to engineering experience, heuristics, intuition or mathematical models. There are mainly two kinds of rule based EMS so far. One is deterministic or heuristic rule-based. In Ref. [12], two kinds of HESSs were implemented with rule based EMS; Ref. [13] proposed an optimized three-mode rule-based strategy, while Ref. [17] investigated a four-mode rule based EMS for a proposed HESS; rule based EMS were also designed in Ref. [15] and [16] for HESS with supercapacitor and battery as main energy source respectively; further, Ref. [14] designed a rule based EMS and compared its results with other controllers, all of the previous work verified that the rule based EMS has high stability and real-time performance. The other is conventional Fuzzy Logic Control (FLC) based. In Ref. [18], FLC was employed in the EMS of a HESS composed by fuel cells, batteries and supercapacitors, and the final results were verified with both simulation and experimental test; a FLC EMS was designed in Ref. [20] to achieve high-efficiency for the vehicle with HESS; in Ref. [19] a wavelet-fuzzy logic based energy management strategy was proposed for a fuel cell/battery/supercapacitor HESS; Ref. [23] proposed a FLC EMS aimed at adjusting and stabilizing the DC bus voltage via a bidirectional DC/DC converter for hybrid powertrain equipped with HESS. The mentioned references validated that the FLC EMS has the features of independence of full mathematical system model and intelligence realizable in real system. Its performance is, nevertheless, determined by fuzzy rules, number and shape of the Membership Functions (MFs).

Optimization approach can be classified into global optimization and real time optimization. Neural network, Dynamic Programming (DP), convex programming and other multi-objective optimization based EMSs presented in the literature belong to global optimization. In particular, Ref. [26] dealt with a neural network and wavelet transform based EMS proposed for a fuel cell/supercapacitor HESS while in Ref. [27], a neural networks based EMS was developed and trained based on optimal results for a lead-acid battery/supercapacitor HESS. In Ref. [28], an offline method named "Improved constraints in Dynamic Programming", allowing having better performance in terms of time computation and consumption cost was presented; Ref. [29] developed a DP based EMS as comparable reference for other kinds of EMSs. In Ref. [33], a sample-based global search oriented dividing rectangles algorithm was employed to solve the formulated multi-objective optimization problem of HESS while Ref. [34] solved the formulated multi-objective optimization problem of a HESS by using Karush—Kuhn—Tucker conditions.

The proposed real time optimization methods in searchable literature to design EMS for HESS consists of Model Predictive Control (MPC), decoupling method, etc. Specially, Ref. [29] created a MPC based EMS and proved that it can achieve better fuel economy than the designed rule-based approach; in Ref. [37], similar model predictive control system for a HESS is proposed and experimentally verified; while Ref. [36] demonstrated the design of a HESS predictive control algorithm utilizing a state-based approach, which was organized as a probability-weighted Markov process to predict future load demands. In Ref. [24] a decoupling-based energy management strategy was implemented on a powertrain deploying two propulsion machines rated at different powers with a battery/supercapacitor HESS; further, Ref. [41] developed a wavelet-based load sharing algorithm to decouple the demand load between the battery and supercapacitor.

However, there is still room to improve the overall performance of the HESS EMS. The deterministic rule based EMS relying on fixed look-up tables can not take into account different kinds of driving conditions, whereas conventional FLC based EMS, which is intelligent but difficult to tune the member functions especially when there are many inputs and outputs, also can not achieve good performance in varying conditions. Global optimization methods requiring prior driving profile knowledge or large number of existing optimal training data are mostly offline methods, thus they can be only adopted as reference for benchmarking purposes. As for real time optimization methods, most of which suffering heavy computational burden caused by nonlinearity and difficult accurate parameters identification of the HESS are also difficult to implement in real embedded systems currently. Besides, most efforts in the related literature chose the reduction of high peak demand power from the battery or overall efficiency as a single evaluation index. Only few studies, for instance, Ref. [34] and [42] take into consideration both of them.

This paper aims at proposing a real time EMS for a fast charging electric urban bus powered by HESS. There are two main contributions of this work. Firstly, a quantifiable evaluation model is derived to evaluate different EMSs. After simplifying the model of HESS, the problem is presented as a multi-objective optimization problem, where a normalized weighting method is used to combine all the evaluation indexes, with the weight of every evaluation index defined according to the different orders of magnitude of them. Secondly, different from Ref. [43], an innovative model in the loop Genetic Algorithm (GA) optimized FLC based real-time EMS is proposed, with the comprehensive evaluation index as fitness function.

This paper is organized as follows: Section 2 presents the details of the fast charging electric bus. Section 3 elaborates the modelling of the HESS and the formulation of the energy management problem. Section 4 details the derivation of the quantifiable evaluation model. In Section 5, a FLC based EMS is developed with conventional methods at first, then a DP based EMS is presented after defining the weights of the evaluation indexes, the model in the loop GA optimized FLC based EMS is proposed at last. The simulation outcome is systematically compared and analyzed with those of conventional FLC and DP based EMSs in Section 6 and conclusions are presented in Section 7.

2. Details of the fast charging electric urban bus

The HESS parameters of the electric urban bus are given in Table 1, and simulation work in this research is based on these data.

The configuration of the electric urban bus and the general structure of the charging station at bus stop is shown in Fig. 1.

Table 1
HESS parameters of the electric urban bus.

Battery	
Number of battery cells (N_{bat})	216
Battery type	38 Ah, $NaNiCl_2$
Total battery capacity	21.17 kWh
Total battery rated voltage	557 V
Maximum discharge current (I_{max_bat})	80 A
Energy density	120 Wh kg^{-1}
Minimum state of charge (SOC_{min})	0.2
Supercapacitor	
Supercapacitor bank capacity	3300 F
Number of supercapacitor banks (N_{cap})	108
Total capacity of supercapacitors	405.4 Wh
Maximum voltage of the supercapacitor bank	3.8 V
Minimum voltage of the supercapacitor bank	2.5 V
Maximum discharge current (I_{max_sc})	270 A
Maximum charge current ($-I_{max\_sc}$)	−270 A
Series resistance (R_s)	7.0e-4 Ω
Parallel resistance (R_L)	45000 Ω
Energy density	12 Wh kg^{-1}
Efficiency of the DC/DC (η_{dc})	0.8
Minimum state of energy (SOE_{min})	0.05

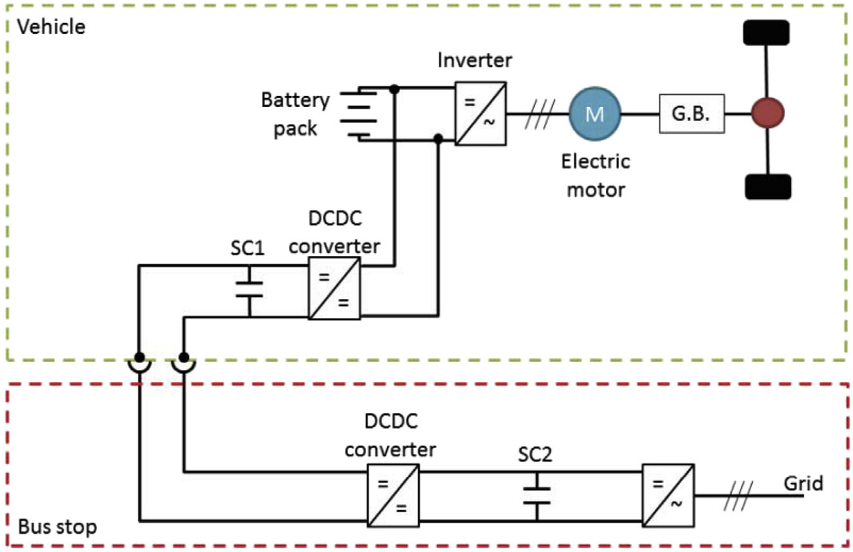

Fig. 1. Scheme of electric bus powertrain and storage system.

The supercapacitor (*SC1*) which can output and absorb high peak power is the main energy storage system of the electric urban bus, which can be charged by the other supercapacitor (*SC2*) through a DC/DC at every bus stop when passengers are getting on and off. *SC2* can be charged by the power grid through an AC/DC converter between them with lower power density before next bus is coming. With this method, the surge impact to the power distribution grid can be avoided. The battery will be used in extreme conditions (such as after long time traffic jam and a longer distance need to be covered) when the supercapacitor is nearly exhausted and it can be only recharged at the start or final stop once a day.

3. Problem description

3.1. Modeling of the HESS

The main objective of this paper is to propose a real time EMS minimizing the high peak power applied to the battery and overall energy loss, so that in this section relatively simple equivalent circuit models which are enough to explore the HESS EMS are adopted.

3.1.1. Battery modeling

A static battery model ignoring the effect of temperature and dynamic response is adopted in this paper, the discharge and charge resistance and voltage changing with *SOC* can be obtained by look-up table method.

The total open-circuit voltage V_{bat} is obtained by (1) assuming that all cells have a uniform behavior

$$V_{bat} = V_{cell} \cdot N_{bat} \tag{1}$$

The current and *SOC* of the battery can be derived by (2) and (3) respectively [15].

$$I_{bat} = \frac{V_{cell} - \sqrt{V_{cell}^2 - 4R_{bat}\left(P_{reqbat}/N_{bat}\right)}}{2R_{bat}} \tag{2}$$

$$SOC(t) = SOC_{\text{int}} - \int_0^t \frac{I_{bat}(t)}{3600C_b}\mathrm{d}t \tag{3}$$

where I_{bat} is the discharge current, V_{cell} is the open-circuit voltage of a single cell, R_{bat} is the equivalent series resistance of the battery cell, P_{reqbat} is the total demand power from the battery, N_{bat} is the total number of battery cells, C_b is the rated capacity expressed in Ampere-Hours [Ah], $SOC(t)$ is the state of charge of the battery in time t and SOC_{int} is the initial state of charge.

The actual total output power of the battery P_{bat} is given as

$$P_{bat} = V_{bat} \cdot I_{bat} \tag{4}$$

3.1.2. Supercapacitor modeling

The equivalent circuit of a supercapacitor bank adopted in this paper is shown as Fig. 2.

The mathematical model of the supercapacitor is derived as

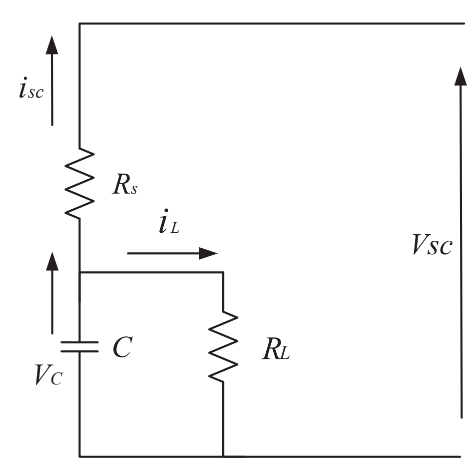

Fig. 2. Equivalent circuit of a supercapacitor.

$$V_c(t) = \int_0^t (V_c/(R_L C_{sc}) + I_{sc}/C_{sc})\mathrm{d}t \tag{5}$$

$$I_{sc} = \frac{V_c - \sqrt{V_c^2 - 4R_s P_{reqsc}/(N_{cap}\cdot\eta_{dc})}}{2R_s} \tag{6}$$

$$SOE(t) = \frac{V_c(t)^2 - V_{cmin}^2}{V_{cmax}^2 - V_{cmin}^2} \tag{7}$$

$$V_{ct} = V_c \cdot N_{cap} \tag{8}$$

where V_c is the open-circuit voltage, V_{int} is the initial open-circuit voltage, i_L is the leakage current, R_L is the parallel resistance, C_{sc} is the capacity, I_{sc} is the discharge current, V_{cmax} is the maximum open-circuit voltage, V_{cmin} is the minimum open-circuit voltage, R_s is the series resistance of one supercapacitor, $SOE(t)$ is the state of energy of the supercapacitor at time t, η_{dc} is the efficiency of the DC/DC converter, V_{ct} is the total open-circuit voltage that assuming all banks have a uniform behavior, N_{cap} is the total number of the banks. The actual total output power of the supercapacitorP_{sc} is represented as

$$P_{sc} = V_{ct} \cdot I_{sc} \tag{9}$$

3.2. Problem formulation

The speed profile, covered distance, positions of all the stations and driver demand power and energy shown in Fig. 3 are known as the prior knowledge of the EMS in this research. The propulsion power and the regenerative power are calculated based on the given speed profile.

There are 9 stations in the given driving cycle, the total driving range is 3178 m, and the total demand energy is 2433 Wh. The energy stored in the supercapacitor is not enough to cover the two relatively long distances between bus stop 0–1 and 7–8. The covered distance *Dis* and demand energy E_t between different stations are calculated and listed in Table 2.

The demand power from the battery and supercapacitor is

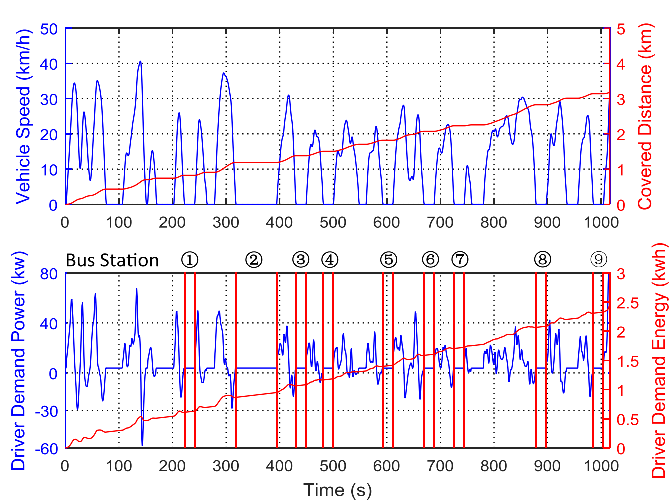

Fig. 3. The input profiles of the EMS.

Table 2
Distance and energy cost between different stations.

Station	0–1	1–2	2–3	3–4	4–5	5–6	6–7	7–8	8–9
Dis (m)	824	367	188	126	314	253	156	597	313
Et (Wh)	609	230	112	67	210	165	93	343	220

derived as

$$P_{reqsc}(k) = P_{req}(k)u(k) \tag{10}$$

$$P_{reqbat}(k) = P_{req}(k)(1 - u(k)) \tag{11}$$

where P_{req} is the overall driver demand power and u is the control vector of the power flow.

The design principle is that in normal driving conditions, the supercapacitor is the main power source of the electric urban bus, only when it is nearly exhausted the battery will be used. There will be high peak power impact on the battery if the battery is used after the supercapacitor is exhausted. The HESS EMS determines when and how much power the battery should output, which aims to use the battery as little as possible and to extend the cycle life of the battery, while ensuring overall efficiency of the HESS.

4. Evaluation model

A quantifiable evaluation model is essential to compare the results of different EMSs, since the aim is to expand the cycle life of the battery and to minimize the total energy cost, the cycle life model of the battery and the efficiency model should be derived. However, actually it is quite difficult to model the cycle life of the battery accurately, especially in real use conditions since the degradation of the battery is influenced by a myriad of factors, such as the temperature, depth-of-discharge, and chemical materials inside the battery.

The demand energy from the battery J_1, the integrator of demand power gradient J_2 to evaluate the impact on the battery, and the total cost energy J_3 are selected to evaluate the performance of the EMS

$$J_1(k) = \sum_{i=1}^{k} \left| dP_{reqbat}(i) \right| \tag{12}$$

$$J_2(k) = \sum_{i=1}^{k} \left| dP_{reqbat}(i) \right| \tag{13}$$

$$J_3(k) = \sum_{i=1}^{k} (P_{bat}(i) + P_{sc}(i)) \quad k = 1, 2, 3 \ldots N \tag{14}$$

where $dP_{req\_bat}(i)$ is the derivative of requested power from the battery which can reveal the transition of the battery output power.

Obviously, this is a multi-objective optimization problem, and a normalized weighting method is utilized to combine all the evaluation indexes to form a comprehensive one

$$J = \sum_{i=1}^{n} w_i J_i \Big/ \sum_{i=1}^{n} w_i \tag{15}$$

where J is the comprehensive evaluation index of the EMS, w_i is the weight of evaluation index J_i which will be defined in following section, and n is the number of evaluation indexes which is 3 in this problem.

5. Energy management strategies for the electric urban bus

In this section, a conventional FLC based EMS is carefully designed first, and the weights of every evaluation indexes are defined with reference of the result. Then a DP based EMS is proposed to see how much the designed EMS can be improved. A model in the loop GA optimization method to improve the MFs of FLC based EMS is proposed and elucidated in detail in the last part of this section.

5.1. Fuzzy logic EMS

Fuzzy logic composed by a set of 'IF-THEN' linguistic control rules based on expert knowledge is suitable for complex system. FLC control process consists of an input stage, a processing stage, and an output stage. The input stage maps inputs to the appropriate membership functions and truth values. The processing stage invokes an appropriate rule and generates a result for every input, then combines the results of the rules. Finally, the output stage converts the combined result back to a specific output value.

5.1.1. Membership functions design

The performance of the fuzzy logic based EMS is determined by the MF and fuzzy rules. There are four inputs and one output in the designed FLC. After repeated tuning, the MFs of the four inputs and one output are designed as Fig. 4, where the linguistic variables 'VS, S, M, B, VB' denote 'very small, small, medium, big and very big', respectively.

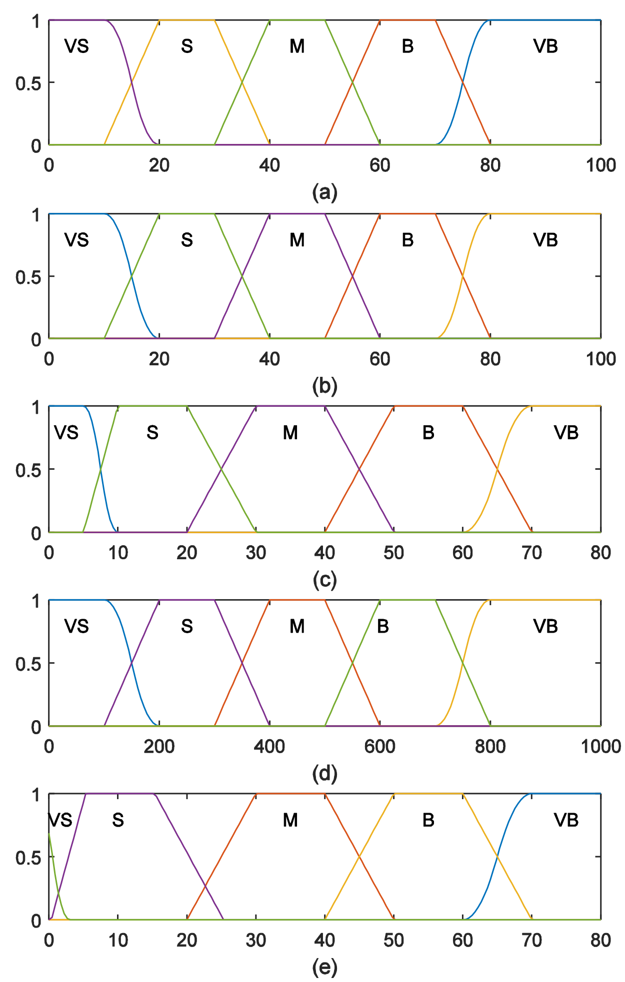

Fig. 4. MFs of (a) *SOE*, (b) *SOC*, (c) P_{req}(kW), (d) *Dis*(m) and (e) P_{reqbat}(kW).

5.1.2. Fuzzy rules

According to the principle described in the previous section, the supercapacitor is the main energy source and the battery should be used only in limited conditions. The fuzzy rules are defined as follows, if *SOE* is 'VB' or 'B', P_{reqbat} is 'VS', when *SOE* is not 'VB' or 'B', the fuzzy rules are shown in Fig. 5, Fig. 6 and Fig. 7.

The basic relationship between the inputs and output is that when the *SOE* is not 'VS' and the covered distance is not 'VB', P_{reqbat} is directly proportional to the driver demand power P_{req}, *SOC* and is inversely proportional to the covered distance *Dis*; when the *SOE* is 'VS' and the covered distance is 'VB', the battery becomes the main energy source to output most of driving demand power.

5.1.3. Simulation results analysis of the FLC based EMS

A simulation of the FLC based EMS is launched after modelling and designing of the fuzzy rules and MFs. As shown in Fig. 8, the electric urban bus is recharged at every bus stop. However, the drawback of the manual set MFs can be observed obviously: when the *SOE* is medium or relatively high and driving demand power is not very big, the FLC based EMS starts to use the battery, especially between stations ④ and ⑤, ⑦ and ⑧, which does not follow the designed fuzzy rules very well. This is caused by the manual set MFs. There is also high peak demand power applied to the battery with the manual set MFs, as shown in Fig. 9, which could be avoided if the MFs are well designed synthetically. The simulation results disclose that the conventional FLC based EMS with manual set MFs can not achieve the desired result even after a long time tuning.

5.1.4. Weights definition of evaluation indexes

The weight of every evaluation index is defined according to the initial result of the fuzzy logic based EMS. The evaluation index: J_1, J_2 and J_3 have different orders of magnitude due to their different physical units. In order to reflect a similar relative importance of the three indexes, the principle to define w_1, w_2, w_3 is to set the three individual evaluation indexes at the same order of magnitude. The weights are finally defined as $w_1 = 3$, $w_2 = 3$,$w_3 = 1$, and the comprehensive evaluation index in this paper is given as

$$J = \frac{3^*J_1 + 3^*J_2 + J_3}{7} \tag{16}$$

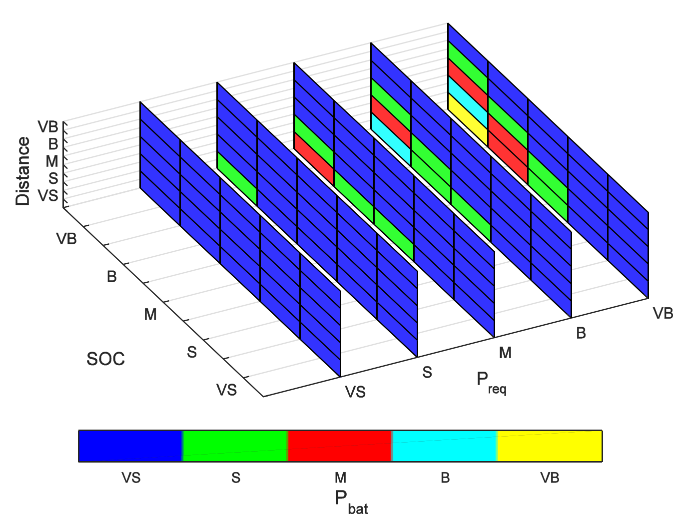

Fig. 5. Fuzzy rules when *SOE* is 'M.'

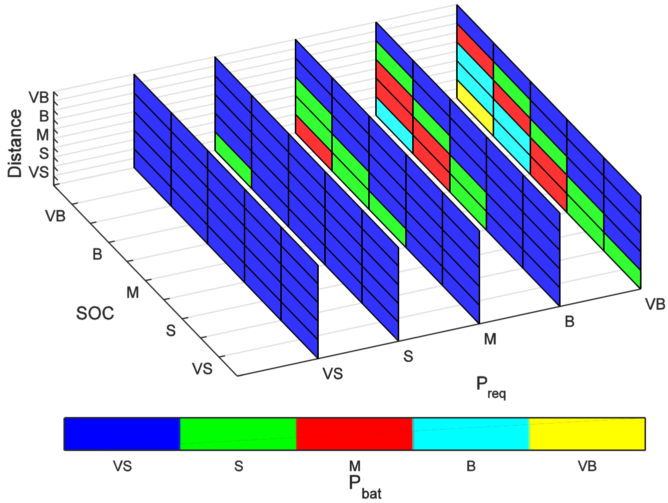

Fig. 6. Fuzzy rules when *SOE* is 'S'.

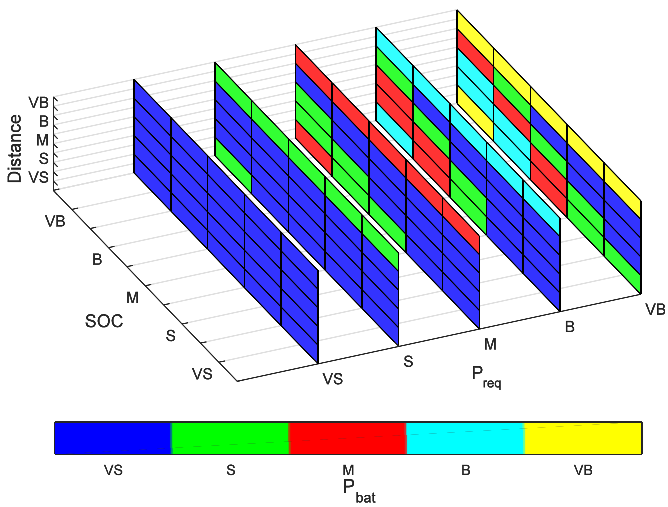

Fig. 7. Fuzzy rules when *SOE* is 'VS'.

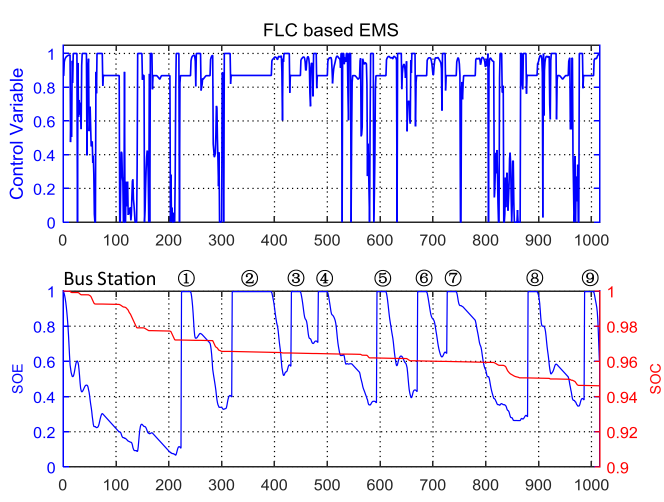

Fig. 8. FLC based control strategy and simulation results of *SOE*, *SOC*.

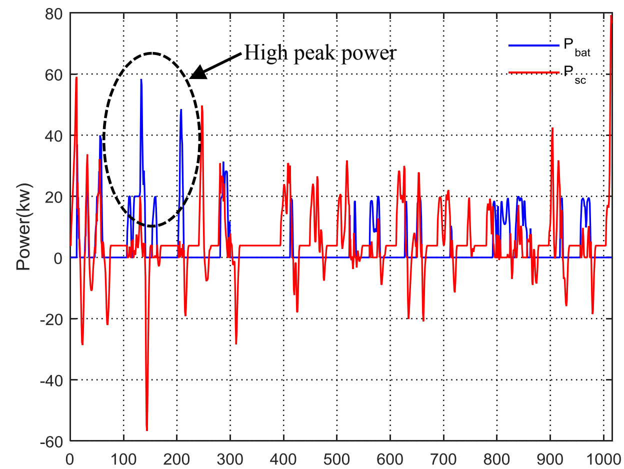

Fig. 9. FLC based power split of the HESS.

5.2. DP based EMS

DP is an optimization approach that transforms a complex problem into a sequence of simpler multistage problems in a recursive manner [44]. Normally, there are constrained state variables, controlled inputs, and cost function in a DP process. The energy management problem formulation based on DP is described in detail as follows.

The state transfer equation of the HESS is

$$x(k+1) = f(x(k), P_{req}(k), Dis(k), u(k)) \quad k = 1, 2, \ldots, N-1 \tag{17}$$

where $x(k)$ is the state vector of the system ($SOC(k)$,$SOE(k)$) at time step k, $P_{req}(k)$, $Dis(k)$ and $u(k)$ are the driver demand power, covered distance and control vector at time step k, respectively.

The state space X and control solution space U are given as (18), in this problem every $x(k)$, $u(k)$ is linearly discretized into 100 numerical values between its minimum and maximum values at every time step in this simulation.

$$U = \{u(1), u(2), \ldots u(k), \ldots, u(N-1)\} \tag{18}$$

$$X = \{x(1), x(2), \ldots x(k), \ldots, x(N)\} \tag{19}$$

The recursions of the state vectors can be derived based on the model given in (2–7) with constraints

$$\begin{aligned} &SOC_{min} < SOC(k) < 1 \\ &SOC_{min} < SOC(k) < 1 \\ &0 < I_{bat}(k) \le I_{max\_bat} \\ &I_{min\_sc} \le I_{sc}(k) \le I_{max\_sc} \\ &0 < u(k) \le 1 \end{aligned} \tag{20}$$

The time step is set to 1 s in this simulation, the length of the input vectors N is 1016, and the DP based EMS is developed to find the optimal control vector U to minimize the cost function in (16), while fulfilling constraints in (20).

5.3. Genetic algorithm optimized fuzzy logic EMS

Generally, it takes long time to tune the parameters of the MFs especially when there are many parameters, and the achieved result is invariably not very good because of heuristic errors.

However, standard optimization algorithms are not suitable since there are 5 MF in this problem involving 40 parameters with a huge state space. GA is a heuristic search approach for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. The algorithm repeatedly modifies a population of individual solutions through selection, crossover and mutation to move the population "evolve" towards an optimal solution. GA is well-suited to solve problems that are not very amenable to standard optimization algorithms, including problems with a large state-space, multi-modal state space, or n-dimensional surface in which the objective function is discontinuous, non-differentiable, stochastic, or highly nonlinear. Therefore, GA is selected in this paper to optimize the MFs of the FLC based EMS.

There are 40 parameters to be optimized, and Fig. 10 shows the first 8 parameters of the MF for *SOE*. When x changes, the shape of MF will be different, for example, when $x(2) = x(3)$, the trapezoid MF will change its shape to triangle.

To avoid the weird shaped MFs and reduce the computation time, there is the need to set a lower bound $LB(i)$ and upper bound $UB(i)$ to constrain each gene of the chromosome $x(i)$ in a valid range

$$LB(i) \le x(i) \le UB(i) \quad i = 1,\ 2, \ldots,\ 40 \tag{21}$$

There are also a set of linear constraints for all $x(i)$ to keep the basic relationships between them.

$$x(i) \le (i+1) \quad i = 1,\ 2, \ldots, 39 \tag{22}$$

The fitness function F is given as (23), where the target is to find the optimal individual that can minimize the comprehensive evaluation index

$$F = \frac{p_1{*}3J_1 + p_2{*}3J_2 + p_3{*}J_3}{7} + \psi \cdot Inf \tag{23}$$

where p_1, p_2, p_3 are the penalty factors of the three evaluation indexes, a specific evaluation index can be controlled in a desired scale by adjusting the related penalty factor, ψ is a penalty vector with large value to penalize infeasible solutions that let the state variables outside the inequality bounds Inf in (20).

A model in the loop optimization which can include the knowledge of the model, improve the robustness of the EMS and adapt to different drive conditions is presented. The optimization process is shown in Fig. 11, where there are two loops in the optimization process. The inner one is the repeat model in the loop simulation based on updated FLC EMS with inputs of the demand power and driving profiles. The outer one is the iteration of the GA optimization. The first step is to randomly produce the initial population with the manual set MFs as one of the individuals, then the fitness of the population will be calculated according to the fitness function, if the optimal individual is not achieved, the

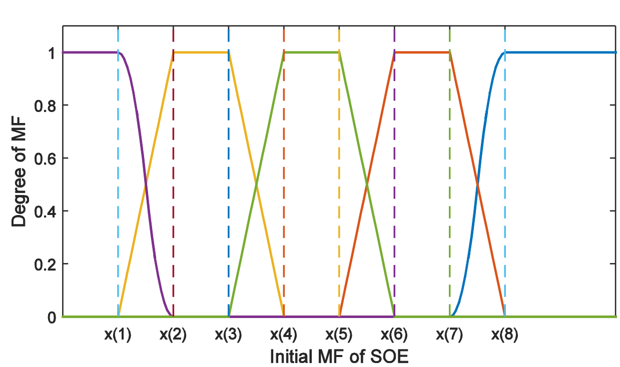

Fig. 10. The manual set MF to be optimized.

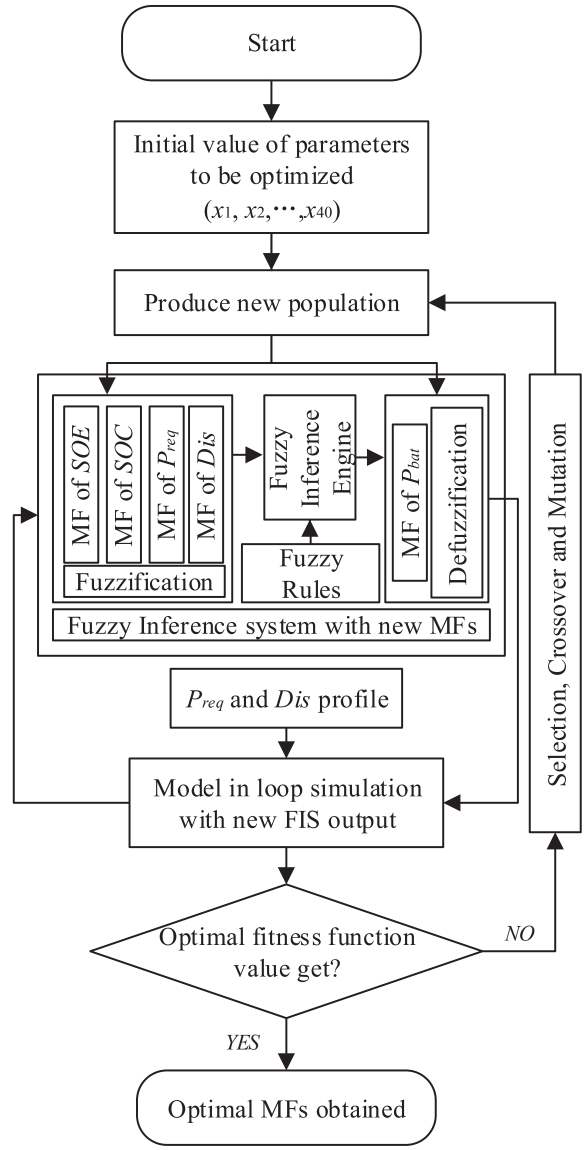

Fig. 11. Diagram of the MFs optimization process based on GA.

optimization will repeat in a loop.

There are three operations in this loop:

1) Selection, the selected individuals with better fitness will be allowed to pass on their genes to the next generation as parents, in this research a stochastic uniform selection method is used, and percentage of the elite individuals which will not participate in the crossover and mutation operations is defined as 5%.
2) Crossover, every two chosen individuals will mate to create new individuals for new generation. In this paper the crossover fraction is 80%.
3) Mutation, in this operation small random changes will happen to a part of individuals to create mutation children for next generation which provides genetic diversity and enables search from a broader space. In this paper the mutation fraction is 1%.

The population size is 400, and the optimization process is set to stop when the average change of the best fitness function value is less than or equal to 1e-6. Besides, the parameter vector of the manual set MFs in Fig. 4 is used as one of the initial populations to seed the genetic algorithm, in this way, futile searching can be avoided, and the searching process can speed up towards a desired direction.

The calculation of the optimization process was conducted in a desktop with Intel I7 CPU (920 @2.67 GHz) and 12 GB RAM. The simulation stopped after 786 generations which took more than three days due to the large search space of the GA in this optimization problem. The optimized MFs are finally shown in Fig. 12.

6. Results and analysis

Fig. 13 indicates that the DP based EMS can control the usage of the battery in such an optimal way that the battery only outputs power between long-distance stations in a smooth way without surge impact, see Fig. 14. Both figures confirm that the DP based EMS is able to follow the design principle of the HESS very well.

Both Fig. 15 and Fig. 16 show that GA optimized FLC EMS can improve the performance of the FLC EMS. As can be seen from Fig. 15 the *SOE* is well controlled above the minimum value SOE_{min}, and the battery is used more only during the bus stops with long distance that the supercapacitors can not cover. The dotted red lines between stations ⓪ and ①,⑦ and ⑧ show that the control variable alters from 1 to 0 which means that the battery outputs augmented power with the increase of driving distance and the decrease of *SOE*.

Fig. 16 further verifies that the peak power output from the battery is reduced significantly. The high peak discharge power is only output from the supercapacitor, and the battery is controlled to output power in a smoother way compared with the FLC based EMS. The maximum discharge current is about 0.5 C rate, which is

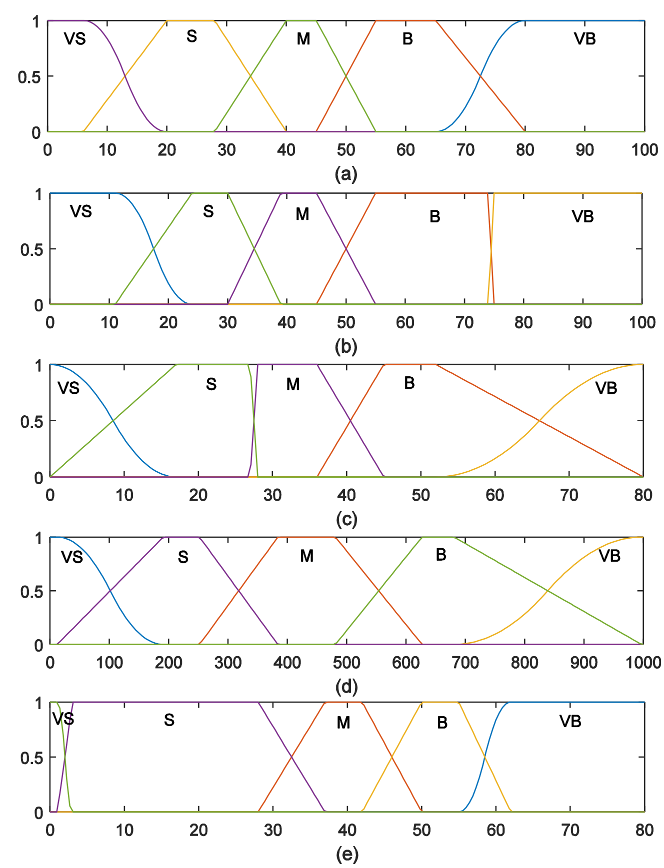

Fig. 12. Optimized MFs of (a) *SOE*, (b) *SOC*, (c) P_{req} (kW), (d) *Dis*(m) and (e) P_{reqbat}(kW).

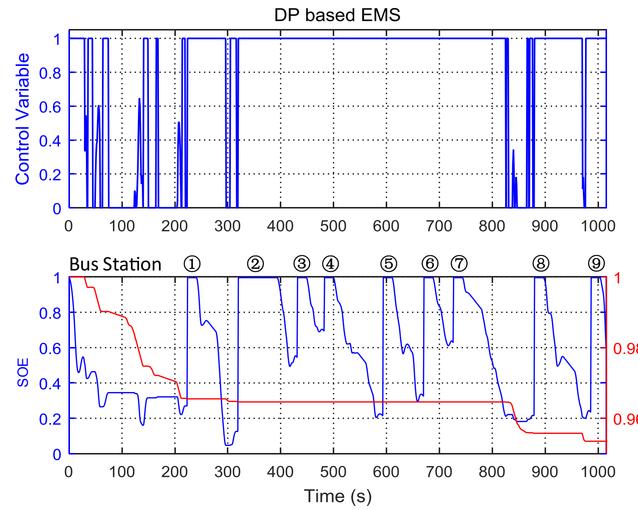

Fig. 13. DP based control strategy and simulation result of *SOE*, *SOC*.

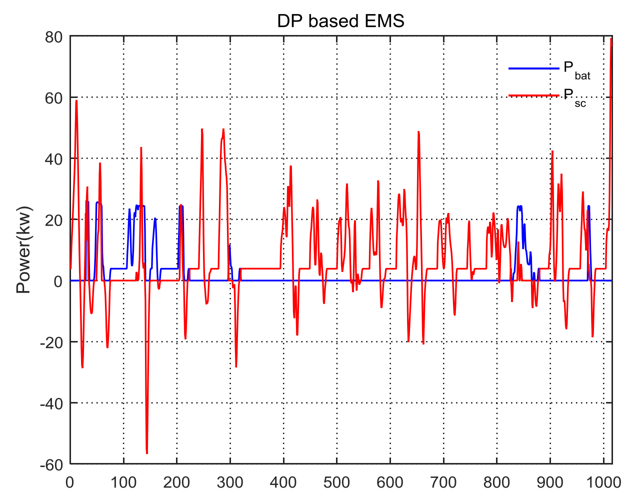

Fig. 14. DP based power split of the HESS.

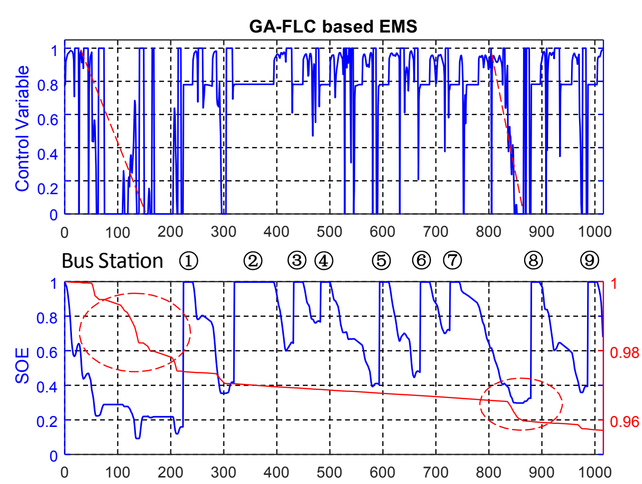

Fig. 15. GA FLC based EMS and simulation result of *SOE*, *SOC*.

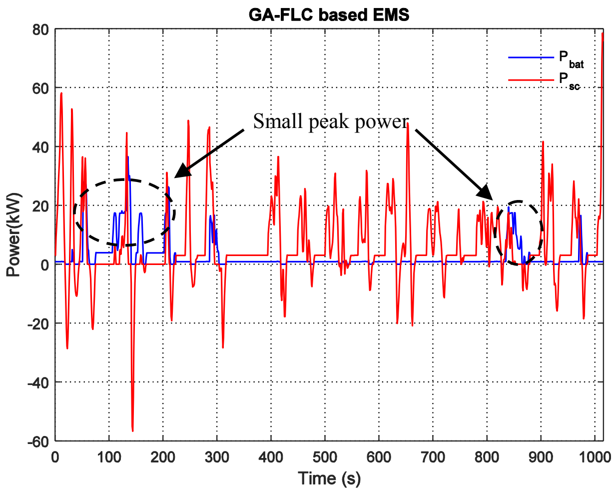

Fig. 16. GA FLC based power split of the HESS.

far below the allowed maximum discharge current.

A comparison of FLC, DP and GA FLC based EMS is illustrated in Fig. 17, which shows the changing of the three evaluation indexes achieved by different EMSs during the entire simulation process. The GA optimized FLC can achieve a better result than conventional FLC and even approach the performance of DP based EMS.

A more detailed comparison is given in Table 3 which shows the distinctions of output energy from battery J_1, peak power impact on the battery J_2, total energy cost J_3, and comprehensive evaluation index J of different EMSs. In particular, smaller J means better overall performance.

7. Conclusions

This paper proposes a model in the loop and genetic algorithm optimized fuzzy logic based energy management strategy for a fast charging electric urban bus with hybrid energy storage system. Based on a derived evaluation model which can evaluate different energy management strategies in a quantitative way, the advantages of the proposed optimization method are underlined. The

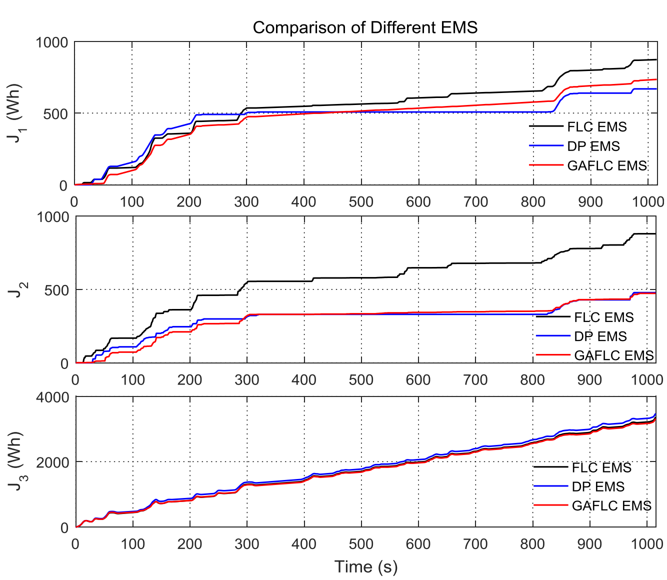

Fig. 17. The comprehensive evaluation indexes of different EMS.

Table 3
Comparison of the three control algorithms.

Indexes	J_1 (Wh)	J_2	J_3 (Wh)	J
FLC	873.2	879.1	3362	1030.6
DP	668.9	478.1	3474	987.8
GA-FLC	735	473.2	3317	991.7

output energy from the battery is reduced by 15.8%, the impact on the battery is reduced by 3.8%, the total cost energy is reduced by 1.3%, and the comprehensive performance is improved by 3.8%, compared with the conventional fuzzy logic based energy management strategy. Simulation results also uncover that the genetic algorithm optimized fuzzy logic based energy management strategy can achieve the performance almost identical to the optimal result obtained by the benchmarking dynamic programming based energy management strategy. With the proposed approach, the arduous and time-consuming manual tuning of large amounts of parameters can be avoided, an adaptive, real-time and intelligent fuzzy logic based energy management strategy with optimal member functions which can achieve better results is more accessible. The energy management strategy design scheme can also be easily tailored for other supervisory energy control or optimization problems in different types of electric and hybrid electric vehicles.

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References

[1] Yong JY, Ramachandaramurthy VK, Tan KM, Mithulananthan N. A review on the state-of-the-art technologies of electric vehicle, its impacts and prospects. Renew Sustain Energy Rev 2015;49:365–85. http://dx.doi.org/10.1016/j.rser.2015.04.130.

[2] Raslavičius L, Azzopardi B, Keršys A, Starevičius M, Bazaras Ž Makaras R. Electric vehicles challenges and opportunities: lithuanian review. Renew Sustain Energy Rev 2015;42:786–800. http://dx.doi.org/10.1016/j.rser.2014.10.076.

[3] Xiong R, Sun F, He H, Nguyen TD. A data-driven adaptive state of charge and power capability joint estimator of lithium-ion polymer battery used in electric vehicles. Energy 2013;63:295–308. http://dx.doi.org/10.1016/j.energy.2013.10.027.

[4] Suri G, Onori S. A control-oriented cycle-life model for hybrid electric vehicle lithium-ion batteries. Energy 2016;96:644–53. http://dx.doi.org/10.1016/j.energy.2015.11.075.

[5] Cao J, Emadi A. A new battery/ultracapacitor hybrid energy storage system for electric, hybrid, and plug-in hybrid electric vehicles. IEEE Trans Power Electron 2012;27:122–32. http://dx.doi.org/10.1109/TPEL.2011.2151206.

[6] Burke A. Ultracapacitors: why, how, and where is the technology. J Power Sources 2000;91:37–50. http://dx.doi.org/10.1016/S0378-7753(00)00485-7.

[7] Burke A. Ultracapacitor technologies and application in hybrid and electric vehicles. Int J Energy Res 2010;34:133–51. http://dx.doi.org/10.1002/er.1654.

[8] Hochgraf CG, Basco JK, Bohn TP, Bloom I. Effect of ultracapacitor-modified PHEV protocol on performance degradation in lithium-ion cells. J Power Sources 2014;246:965–9. http://dx.doi.org/10.1016/j.jpowsour.2012.09.038.

[9] Hu X, Johannesson L, Murgovski N, Egardt B. Longevity-conscious dimensioning and power management of the hybrid energy storage system in a fuel cell hybrid electric bus. Appl Energy 2015;137:913–24. http://dx.doi.org/10.1016/j.apenergy.2014.05.013.

[10] Ortúzar M, Moreno J, Dixon J. Ultracapacitor-based auxiliary energy system for an electric vehicle: implementation and evaluation. IEEE Trans Ind Electron 2007;54:2147–56. http://dx.doi.org/10.1109/TIE.2007.894713.

[11] Tie SF, Tan CW. A review of energy sources and energy management system in electric vehicles. Renew Sustain Energy Rev 2013;20:82–102. http://dx.doi.org/10.1016/j.rser.2012.11.077.

[12] Lu S, Corzine KA, Ferdowsi M. A new battery/ultracapacitor energy storage system design and its motor drive integration for hybrid electric vehicles. IEEE

Trans Veh Technol 2007;56:1516–23. http://dx.doi.org/10.1109/TVT.2007.896971.
[13] Hung Y-H, Wu C-H. An integrated optimization approach for a hybrid energy system in electric vehicles. Appl Energy 2012;98:479–90. http://dx.doi.org/10.1016/j.apenergy.2012.04.012.
[14] Song Z, Hofmann H, Li J, Hou J, Han X, Ouyang M. Energy management strategies comparison for electric vehicles with hybrid energy storage system. Appl Energy 2014;134:321–31. http://dx.doi.org/10.1016/j.apenergy.2014.08.035.
[15] Mapelli FL, Tarsitano D, Annese D, Sala M, Bosia G. A study of urban electric bus with a fast charging energy storage system based on lithium battery and supercapacitors. In: 8th int. Conf. Exhib. Ecol. Veh. Renew. Energies, EVER 2013; 2013. http://dx.doi.org/10.1109/EVER.2013.6521614.
[16] Mapelli FL, Tarsitano D. Energy control for plug-in HEV with ultracapacitors lithium-ion batteries storage system for FIA alternative energy cup race. In: IEEE veh power propuls Conf VPPC 2010; 2010. http://dx.doi.org/10.1109/VPPC.2010.5729147.
[17] Xiang C, Wang Y, Hu S, Wang WA. New topology and control strategy for a hybrid battery-ultracapacitor energy storage system. Energies 2014;7:2874–96. http://dx.doi.org/10.3390/en7052874.
[18] Zandi M, Payman A, Martin JP, Pierfederici S, Davat B, Meibody-Tabar F. Energy management of a fuel cell/supercapacitor/battery power source for electric vehicular applications. IEEE Trans Veh Technol 2011;60:433–43. http://dx.doi.org/10.1109/TVT.2010.2091433.
[19] Erdinc O, Vural B, Uzunoglu M. A wavelet-fuzzy logic based energy management strategy for a fuel cell/battery/ultra-capacitor hybrid vehicular power system. J Power Sources 2009;194:369–80. http://dx.doi.org/10.1016/j.jpowsour.2009.04.072.
[20] Michalczuk M, Ufnalski B, Grzesiak L. Fuzzy logic control of a hybrid battery-ultracapacitor energy storage for an urban electric vehicle. In: Ecol. Veh. Renew. Energies (EVER), 2013 8th iInt. Conf. Exhib; 2013. p. 1–7. http://dx.doi.org/10.1109/EVER.2013.6521580.
[23] Xie C, Xu X, Bujlo P, Shen D, Zhao H, Quan S. Fuel cell and lithium iron phosphate battery hybrid powertrain with an ultracapacitor bank using direct parallel structure. J Power Sources 2015;279:487–94. http://dx.doi.org/10.1016/j.jpowsour.2015.01.029.
[24] Dusmez S, Khaligh A. A supervisory power-splitting approach for a new ultracapacitor–battery vehicle deploying two propulsion machines. IEEE Trans Ind Inf 2014;10:1960–71. http://dx.doi.org/10.1109/TII.2014.2299237.
[26] Ates Y, Erdinc O, Uzunoglu M, Vural B. Energy management of an FC/UC hybrid vehicular power system using a combined neural network-wavelet transform based strategy. Int J Hydrogen Energy 2010;35:774–83. http://dx.doi.org/10.1016/j.ijhydene.2009.11.021.
[27] Moreno J, Ortúzar ME, Dixon JW. Energy-management system for a hybrid electric vehicle, using ultracapacitors and neural networks. IEEE Trans Ind Electron 2006;53:614–23. http://dx.doi.org/10.1109/TIE.2006.870880.
[28] Neffati A, Guemri M, Caux S, Fadel M. Energy management strategies for multi source systems.pdf. Electr Power Syst Res 2013;102:42–9.
[29] Rotenberg D, Vahidi A, Kolmanovsky I. Ultracapacitor assisted powertrains: modeling, control, sizing, and the impact on fuel economy. IEEE Trans Control Syst Technol 2011;19:576–89. http://dx.doi.org/10.1109/TCST.2010.2048431.
[33] Shen J, Dusmez S, Khaligh A. Optimization of sizing and battery cycle life in battery/UC hybrid energy storage system for electric vehicle applications. Ind Inf IEEE Trans 2014:1. http://dx.doi.org/10.1109/TII.2014.2334233.
[34] Yin H, Zhao C, Li M, Ma C. Utility function-based real-time Control of A Battery ultracapacitor hybrid energy system. IEEE Trans Ind Inf 2015;11:220–31. http://dx.doi.org/10.1109/TII.2014.2378596.
[36] Laldin O, Moshirvaziri M, Trescases O. Predictive algorithm for optimizing power flow in hybrid ultracapacitor/battery storage systems for light electric vehicles. IEEE Trans Power Electron 2013;28:3882–95. http://dx.doi.org/10.1109/TPEL.2012.2226474.
[37] Hredzak B, Agelidis VG, Jang M. A model predictive control system for a hybrid battery-ultracapacitor power source. IEEE Trans Power Electron 2014;29:1469–79. http://dx.doi.org/10.1109/TPEL.2013.2262003.
[41] Uzunoglu M, Alam MS. Modeling and analysis of an FC/UC hybrid vehicular power system using a novel-wavelet-based load sharing algorithm. IEEE Trans Energy Convers 2008;23:263–72. http://dx.doi.org/10.1109/TEC.2007.908366.
[42] Choi ME, Kim SW, Seo SW. Energy management optimization in a battery/supercapacitor hybrid energy storage system. IEEE Trans Smart Grid 2012;3:463–72. http://dx.doi.org/10.1109/TSG.2011.2164816.
[43] Caux S, Hankache W, Fadel M, Hissel D. On-line fuzzy energy management for hybrid fuel cell systems. Int J Hydrogen Energy 2010;35:2134–43. http://dx.doi.org/10.1016/j.ijhydene.2009.11.108.
[44] Sundström O, Guzzella L. A generic dynamic programming Matlab function. Proc IEEE Int Conf Control Appl 2009:1625–30. http://dx.doi.org/10.1109/CCA.2009.5281131.