*Int. J. Electrochem. Sci.*, 17 **(2022)** Article Number: 220121, doi: 10.20964/2022.01.21

**International Journal of ELECTROCHEMICAL SCIENCE**
www.electrochemsci.org

# Energy Management Control Strategy for Hybrid Energy Storage Systems in Electric Vehicles

*Qiao Zhang*[1,*], *Xu Chen*[1] *and Shaoyi Liao*[2]

[1] School of Automobile and Traffic Engineering, Liaoning University of Technology, Jinzhou 121000, China
[2] Information systems Department, City University of Hong Kong, Hong Kong, 999077, China.
Corresponding author: Q. Zhang
[*]E-mail: zq_625@163.com

*Received:* 26 September 2021 / *Accepted:* 31 October 2021 / *Published:* 6 December 2021

This study describes an energy flow distribution control strategy based on a combined method for hybrid energy storage systems to achieve multiple control objectives. The strategy including wavelet transform algorithm, fuzzy logic controller and Markov chain model. Firstly, Wavelet Transform based frequency control algorithm is introduced to extract low frequency power demand from load power for satisfying battery dynamics. At the same time, the remaining high frequency power demand is assigned to supercapacitor. Benefiting from this mode, the battery is protected from rapid heat generation because of high frequency charging and discharging operations. Then, to control battery peak current as small as, a fuzzy logic controller is constructed using a series of preset control logics. Besides, future driving cycle information is predicted by a Markov chain model to improve the fuzzy controller. Finally, the proposed strategy is validated by comparing with wavelet transform and dynamic programming algorithms based on a scaled down hybrid energy storage system experimental test platform.

**Keywords:** Electric vehicles, battery, hybrid system, energy management.

## 1. INTRODUCTION

For the last few years, climate variation, environment pollution, and oil energy crisis have speeded up new energy automobile markets, including hybrid, Plug-in, pure electric vehicles. Lithium batteries are potential energy storage units for supplying energy and power demands of various electric vehicles. Lithium batteries have many preponderances, for instance large specific energy, high cell voltage, high charge efficiency,etc. Of all energy storage devices, Lithium batteries are the excellent candidate for powering electrocars to meet kinds of performance requirements. However, Lithium batteries have their drawbacks in reality, such as short lifetime, poor adaptability to low temperature, slow charge and discharge rate, etc. In addition, large current and continual charge operations would accelerate the aging process of the battery. These drawbacks are inherent characteristics of the battery and are hard to be overcame based on current battery technology[1][2]. Composite energy storage unit contributes to a feasible alternative to battery awkward situation in application of pure electric vehicles. Supercapacitor is an ideal candidate for paring with the battery to construct such a hybrid system. Supercapacitor possess large specific power density and extremely long lifetime. Besides, it can be frequently used with large charge and discharge current. However, the specific energy of supercapacitor is too low to match the energy requirement of an electric vehicle [3][4]. Theoretically, composite energy storage unit composed of two kinds of energy sources can show better performance compared with any single system (battery or supercapacitor only) through optimized designed and efficient energy management.

Energy management control strategy is the core technology of hybrid energy storage system for ensuring performance. At each sample interval, energy management control strategy decides the amount of the power allocated to each energy source depending on series of input variables, such as load power, battery SOC and supercapacitor SOC. From present research literature, a mass of energy management control strategies has been reported to regulate power flow between the two energy sources. These strategies have been designed using various control principles. From this perspective, the existing energy flow control methods can be roughly grouped into two types of families, namely optimal design and logic control[5][6].

Optimal design uses optimal algorithms to solve power flow allocation problem for composited energy storage units. They can find optimal power distribution sequences to achieve perfect control performance, however typically being time-consuming. Dynamic programming (DP) algorithm is representative and most time employed to compute the optimum distribution problems of energy management [7]. The DP algorithm adopts backward solution method to find optimal power distribution according to the state of charges (SOCs) of both battery and supercapacitor. The computation time-consuming depends on the sizes of the SOC grid. Owing to large computation burden, the DP algorithm fails to work in on-line scenarios, however the optimized results can be utilized as a reference of rule energy management strategy design. Some other optimization algorithms, such as particle swarm optimization (PSO) [8], genetic algorithm (GA) [9], DIRECT global optimization[10], are all belong to heuristic optimization algorithms, which can find the optimal power distribution results with a certain probability. The computation time of these heuristic optimization algorithms is less than that of the DP algorithm, and therefore they are also widely applied in offline optimization problem. Some researchers have simplified the complex optimization algorithms into simple ones for improving computation efficiency. For example, among the energy management optimization problems, equivalent energy expend minimum control method has been proposed to in-time compute optimal power flow distribution problem among energy sources. In this algorithm, the battery charge cost is transformed into fuel consumption cost at each sampling instant. To control the state parameters of battery and supercapacitor within preset limits during the optimization, model predictive controller (MPC) algorithm was proposed to minimize the variations of supercapacitor in [12]. However, the MPC algorithm strongly depend on accurate mathematic model, which further limits its engineering application.

By comparison, rule-based strategies use logic thresholds to define the switching points of state variables during the implementation. For each switching operation, a series of control rules are often designed for carrying out power distribution mission. The switching points and control rules are usually tested repeatedly for obtaining better control performance. The rule-based strategies have good real-time performance, and therefore they can be applied in real hardware system. Such strategies include logic threshold control, fuzzy logic control, filtration control, etc. The researcher designed a logic threshold control strategy to regulate power flow between the energy sources[13]. According to the SOC fluctuation areas of battery and supercapacitor, different control logics were developed to satisfy the vehicle power requirement. A multi-mode control strategy with nine switch logics was designed to control the energy sources in [14]. The rules were designed to implement power distribution operation to improve the energy efficiency of the bidirectional DC/DC converter. A straightforward logic rule control method was designed to control the supercapacitor discharge in [15]. In this study, the regenerative braking energy of the electric vehicle was absorbed by the supercapacitor effectively by using a series of control rules. As a result, the electric vehicle range was extended successfully. Fuzzy logic control is a tool that uses expert information to make decisions and has been successfully applied in solving energy management problem of various hybrid systems [16-20]. For instant, the researcher proposed an adaptive fuzzy control strategy to regulate pow flow between the energy sources in [17]. The results have demonstrated that the fuzzy logic control can achieve satisfactory performance. To remove high frequency power component from the battery, Filtration-based approach was proposed. Haar Wavelet algotirhm is an efficient method to deal with such problem. In [19], Wavelet Transform was employed to decomposing charge and discharge power into some frequency parts to adapt to the power variations of each energy source.

From above literature review, although various energy management control strategies have been proposed, however, all of them fail to cope with the fluctuation and magnitude of battery charge demand at the same time. For example, frequency-separation algorithms can reduce the variation of battery current demand, but they cannot suppress the battery peak current effectively. Fuzzy logic controllers can successfully reduce battery peak current, but they fail to remove the high frequency components of battery current demand. Optimization-based strategies cannot be applied in real-time hardware systems. With these problems in consideration, a combined strategy including a frequency-separation algorithm and an energy flow regulator with a series of fuzzy rules is thus described for deal with magnitude and variation of battery current demand. In addition to this, considering the stochastic and adverse impact of vehicle driving condition on optimal energy flow distribution, Markov chain model is further developed and integrated into the control strategy. To the best knowledge of the author, this is the first time that such a combined strategy is used for hybrid energy storage system to deal with multiple performance objectives. Besides, it has good real-time performance for engineering application.

## 2. ENERGY FLOW CONTROL METHOD

In the control method, HWT (Haar wavelet transform) algorithm is employed to separate driving and braking current into high and low parts. Then energy flow regulator with a series of fuzzy rules is designed to suppress battery peak current according to the state of charge of supercapacitor and load current demand, which is predicted by a Markov chain model.

### *2.1. Harr Wavelet Transform Algorithm*

The Haar WT algorithm is basically described by the following expression.

$$W_z x(t) = x(t)\emptyset_z(t) = \frac{1}{z}\int_{-\infty}^{+\infty} S(t)\,\emptyset(\frac{t-u}{z})du \quad (1)$$

where signal $z$ is a ratio factor, $x(t)$ is system input variable.

The implementation process of the algorithm can be expressed by Mallat formula:

$$S_j x(n) = \sum_{k\in Z} h_k S_2 x\left(n - 2^{j-1}k\right) \quad (2)$$

$$W_j x(n) = \sum_{k\in Z} g_k S_2 x\left(n - 2^{j-1}k\right) \quad (3)$$

where $h_k$ and $g_k$ are the high and low pass filtering factors, $H(\omega)$ and $G(\omega)$ can be calculated by

$$H(\omega) = \sum_{k\in Z} h_k e^{-ik\omega} \quad (4)$$

$$G(\omega) = \sum_{k\in Z} g_k e^{-ik\omega} \quad (5)$$

The elementary procedure of the WT algorithm is shown in Fig. 1. The implementation operation includes decomposition and reconstruction two parts. The function of the first part is to decompose original signal into different frequency components according to specific requirement. The function of the second part is to reconstruct the original signal.

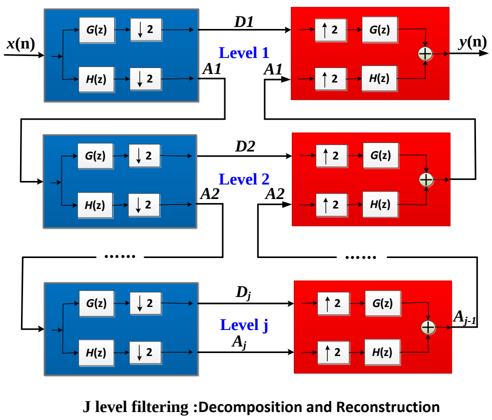



**Figure 1.** Schematic of decomposition and reconstruction.

The WT decomposition involves approximation and detail, which can be calculated by

$$eA_1(k) = \sum_n h_0(k-2f)\,cA_0(n) \quad (6)$$

$$eD_1(k) = \sum_n h_1(k-2f)\,cA_0(n) \quad (7)$$

Consequently, the original input variable $x(t)$ includes following two parts.

$$x(t) = \sum_k cA_1 \emptyset_{j-1,k}(t) + \sum_k cA_1 \emptyset_{j-1,k}(t) \quad (8)$$

In this study, the load demand $x(n)$ generated from driving cycles would be decomposed. As shown in Fig. 1, after decomposing with four levels, the low frequency power signal $x_0(n)$ is extracted from load power and assigned to the battery. Other high frequency parts will be assigned to the supercapacitor. Detailed distribution process is written by

$$\begin{cases} \mathrm{P_{bat,1}} = \mathrm{x}_0(n) \\ \mathrm{P_{SC,1}} = \mathrm{x}_1(n) + \mathrm{x}_2(n) + \mathrm{x}_3(n) + \mathrm{x}_4(n) \end{cases} \quad (9)$$

$$\begin{cases} \mathrm{P_{bat,2}} = \mathrm{x}_0(n) \\ \mathrm{P_{SC,2}} = \mathrm{x}_1(n) + \mathrm{x}_2(n) + \mathrm{x}_3(n) \end{cases} \quad (10)$$

$$\begin{cases} \mathrm{P_{bat,3}} = \mathrm{x_0(n)} \\ \mathrm{P_{SC,3}} = \mathrm{x_1(n)} + \mathrm{x_2(n)} \end{cases} \quad (11)$$

### *2.2 Load Power Prediction Using Markov Chain Model*

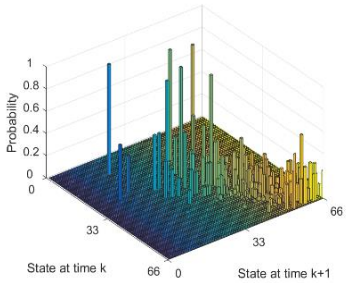
In order to obtain possible vehicle running states at the next moment, the acceleration action of a driver is assumed to be Markov process, therefore the prediction model is constructed as following probability form.

$$P_{ijm} = \Pr ob\left(c_{k+1} = w \mid c_k = v, s_k = s\right) \quad (12)$$

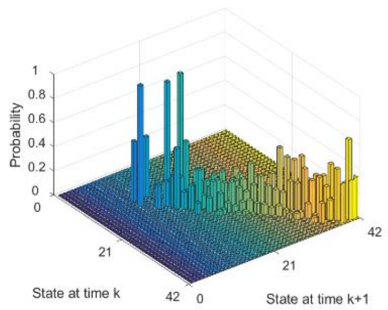
where the variables $s_k$ and $c_k$ represent speed and acceleration, the variable *Pijm* represents a specific transition probability value. To obtain all the transition probability values in the matrix, the following calculation method is used.

$$P_{i,j} = \frac{m_{i,j}}{m_i} \quad (13)$$

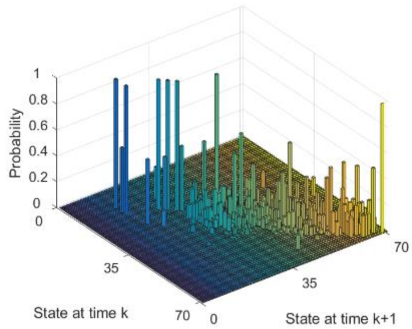
where the variable mi,j represents the occurrence number of the state variables moving from one state to another.



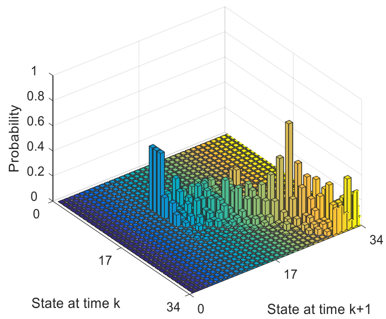

(1) State transition probabilities of ArtRoad




(2) State transition probabilities of INDIA_HWY_SAMPLE




(3) State transition probabilities of LA92




(4) State transition probabilities of WLTP

**Figure 2.** State transition probabilities of ArtRoad, INDIA_HWY_SAMPLE, LA92 and WLTP driving cycles.

Fig. 2 gives the state transition probability maps of four driving cycles including INDIA_HWY_SAMPLE, ArtRoad, LA92 and WLTP. Based on these maps, the upcoming vehicle speed can be predicted using the following expression.

$$\begin{cases} v_{k+1} = v_k + a_k \cdot t \\ a_{k+1} = \sum_{i=1}^{m} a_i / m \\ v_{k+2} = v_{k+1} + a_{k+1} \cdot t \end{cases} \tag{14}$$

After the prediction, vehicle running power requirement can be obtained using following expression.

$$P_{k+1} = \frac{v_{k+1}}{\eta}\left( mfg\cos(\theta) + mg\sin(\theta) + \frac{C_d A}{21.15} u_{k+1}^2 + \delta m a_{k+1} \right) \tag{15}$$

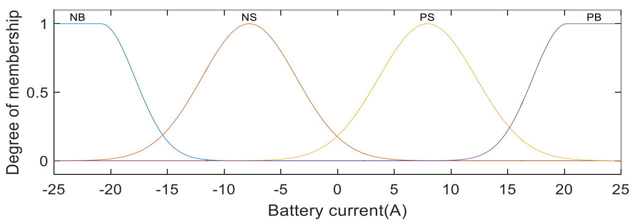
All the parameters involved in expression (15) and related to studied objective electric vehicle are itemized in Table 1.

**Table 1.** Vehicle parameter items from vehicle manufacturers

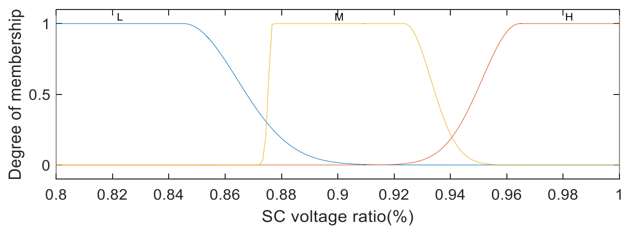
| Parameter items | Values |
|---|---|
| $m$ | 800 |
| $A$ | 1.13 |
| $C_d$ | 0.2 |
| $A$ | 0.26 |
| $f$ | 0.01 |
| $\delta$ | 1.08 |

*2.3. Energy Flow Regulator Design*

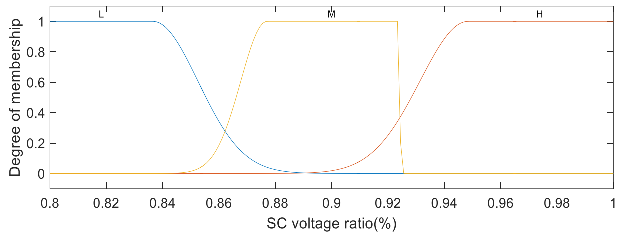
The energy flow regulator is realized based on a well-designed fuzzy rule controller. The main function of the fuzzy controller is to remove peak current from the battery power demand obtained according to the wavelet transform algorithm. According to the battery current (including low frequency current and predictive current) and the supercapacitor voltage, the fuzzy rule controller will implement the power amount of the battery reduction. With this in mind, the battery current (including low frequency current and predictive current) and supercapacitor voltage three parameters are used as inputs of the fuzzy logic controller, the system output variable refers to the removed electricity that delivering to the supercapacitor power system. The Gaussian membership function is used to define the control domains of the system input-output values of the designed fuzzy rule controller. Both the electronic current and the removed current have the same fuzzy control domains.Table 2 displays the fuzzy rules that are utilized to combine removed current to battery current and supercapacitor voltage.



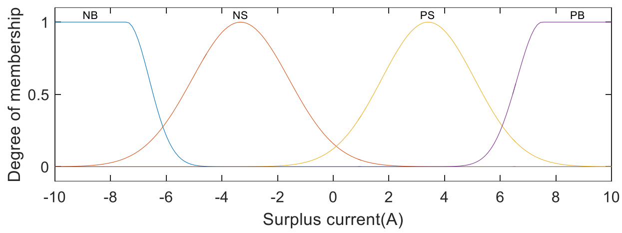

(a) The electronic current.




(b) The supercapacitor voltage.




(c) The supercapacitor voltage when a vehicle has continuous braking demand.




(d) The added current.

**Figure 3.** The membership degrees of the described fuzzy controller.

**Table 2.** The control rules designed in the study.

| | $\Delta$ A | SC voltage | | |
|---|---|---|---|---|
| | | L | M | H |
| $C_{bat}$ | BL | BL | BL | BS |
| | BS | BS | BS | BS |
| | DS | DS | DS | DL |
| | DL | DL | DL | DL |

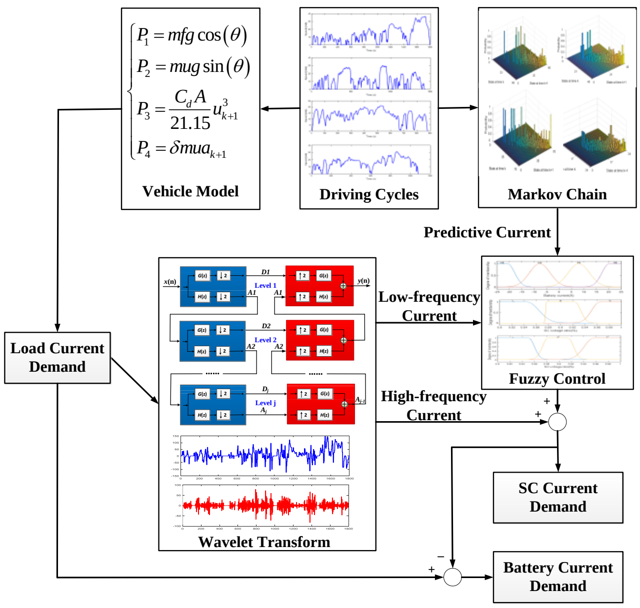



**Figure 4.** The outline of energy flow distribution strategy.

Here, the described energy flow distribution framework has been given in Fig. 4. First, according to vehicle model and driving cycle data, the load current demand of composite energy storage unit can be calculated. Second, the load current demand is decomposed into the low frequency and the high frequency two parts, and the former is used as the input of fuzzy logic controller. The fuzzy decisions can be made according to the predictive load current demand and the supercapacitor voltage.

## 3. EXPERIMENTAL PREPARATION FOR ENERGY STRATEGY VALIDATION

To implement the proposed energy management control strategy and validate its effectiveness in a practical way, a reconfigurable scaled-down hybrid energy storage system hardware-in-loop experimental platform is installed and tested, as displayed in Fig. 5. This hardware-in-loop test platform includes a battery pack, a supercapacitor pack, a bidirectional DC/DC converter, a rapid prototyping ECU controller, a load simulator and some other auxiliary equipment. For each device, the primary parameters can be found in [32]. The load simulator is used to generate frequency charge and discharge electronic currents of composite energy storage unit. The current demands can be obtained according to embedded vehicle model and driving cycle data. The load simulator transmits data signals to devices or receive data signals from devices by data bus technology. The energy flow management distribution model is established by matrix laboratory, then simulation model will be downloaded to the rapid prototyping controller for implementation operation. For each sampling step, the actual distributed current demands of the battery pack and the supercapacitor pack are in comparison with current values obtained from yielded from above designed controller.

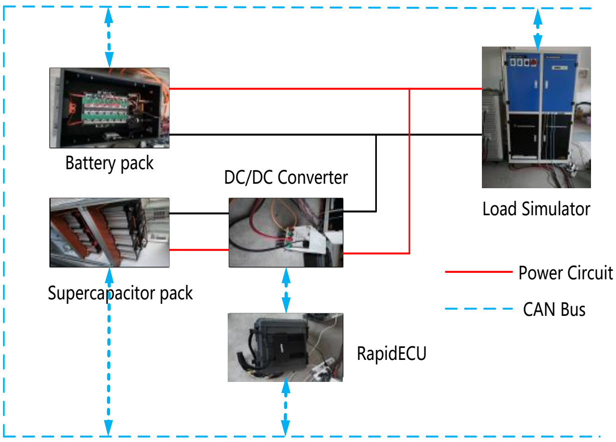



**Figure 5.** An experimental platform used in this work.

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

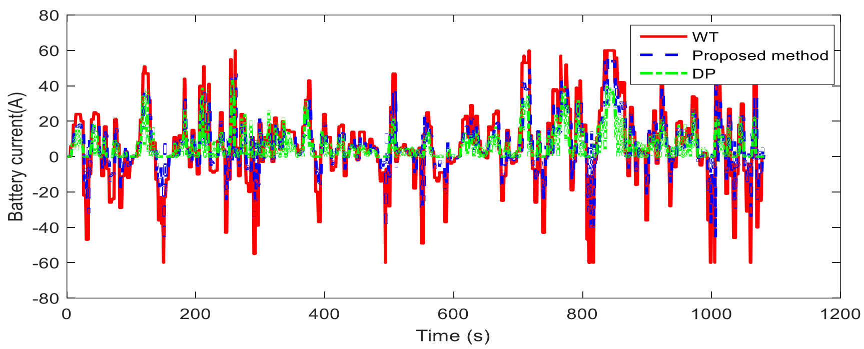
The developed energy flow controller is validated based on above experimental platform. A combined profile consisting of ArtRoad, INDIA_HWY_SAMPLE, LA92 and WLTP standard driving cycles, are employed as vehicle condition. Since the experimental platform is scaled one, therefore the charge and discharge current is scaled down according to actual physical limits. Figs. 6-9 give the experimental results of wavelet transform(WT), the proposed strategy and dynamic programming(DP).

The battery current dynamic behaviors tested under ArtRoad vehicle cycle are described in Fig. 6(a). Observed from the curves, it can clearly conclude that the maximum current of battery by the described method is obviously shaved compared with the WT. The battery current of the DP is used as a benchmark for quantifying the performance of other two methods. In fact, the battery current reduction is achieved by the fuzzy logic controller. It can be observed that the braking current absorbed is also be reduced by the proposed method. As a result, more braking current is absorbed by the supercapacitor. This can be demonstrated from the displayed results in Fig.6(c). Since the supercapacitor have higher energy efficiency, therefore more baring power is reasonably assigned to the supercapacitor, which can help to improve energy efficiency of the whole vehicle.

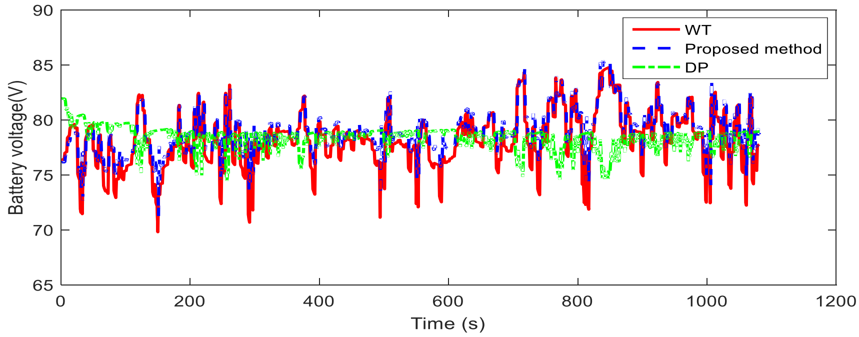
Figs. 6-9(b) give battery voltage results based on the above three methods. We can observe that the described method successfully realize an excellent voltage performance. As for the ArtRoad driving cycle, the maximum voltage drop is11V by maximum probability estimation, which is obviously smaller than 15V by the WT. Still, at most interval of the test cycle, the voltage drops using the described method is much smaller than that by the WT. From the voltage results of other three driving cycles, these results indicate that the proposed method can improve the work condition of the battery.

The curve evolutions of supercapacitor current based on the three methods are illustrated in Figs. 6-9(c). From the current description, it can be seen the supercapacitor is enabled to supply the large electronic current demand during the whole vehicle running cycle. Consequently, the battery work burden is effectively relieved. In addition to this, the supercapacitor is also assumed to undertake the the high frequency current demand that is extracted from the vehicle cycle. As a result, the battery is protected from the fluctuating current damage.

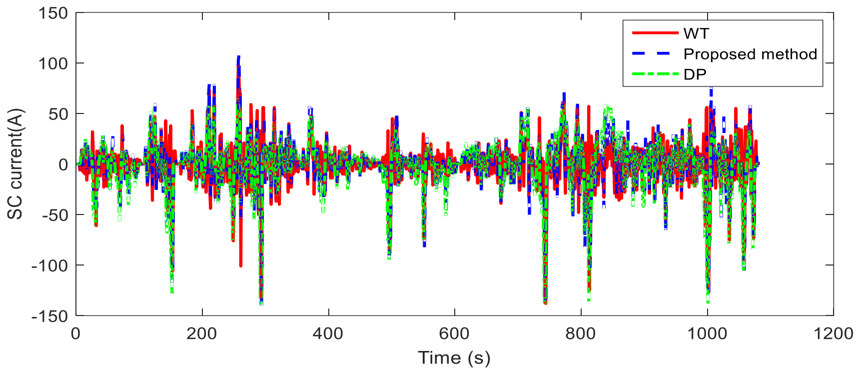
Fig. 6-9(d) displays the supercapacitor voltage variations by the three energy flow controls. From the comparisons, it is clearly demonstrated that the described method can enable the supercapacitor to participate in the load current distribution more actively compared with the WT method, namely the voltage curves of the supercapacitor fluctuate more frequently as the load current variation. It demonstrates that the design fuzzy rule regulator is effective in adjusting current demand between the two sources.



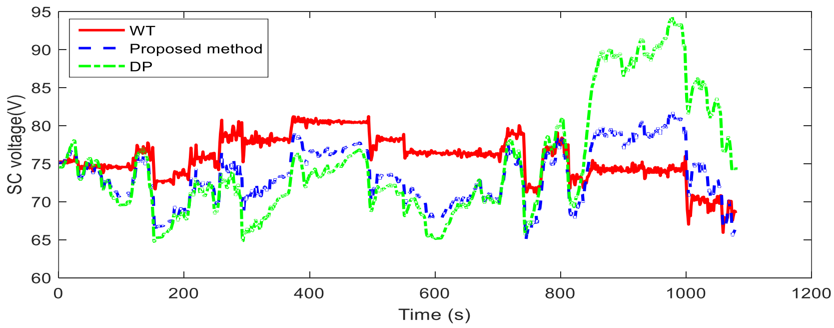

(a) Experimental comparative results of battery current.




(b) Experimental comparative results of battery voltage.

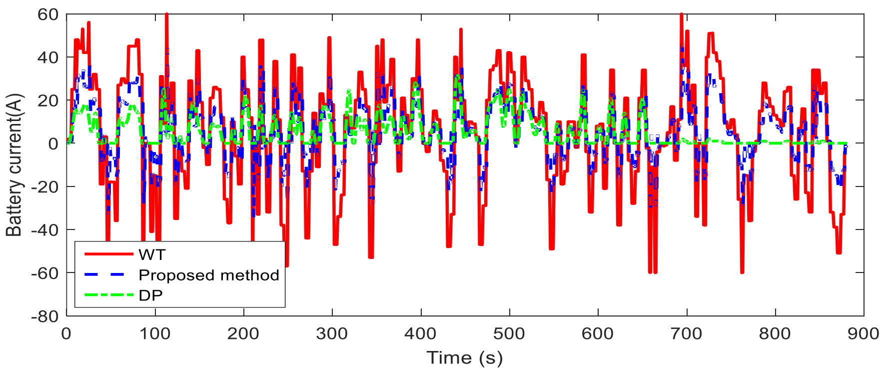



(c) Experimental comparative results of supercapacitor current.

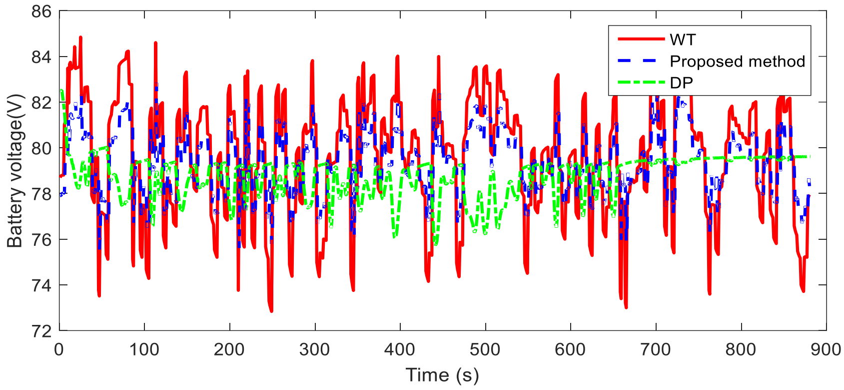



(d) Experimental comparative results of supercapacitor voltage.

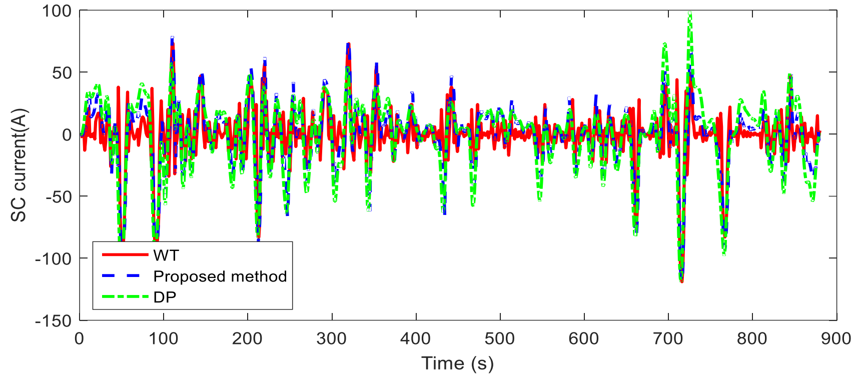
**Figure 6.** Test result comparisons based on ArtRoad driving profile.



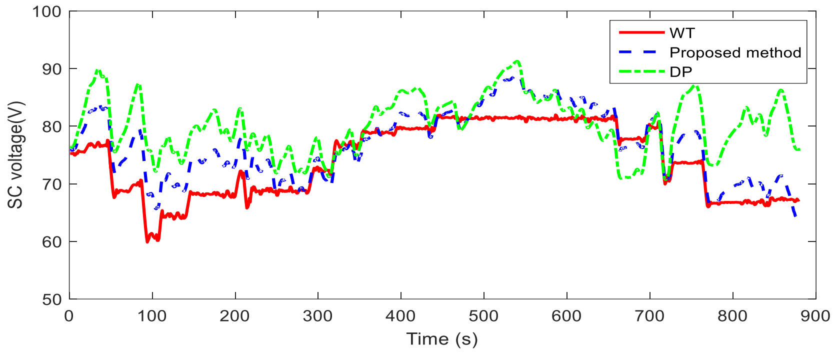

(a) Experimental comparative results of battery current.




(b) Experimental comparative results of battery voltage.

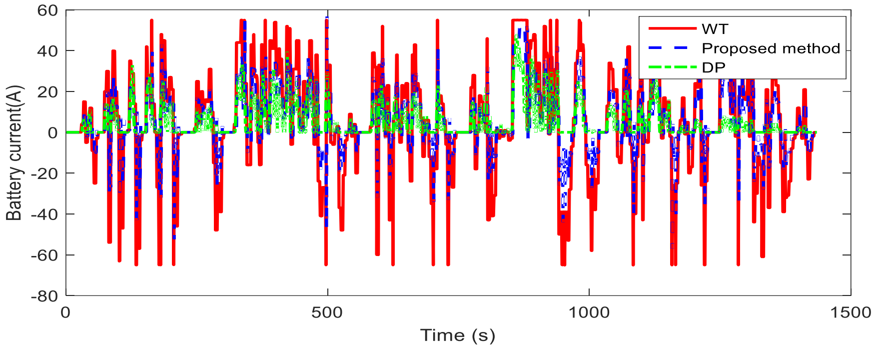



(c) Experimental comparative results of supercapacitor current.

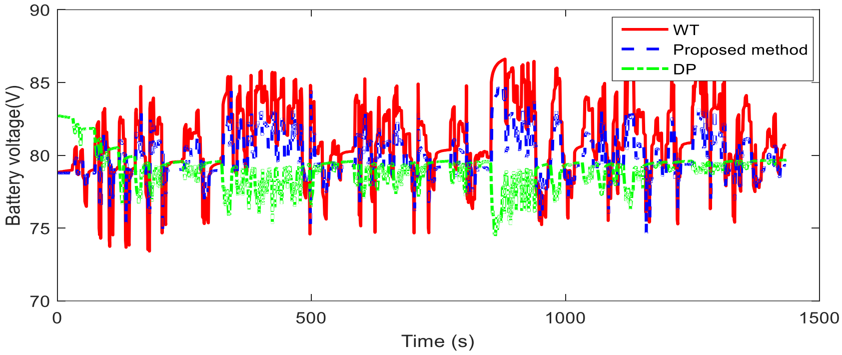



(d) Experimental comparative results of supercapacitor voltage.

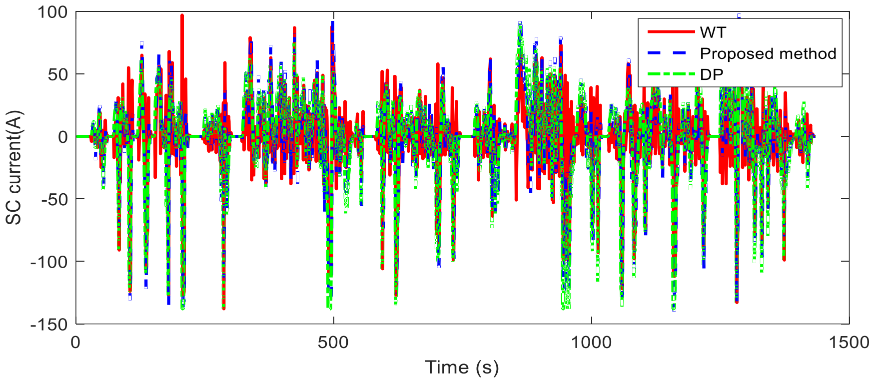
**Figure 7.** Test result comparisons based on INDIA_HWY_SAMPLE driving profile.



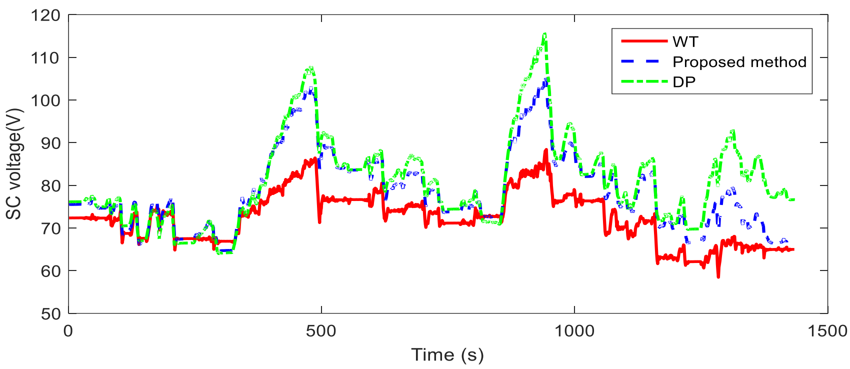

(a) Experimental comparative results of battery current.




(b) Experimental comparative results of battery voltage.

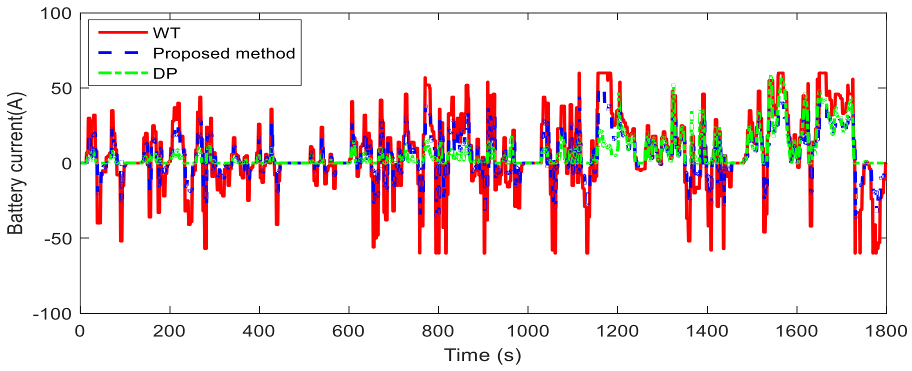



(c) Experimental comparative results of supercapacitor current.

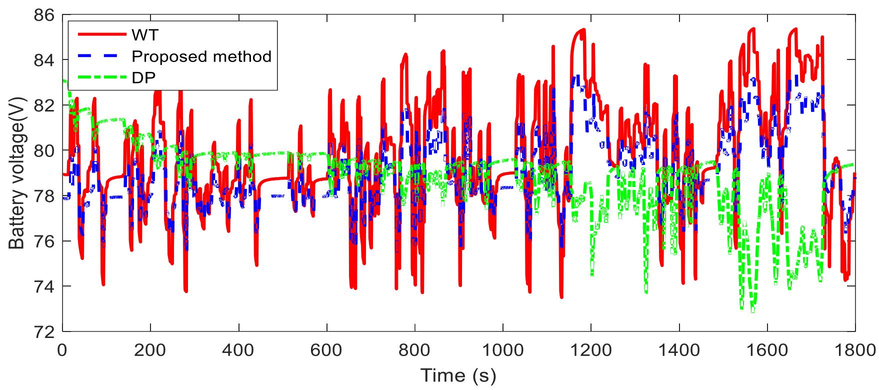



(d) Experimental comparative results of supercapacitor voltage.

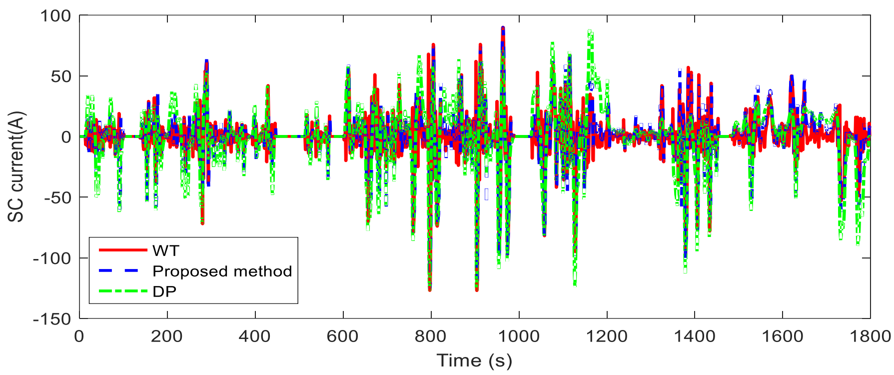
**Figure 8.** Test result comparisons based on LA92 driving profile.



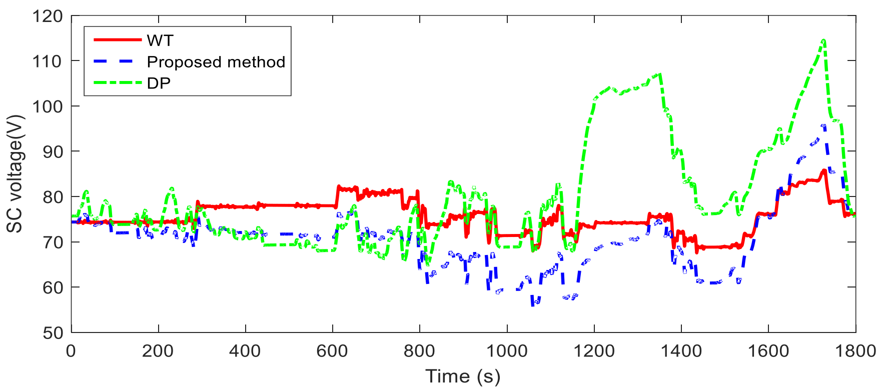

(a) Experimental comparative results of battery current.




(b) Experimental comparative results of battery voltage.




(c) Experimental comparative results of supercapacitor current.




(d) Experimental comparative results of supercapacitor voltage.

**Figure 9.** Test result comparisons based on WLTP c

## 5. CONCLUSIONS

This paper introduced a combined energy management strategy and its experimental implementation for multi-source composite energy storage units of pure electric vehicles. A scaled down battery and supercapacitor hybrid system experimental test platform was developed to implement energy management strategy based on ArtRoad, INDIA_HWY_SAMPLE, LA92 and WLTP Driving cycles. The proposed energy flow control method is designed with three algorithms including wavelet transform, fuzzy logic control and Markov chain model. Experimental results showed that the proposed strategy can remove the high frequency current from the battery current demand at the same time the battery peak current can be suppressed effectively, which can eventually increase the lifetime of the battery.

Future research work would introduce battery life test and its evaluation based on the proposed energy management control strategy.

ACKNOWLEDGMENTS
The research paper is partly subsidized by Scientific Research Project of Liaoning Education Department (grant NO. JQL202015405) and the development grants from Shenzhen Science, Technology and Innovation Commission (grant NO. JSGG20170822145318071).

## References

1. C. M. Martinez, X. Hu, D. Cao, E. Velenis, B. Gao, and M. Wellers, *IEEE Trans. on Vehicular Technology*, 66(2017) 4534.
2. S. Manzetti and F. Mariasiu, *Renew. Sustain. Energy Reviews*, 51(2015) 1004.
3. A. M. Andwari, A. Pesiridis, S. Rajoo, M.B. Ricardo and V. Esfahanian, *Renew. Sustain. Energy Reviews*, 78(2017) 414.
4. M. Hannan, F. Azidin and A. Mohamed, *Renew. Sustain. Energy Reviews*, 29(2014) 135.
5. S. G. Wirasingha and A. Emadi, *IEEE Trans. on Vehicular Technology*, 60(2011) 111.
6. L. Kouchachvili, W. Yaïci, E. Entchev, *J. Power Sources*, 374(2018) 237.
7. L. Xu, M. Ouyang, J. Li and F. Yang, in Proc. IEEE ISIE, Hangzhou, China, May, 2012, 1490–1495.
8. O. Hegazy and J. V. Mierlo, *Int. J. Veh. Des*., 58(2012) 2.
9. J. P. Ribau, C. M. Silva and J. M. C. Sousa, *Appl. Energy*, 129(2014) 320.
10. C. Li and G. Liu, *J. Power Sources*, 192(2009) 525.
11. C. Yang, S. Du, L. Li, S. You, Y. Yang, Y. Zhao, *Appl Energy*, 203(2017) 883.
12. B. Hredzak, G. V. Agelidis and M. Jang, *IEEE Trans. Power Electron*., 29(2014) 1469.
13. J. P. Trovão, P. G. Pereirinha, H. M. Jorge and C. H. Antunes, *Appl. Energy*, 105(2013) 304.
14. B. Wang, J. Xu, B. Cao and X. Zhou, *J. Power Sources*, 281(2015) 432.
15. J. Armenta, C. Núnez, N. Visairo and I. Lazaro, *J. Power Sources*, 284(2015) 452.
16. A. Ferreira, J. Pomilio, G. Spiazzi and L. A. Silva, *IEEE Trans. Power Electron*., 23(2008) 107.
17. Q. Zhang, G. Li, *IEEE Trans. Power Electron*., 35(2020) 1014.
18. Y. He, W. Zhou, M. Li, C. Ma and C. Zhao, *IEEE Trans. Transportation Electrification*., 2(2016) 300.
19. M. Michalczuk, B. Ufnalski and L. M. Grzesiak, *International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, 34(2008) 173.
20. Y. Wang, W. Wang, Y. Zhao, L. Yang and W. Chen, *Energies*, 9(2016) 1.
21. X. Zhang, C. C. Mi, A. Masrur, D. Daniszewski, *J. Power Sources*, 185(2015) 1533.

22. B. Asadi and A. Vahidi, *IEEE Trans. on Contr. Syst. Technol.*, 19(2011) 3.
23. C. Zhang, A. Vahidi, P. Pisu, X. Li, K. Tennaut, *IEEE Trans. Veh. Technol*., 3(2010) 1139.
24. Erik Hellstrom, Maria Ivarsson, Jan Aslund, Lars Nielsen, *Control Engineering Practice*, 17(2009) 245.
25. C. Zhang, A. Vahidi, P. Pisu, X. Li, and K. Tennant, *IEEE Trans. Veh. Technol*., 59(2010) 1139.
26. Chen Zhang and Ardalan Vahidi, *IEEE Trans. on Contr. Syst. Technol.*, 20(2012) 546.
27. Nianfeng Wan, S. Alireza Fayazi, Hamed Saeidi, Ardalan Vahidi, in Proc. 2014 American Control Conference, pp. 3462-3467, Portland, Oregon, USA.
28. R. Langari, J.S. Won, *IEEE Trans. Veh. Technol*., vol. 3, pp. 925–934, May 2005.
29. K. Song, F. Li, X. Hu, L. He, W. Niu, S. Lu, T. Zhang, *J. Power Sources*, 389(2018) 230.
30. H. Hemi, J. Ghouili, A. Cheriti, *Energy Conver. and Manage*., 91(2015) 387.
31. Y. Zhou, A. Ravey, M. C. Péra, *Appl. Energy*, 258 (2020)1140-1157
32. Q. Zhang, L. J. Wang, G. L, S. Y. Liao, *International Journal of Electrochemical Science*, 15 (2020) 10866 – 10884.