

RESEARCH ARTICLE

Energy Consumption Prediction of Electric Construction Machinery Based on Condition Identification

ZHONGSHEN LI\textsuperscript{1,2}, TIANLIANG LIN\textsuperscript{1,2}, AND QIFA GAO\textsuperscript{1}
\textsuperscript{1}College of Mechanical Engineering and Automation, Huaqiao University, Xiamen 361021, China
\textsuperscript{2}Fujian Key Laboratory of Green Intelligent Drive and Transmission for Mobile Machinery, Huaqiao University, Xiamen 361021, China

Corresponding author: Tianliang Lin (ltlkxl@163.com)

This work was supported in part by the National Key Research and Development Program under Grant 2020YFB2009900, in part by the National Natural Science Foundation of China under Grant 51875218 and Grant 52175051, in part by the Key Projects of Natural Science Foundation of Fujian Province under Grant 2021J02013, in part by the Collaborative Innovation Platform of Fuzhou-Xiamen-Quanzhou Independent Innovation Demonstration Area under Grant 3502ZCQXT202002, and in part by the Fujian University Industry University Research Joint Innovation Project Plan under Grant 2022H6007.

\textbf{ABSTRACT} Energy saving and emission reduction have become the consensus of the global development. Electric construction machinery has drawn more and more attentions due to its zero emission and high efficiency. However, because of the installed capacity of the battery, the complex working conditions and the time-varying load of construction machinery, the working time of electric construction machinery is hard to estimate. It is important to accurately predict the remaining working time of the whole machine to ensure that the driver can reasonably arrange the operation time. In this paper, the electric loader is studied. To improve the estimation accuracy of the working time of electric loader, the typical working conditions are analyzed. The data of V-type working mode cycles of the actual experimental prototype, which provides the basis for the segmentation of working conditions and the extraction of characteristic parameters are analyzed. The fuzzy C-means clustering algorithm is used, an estimation method of operation energy consumption based on working condition identification is proposed. The results show that the energy consumption estimation method based on the motor average torque proposed in this paper has better estimation accuracy than the traditional estimation method based on the latest unit time energy consumption.

\textbf{INDEX TERMS} Electric loader, working time, condition identification, fuzzy C-means clustering, energy consumption.

\section{I. INTRODUCTION}

With the fast development of electric loaders [1], [2], the research on the working time estimation is important [3], [4]. Because most of electric loaders are still in the research and experimental prototype stage, the research on the working time estimation is relatively small. While, the research on the driving distance estimation for the electric vehicles (EV) is large.

With the development of the electric technology and consumer expectations for EVs, EVs manufacturers need to improve the user experience. In the EV instruments, the owner uses remaining mileage and battery SOC to judge whether the vehicle needs to be recharged. The driving distance can make the user understand the vehicle’s driving state intuitively. In the report “2019 China New Energy Vehicle Industry Consumer Survey Report”, it points out that the accuracy of the remaining driving distance is one of the indicators that cannot be ignored [5]. This indicator shows that the user satisfaction is low and there is a large space for improvement.

Considering the EV driving distance estimation precision of the environment and complex conditions, through the multidimensional testing and comparison of EVs under different scenarios and specific driving distance, a comprehensive and objective reference can be provided for the customers to ease the worries of the EVs driving distance [6], [7], [8]. Yao established an energy consumption factor model that could...
reflect the impact of frequent acceleration and deceleration of urban roads [9]. Based on the average driving speed of the real-time link, a method to estimate the EV cruising distance on the planned route according to the driver’s demand was proposed. This method was important to choose the driving route, but it did not take into account the errors caused by different driving habits. To solve the major challenges EVs faced with short cruising, charging and on-road acceleration, Tajima proposed a method to achieve unlimited cruising range for EVs through simultaneous energy supply and charging while running [10]. They used a contact-type, high-power charge-while-driving system, and the installation cost was estimated to be about 1/20 of the cost of a non-contact system. Du established an EV simulation model based on GT-Drive and MATLAB to estimate the remaining driving range under dynamic working conditions [11]. This model used the modified parameters to reduce the initial estimate error. The method was simple and feasible, but the modifying parameters law was not summarized. Dai made an in-depth study on the estimation accuracy of the EV driving distance under different environmental temperature conditions and complex test cycle conditions of long-distance high-speed driving [12], [13]. A fast evaluation method for EV distance estimation accuracy based on CLTC-P was constructed. The method could be accurately and quickly evaluated the EV driving distance based on different environmental temperatures, air conditioning, test scenarios, high-speed operating conditions and other conditions. To solve the random range of the EVs user, Miri established an accurate power-based EV energy consumption model based on a real EV (BMW i3) and developed a regenerative braking strategy based on a series brake system [14]. The results showed that a satisfactory level of accuracy with 2% to 6% error between estimation and experimental results for Environmental Protection Agency and NEDC tests.

Research on estimation of EV driving distance brings valuable experience to electric loaders. Compared with EVs, considering that the operating environment and working conditions of loaders are more complex, the research methods in EVs are difficult to be directly applied to electric loaders [15], [16]. The endurance time of most existing new energy vehicles is determined by the SOC and energy consumption per time unit in the recent period. This traditional method is easy to implement but does not consider the large variation of power consumption in front and back caused by variable working conditions, which leads to a large error in the estimation results of the working time. This situation is particularly common when the loader is in a complex operating condition. Therefore, the fuzzy C-means (FCM) clustering algorithm is used to identify the driving conditions online to estimate the energy consumption state and the working time of the electric loader.

II. TYPICAL OPERATING CONDITIONS ANALYSIS

At present, there are few studies on the typical working conditions of electric loaders. Compared with the traditional passenger car road driving conditions, there are no relevant national standards of typical operating conditions for electric loader. The electric loaders main working modes are V-type, L-type, T-type, and T-type. Among of them, the V-type operations are widely used because of its higher operating efficiency [17]. The analysis of typical working conditions in this paper is based on the experimental prototype loader shown in FIGURE 1. According to the experience of the driver, the V-type working mode under a specific scenario is selected to collect the experimental data. The speed and torque of the walking motor, and the speed and torque of the main pump under typical working conditions are used to analyze the cycle operation.

The V-type working mode diagram of loader is given in FIGURE 2. The operation process includes 5 working cycles. I: The loader moves from position X to position Y without load. II: The loader shovels loading with low speed. III: The loader moves back from position Y to position X with load. V: The loader moves forward from position X to Z and unloads. VI: The loader returns to position X from position Z without load.

The data of speed and torque of walking motor and main pump is given in FIGURE 3. It can be seen that there are 5 operation cycles within a 600 s period, and each cycle is about 120 s. During 0-40 s, the experimental prototype loader moves from position X to position Y without load and with high speed (I process). In the 40-45 s, the loader shovel loading (II process). The walking motor works with high torque and nearly zero speed. While the main pump works with high speed and high torque to drive the boom and bucket lifting. During 45-85 s, the loader moves back to position X with heavy load (III process). The walking motor reaches high speed. During 85-100 s, the loader moves forward to position Z to unload (V process). To meet the unloading height demand, the boom and bucket continue to lift, which
leads the main pump to work at high speed and high torque again. During 100-120 s, the loader returns to position X without load (VI process). The walking motor reaches high speed again.

### III. OPERATING CONDITION SEGMENTATION AND CHARACTERISTIC PARAMETERS

The driving conditions of passenger cars are relatively stable, and the driving conditions are usually divided into several short trips by idling points for analysis. While, the periodicity of the actual operation process of the electric loader (FIGURE 3) is not as strong as passenger cars. In addition, different operating scenarios, operating modes and operating purposes will affect its periodicity. As a result, there is no standard for dividing the short trips cycle of electric loaders. Therefore, the segment segmentation in this paper is carried out according to the analyzed data with a unit segment of 120 s shown in FIGURE 3 (b).

![FIGURE 3. Curves of speed and torque of walking motor and main pump motor.](image)

Characteristic parameters are an important reference for the division of working conditions. Through many years of research, several good characteristic parameter groups have been obtained for passenger cars at present. Compared with passenger cars, in addition to the walking drive device, the electric loader also includes the hydraulic device for shoveling. In the process of working condition segmentation, the walking conditions which can be represented by the speed or the walking motor parameters. While, the loader needs to consider the influence of the hydraulic working device caused by the change of load when operating. Therefore, it is necessary to analyze the working state of the main pump when extracting characteristic parameters. With the change of load, the hydraulic system pump flow rate, pressure and other parameters will vary when the electric loader works. The change of these parameters can directly or indirectly affect the data of the walking motor and the main pump.

The speed, torque and power curves of the experimental prototype loader under typical cycle conditions are given in FIGURE 4. It can be seen from the power curve that the power reaches the peak value in the process of shoveling as well as the boom and bucket lifting. In the shoveling process, the torque of the walking motor reaches its peak value at near zero speed. Meanwhile, the torque of the main pump also reaches its peak value with the load increasing. In the lifting process, the loader is moves forwards to position Z, and to meet the unloading height, the boom and bucket lift with load to make the torque of the main pump reach the peak value again. As can be seen in FIGURE 4, the changing trend of the battery power curve is very similar between the torque of the walking motor and the main pump. while, the changing trend of the motor speed curve is difficult to reflect the battery power level. Combining reference and experimental data analysis, a set of characteristic parameters to represent the working condition of data and to reflect the energy consumption of the segmented segment level is selected. This set of characteristic parameters contains four parameters, they are walking motor average torque, walking motor maximum torque, main pump average torque, and main pump maximum torque.

### IV. WORKING CONDITION SEGMENT CLUSTERING

#### A. FCM CLUSTERING

Cluster analysis is a common data analysis method which classifies sample objects without prior classification experience. Through continuous attempts, the similarity between samples of the same category is maximized and the similarity between samples of different categories is minimized [18], [19], [20]. FCM algorithm is used to cluster the four characteristic parameters of the segment in this study and adds the concept of ambiguity and membership. It is essential to find the corresponding membership matrix and clustering center when the objective function reaches the minimum value through continuous iteration to meet the actual application requirements.

Suppose that the dataset has \( n \) vectors \( x_i \) \((i = 1, 2, 3, \ldots, n)\) to be classified. The \( n \) vectors are clustered into \( c \) category and the center of each category is found, so that the dissimilarity is minimized and the atoms in each category sample stick together. Where, \( \mu_{ij} \) is the membership degree to represent the degree of the vector \( x_i \) belongs to
category $c_i$, $\mu_{ij}$ is the number between 0 and 1. Each $x_j$ has a membership degree for each category. The sum of the membership degree of each category for a particular vector is equal to 1, namely,
\[
\sum_{i=1}^{c} \mu_{ij} = 1, \quad \forall j \in \{1, 2, 3, \ldots, n\}
\] (1)

The objective function of FCM clustering algorithm is defined as
\[
J_m(U, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^m d_{ij}^2
\] (2)
\[
U = \left( \begin{array}{c} \mu_{11} \cdots \mu_{1n} \\ \vdots \cdots \vdots \\ \mu_{c1} \cdots \mu_{cn} \end{array} \right) \quad (3)
\]
\[
V = \left( v_1, v_2, v_3, \ldots, v_c \right)
\] (4)

where, $U$ is the membership matrix, $V$ is the clustering center vector matrix, $\mu_{ij}$ is the membership, $m$ is the flexible control parameter. $d_{ij}^2$ is the distance between the element object $x_j$ and the center point $c_i$.

When the objective function takes the minimum value, the optimal clustering result is obtained as
\[
\min(J_m(U, V)) = \min\left( \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^m d_{ij}^2 \right)
\] (5)

The constraint condition $\sum_{i=1}^{c} \mu_{ij} = 1$ is used to calculate the minimum value of the objective function. According to the number of Lagrange method, the construction function can be obtained as
\[
\mathcal{J}(U, c_1, \ldots, c_c, \lambda_1, \ldots, \lambda_n) = J(U, c_1, \ldots, c_c) + \sum_{j=1}^{n} \lambda_j \left( \sum_{i=1}^{c} \mu_{ij} - 1 \right)
\] (6)

Let the value of Eq. (6) be 0, and obtain as
\[
c_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m x_j}{\sum_{j=1}^{n} \mu_{ij}^m}
\] (7)

The variable is derivative to make the objective function reach minimize value, it satisfies,
\[
\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \frac{d_{ij}}{d_{kj}} \right)^{2m}}
\] (8)

In the clustering process, the membership function and the clustering center are updated iteratively until the cluster center no longer changes or the change value of the objective function $J_m(U, V)$ is less than $\varepsilon$ ($\varepsilon > 1$).

The value of flexible control parameter $m$ has no qualitative theoretical guidance till now. According to experience, the larger the $m$ value is, the higher the fuzzy degree of FCM classification will be, and each classification tends to produce evenly distributed classification results. The smaller the $m$ value is, the closer FCM to the hard classification result will be. The default value of $m$ is usually 2 [21], [22], [23].

The classification of sample segments is determined by the minimum distance principle according to the distance between the coordinate points of the characteristic parameter values and the center of each cluster. Since the values of the two maximum torque characteristic parameters in the segments are much greater than the values of the average torque, they play a leading role in the classification process. To increase the accuracy of clustering, it is necessary to weaken the role of the maximum torque parameter in the segment during the classification process, so the proportion of the maximum torque in the segment and the maximum torque in the normal working range is selected to participate in the clustering. Therefore, four characteristic parameters of the set of characteristic parameters are selected, which are average torque of walking motor $T_{Zave}$, average torque of main pump $T_{Xave}$, percentage of maximum torque of walking motor $P_{Xmax}$, and percentage of maximum torque of main pump $P_{Zmax}$.

1. Average torque of the walking motor can be expressed as
\[
T_{Xave} = \frac{\int_{t_0}^{t_1} T_{Xave} \, dt}{(t_1 - t_0)}
\] (9)

where, $T_{Xave}$ is the average torque of the walking motor. $t_0$ is the initial time. $t_1$ is the final time. $T_x$ is the torque of the walking motor in real time.

2. Average torque of the main pump can be expressed as
\[
T_{Zave} = \frac{\int_{t_0}^{t_1} T_{Zave} \, dt}{(t_1 - t_0)}
\] (10)

where, $T_{Zave}$ is the average torque of the main pump. $T_z$ is the torque of the main pump in real time.

3. Percentage of the maximum torque of the walking motor can be expressed as
\[
P_{Xmax} = \max(T_{X1}, T_{X2}, \ldots, T_{Xn})
\] (11)

where, $P_{Xmax}$ is the percentage of the maximum torque of the walking motor. $T_{Xn}$ is the maximum torque of the walking motor.

4. Percentage of the maximum torque of the main pump can be given as
\[
P_{Zmax} = \max(T_{Z1}, T_{Z2}, \ldots, T_{Zn})
\] (12)

where, $P_{Zmax}$ is the percentage of the maximum torque of the main pump. $T_{Zn}$ is the maximum torque of the main pump. The working condition segment data of 425 experimental prototypes loader are selected and expressed in the form of characteristic parameter values, as shown in TABLE 1.
TABLE 1. Data table of characteristic parameters.

| Segment number | T_{Xmax} | T_{Zmax} | P_{Xmax} | P_{Zmax} |
|---------------|---------|---------|---------|---------|
| 1            | 22.87   | 19.06   | 0.41    | 0.36    |
| 2            | 126.29  | 30.59   | 0.64    | 0.82    |
| 3            | 71.17   | 24.53   | 0.57    | 0.78    |
| 4            | 74.20   | 28.21   | 0.95    | 0.81    |
| 5            | 135.77  | 36.45   | 0.66    | 0.61    |
| 6            | 44.52   | 46.50   | 0.48    | 0.84    |
| 7            | 66.31   | 76.25   | 0.97    | 0.93    |
| 8            | 69.20   | 69.21   | 0.42    | 0.98    |
| 9            | 59.99   | 37.52   | 0.45    | 0.80    |
| 10           | 31.07   | 6.84    | 0.33    | 0.61    |
| ...          | ...     | ...     | ...     | ...     |
| 424          | 48.69   | 65.35   | 0.57    | 0.98    |
| 425          | 34.99   | 22.11   | 0.34    | 0.61    |

Shown in FIGURE 5, 425 working condition segments are divided into 5 categories after 58 iterations through FCM clustering analysis. The clustering centers of each category are shown in TABLE 2.

The distance between the characteristic parameter coordinates of the working condition segments to be recognized and the center of each cluster is obtained as Eq. (13).

\[ d_i = \sqrt{\sum_{k=1}^{4} (x_k - c_{ik})^2}, \quad i = 1, 2, 3, 4, 5 \]  

where, \( d_i \) is the \( i \)th distance between the characteristic parameter coordinates of the working condition segments to be recognized and the center of each cluster. \( x_k \) is the \( k \)th segment characteristic parameter value. \( c_{ik} \) is the value of the \( k \)th characteristic parameter of the \( i \)th category clustering center.

B. SEGMENT ENERGY CONSUMPTION CALCULATION

The off-line data of 425 segments are analyzed for their energy consumption, and the energy consumption distribution as shown in FIGURE 6 can be calculated as.

\[ E_a = \int_{t}^{t+\Delta t} P_b dt \]  

where, \( E_a \) is the segment energy consumption. \( P_b \) is the battery output power. \( \Delta t \) is the data collection interval.

\[ P_{ai} = \frac{\sum_{k=1}^{n_i} E_{ik}}{n_i \Delta t} \]  

where, \( P_{ai} \) is the average power of \( i \)th category segment. \( n_i \) is the number of segments belonging to \( i \)th category. \( E_{ik} \) is the energy consumption of segment \( k \)th in \( i \)th category. \( \Delta t \) is the unit segment length, in this paper it is 120 s.

According to Eq. (15), the average energy consumption of each category is calculated and listed in TABLE 3.

Considering that when the distance between the coordinate of the segment characteristic parameter and the clustering center is large, especially when it is located at the junction or the different categories edge, if the segment average consumed power is directly taken as the segment consumed power according to the category to which the segment belongs, a relatively large error will be caused. Therefore, a power compensation method is proposed according to the linear regression analysis performed on MATLAB containing the difference \( y \) between the segment actual power consumption and the average power of the category to which the segment belongs, the walking motor average torque \( x_1 \), and the main pump motor average torque \( x_2 \) in the set of characteristic parameters of the segment. Its essence is the least square method. The fitting function is shown in Eq. (16), and each category uses regress to obtain its fitting formula according to the segment characteristic parameter values in its category, namely the coefficients \( b_1 \sim b_6 \).

\[ y = b_1 + b_2 x_1^2 + b_3 x_2^2 + b_4 x_1 + b_5 x_2 + b_6 x_1 x_2 \]  

Select one of the categories for analysis, such as category 2 in FIGURE 7 which shows the power compensation. As can be seen, most of the segments can fit its fitting function surface. The total number of segments taken into consideration for the fitting is 80. The error between the actual consumed power and the compensated estimated power (the sum of the compensated power obtained according to the average power of the category and the fitting formula corresponding to the category) of 87.5% of the segments is less than 1 kW.

The comparison curve of power and energy consumption before and after power compensation is given in FIGURE 8.
As can be seen in FIGURE 8 (a), the energy consumption is estimated according to the average power of each segment. The trend of the energy consumption curve is very close to the actual situation. In the working process of 2.25 h, there are two large errors between the estimated power and the actual power, which lead to the trend of the energy consumption curve slightly deviating from the actual energy consumption curve. As can be seen in FIGURE (b), the accuracy of estimated power is improved compared with that before compensation, and the trend of energy consumption curve is more in line with the actual energy consumption.

V. ESTIMATION METHOD AND VERIFICATION OF WORKING TIME

A. ESTIMATION METHOD OF WORKING TIME

The working time estimation process is shown in FIGURE 9. The estimation steps include three parts: offline, online and identification.

(1) Offline part: The set of characteristic parameters is determined by analyzing the operation data of the experimental prototype loader. The 425 segments data are classified by FCM clustering analysis and the clustering center and the average power consumption of each category are obtained.

(2) Online part: The characteristic parameters are extracted from the latest segment data during the working process.

(3) Identification part: The distance between the coordinates of characteristic parameters and the center of each cluster is calculated. The category of the latest segment by the minimum distance principle is determined.

(4) Working time estimation step: According to the category of the latest segment of the experimental prototype loader, the segment consumed power is taken as the sum of the average consumed power of this category and the compensated power obtained according to Eq. (16). In addition, the power of the latest 10 segments is stored, and the iteration is carried out with Eq. (17). The power obtained is taken as the current energy consumption of the whole machine. Finally, the battery SOC value is obtained. The working time is estimated by Eq. (18).

\[
P_t = \frac{1}{10} \sum_{j=1}^{10} P_j
\]

\[
\Delta P_t = \frac{10}{\Delta P_t}
\]

\[
T_{\text{rdt}} = \frac{E_{\text{total}} \cdot \text{SOC}}{\Delta P_t}
\]

where, \( P_j \) is the \( j \)th segment estimated power. \( \Delta P_t \) is the iterative power. \( \text{SOC} \) is the percentage of remaining battery energy. \( E_{\text{total}} \) is the nominal quantity of power battery, it is 109.3 kWh in the studied loader. \( T_{\text{rdt}} \) is the working time.

B. ESTIMATION METHOD VALIDATION FOR WORKING TIME

The operational data of the prototype loader that do not participate in the cluster analysis are extracted from the offline database to verify the accuracy and universality of the proposed energy consumption model.

The estimated power and energy consumption curves with different energy consumption models is given in FIGURE 10. The total working time is 2.75 h and energy consumption under different models is listed in TABLE 4. From both the power and energy consumption curves, the proposed energy consumption model can better follow the actual power consumption level of whole machine. While, the traditional average energy consumption method within 1200 s is closely related to the loader energy consumption in the latest period.
When the past latest period has large power changes, the error is large in accordance.

The curve of iteration power, working time, actual power and energy consumption, and the power and energy consumption estimated by the proposed model during the operation of loader SOC from 100% to 0% are given in FIGURE 11. The total working time is 9.7 h. The battery nominal electricity, actual energy consumption and estimated energy consumption are listed in TABLE 5. Seen from the iterative power in FIGURE 11, with the continuous update of the latest segment estimated power, the iteration power also changes slightly. The working time fluctuates negatively with the iteration power curve. At the beginning of the operation, due to the high SOC value, fluctuation amplitude of the working time is large, while when SOC value approaches 0, it is relatively stable and close to 0.

FIGURE 12 shows the application of working time on the experimental prototype loader. The average power of 10 segments is iterated as the energy consumption state of the whole machine. Based on monitor hardware terminal, the power data of the latest segment is stored in a memory with power failure protection function in real time. The working time of the whole machine is displayed according to Eq. (18).

VI. CONCLUSION

(1) Considering the segments average torque of the motor as the characteristic parameter, FCM clustering algorithm online identification of each segment category is adopted to estimate the consumed power level according to the offline analysis of all kinds of other segments of the average power consumption and power compensation. The results show that the proposed energy consumption method has better estimation precision than the traditional method.

(2) The proposed working time estimation method of electric loader can feedback the working time of whole machine online from human-computer interactive terminal. The results
show that the working time curve fluctuates negatively with the iteration power curve.

(3) The working condition segment segmentation is carried out based on the analysis of the typical V-type working mode in a fixed environment in this study. The proposed estimation method can give guidance for further study on the complex operating environment and working mode.

ACKNOWLEDGMENT
The authors would like to thank the help of Hitachi Construction Machinery Company and Fujian Southchina Heavy Machinery Manufacture Company Ltd. for their technical support.

REFERENCES
[1] Q. Chen, S. Cai, X. Li, and T. Lin, “Power train system control of electric loader based on positive flow system,” Appl. Sci., vol. 12, no. 12, p. 6032, Jun. 2022.
[2] S. Cai, Q. Chen, T. Lin, M. Xu, and H. Ren, “Automatic shift control of an electric motor direct drive for an electric loader,” Machines, vol. 10, no. 5, p. 403, May 2022.
[3] Y. Zhang, W. Wang, Y. Kobayashi, and K. Shirai, “Remaining driving range estimation of electric vehicle,” in Proc. IEEE Int. Electr. Vehicle Conf., Mar. 2012, pp. 1–7.
[4] T. E. Kalayci, E. G. Kalayci, G. Lechner, N. Neuhuber, M. Spitzer, E. Westermeier, and A. Stocker, “Triangulated investigation of trust in automated driving: Challenges and solution approaches for data integration,” J. Ind. Inf. Integr., vol. 21, Mar. 2021, Art. no. 100186.
[5] Y. Luo, “2019 China new energy vehicle industry consumer survey report,” NBD Think Tank, Beijing China, Tech. Rep., 2019.
[6] W. Wu, J. Liu, M. Liu, Z. Rao, H. Deng, Q. Wang, X. Qi, and S. Wang, “An innovative battery thermal management with thermally induced flexible phase change material,” Energy Convers. Manage., vol. 221, Oct. 2020, Art. no. 113145.
[7] Y. Xie, J. Tang, S. Shi, Y. Xing, H. Wu, Z. Hu, and D. Wen, “Experimental and numerical investigation on integrated thermal management for lithium-ion battery pack with composite phase change materials,” Energy Convers. Manage., vol. 154, pp. 562–575, Dec. 2017.
[8] J. Meng, M. Ricco, A. B. Acharya, G. Luo, M. Swierczynski, D. J. Stroe, and R. Teodorescu, “Low-complexity online estimation for LiFePO4 battery state of charge in electric vehicles,” J. Power Sources, vol. 395, pp. 280–288, Aug. 2018.
[9] E. J. Yao, Z. Q. Yang, H. N. Dai, and T. Zao, “Estimation of electric vehicle’s cruising range based on real-time links average speed,” Appl. Mech. Mater., vol. 361, pp. 2100–2103, Aug. 2013.
[10] T. Tajima, W. Noguchi, and T. Aruga, “Study of a dynamic charging system for achievement of unlimited cruising range in EV,” SAE, USA, Tech. Rep. 2015-01-1686, 2015, doi: 10.4271/2015-01-1686.
[11] C. Du, G. Du, K. C. Tan, and Y. S. Liu, “Research on remaining driving range estimation of electric vehicle based on dynamic working condition,” Adv. Mater. Res., vol. 945, pp. 509–515, Jun. 2014.
[12] T. Dai, Z. Zhang, F. Wang, L. Sun, and R. Wang, “Accuracy of range estimation of pure electric vehicles under compound conditions comparative analysis,” J. Phys. Conf., vol. 1634, no. 1, Sep. 2020, Art. no. 012120.
[13] T. Dai, B. Zhou, Y. Zhang, G. Chen, and P. Liu, “Rapid evaluation method for accuracy of range estimation of pure electric vehicle range estimation based on CLTC-P” in Proc. E3S Web Conf., vol. 235, no. 2, 2021, p. 1035.
[14] I. Misi, A. Fotouhi, and N. Ewin, “Electric vehicle energy consumption modelling and estimation—A case study,” Int. J. Energy Res., vol. 45, no. 1, pp. 501–520, Jan. 2020.
[15] T. Lin, Y. Lin, H. Ren, H. Chen, Q. Chen, and Z. Li, “Development and key technologies of pure electric construction machinery,” Renew. Sustain. Energy Rev., vol. 132, Oct. 2020, Art. no. 110080.
[16] W. Zhang, S. Wang, L. Hou, and R. J. Jiao, “Operating data-driven inverse design optimization for product usage personalization with an application to wheel loaders,” J. Ind. Inf. Integr., vol. 23, Sep. 2021, Art. no. 100212.
[17] S. Wang, S. Wang, L. Hou, and R. J. Jiao, “Optimization design of loader gearbox considering big data of product operation,” J. Mech. Eng., vol. 54, pp. 218–232, Sep. 2018.
[18] H. Xie, G. Tian, H. Chen, J. Wang, and Y. Huang, “A distribution density-based methodology for driving data cluster analysis: A case study for an extended-range electric city bus,” Pattern Recognit., vol. 73, pp. 131–143, Jan. 2018.
[19] M. Montazeri-Gh, A. Fotouhi, and A. Naderpour, “Driving patterns clustering based on driving feature analysis,” ARCHITECTURE, vol. Inst. Mech. Eng. C, J. Mech. Eng. Sci., vol. 225, no. 6, pp. 1301–1317, 2011.
[20] O. Komori and S. Eguchi, “A unified formulation of K-means, fuzzy C-means and Gaussian mixture model by the Kolmogorov–Nagumo average,” Entropy, vol. 23, no. 5, p. 518, Apr. 2021.
[21] K. Zhou, S. Yang, and Z. Shao, “Household monthly electricity consumption pattern mining: A fuzzy clustering-based model and a case study,” J. Cleaner Prod., vol. 141, pp. 900–908, Jan. 2017.
[22] F. Zhao, Y. Chen, H. Liu, and J. Fan, “Alternate PSO-based adaptive interval type-2 intuitionistic fuzzy C-means clustering algorithm for color image segmentation,” IEEE Access, vol. 7, pp. 64028–64039, 2019.
[23] Z. Wu, Z. Wu, and J. Zhang, “An improved FCM algorithm with adaptive weights based on SA-PSO,” Neural Comput. Appl., vol. 28, no. 10, pp. 3113–3118, Oct. 2017.

ZHONGSHEN LI received the B.E. degree from Zhejiang University, Hangzhou, China, and the Ph.D. degree from Huqiao University, Xiamen, China. He is a Professor with the College of Mechanical Engineering and Automation, Huqiao University. His current research interests include energy saving, powertrain, and control for the electric construction machinery.

TIANLIANG LIN received the Ph.D. degree in mechatronic engineering from the State Key Laboratory of Fluid Power and Mechatronic Systems, Zhejiang University. In 2016, he joined at the College of Mechanical Engineering and Automation, Huqiao University. He is currently a Professor and the Vice President of the College of Mechanical Engineering and Automation. His research interests include energy saving technology and control methods of electro hydraulic transmission for electric construction machinery and design of advanced equipment.

QIFA GAO received the B.E. degree from Huqiao University, Xiamen, China, where he is currently pursuing the M.E. degree. His current research interest includes condition identification for electric construction machinery.