Article

Big-Data-Based Thermal Runaway Prognosis of Battery Systems for Electric Vehicles

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Abstract: This paper presents a thermal runaway prognosis scheme based on the big-data platform and entropy method for battery systems in electric vehicles. It can simultaneously realize the diagnosis and prognosis of thermal runaway caused by the temperature fault through monitoring battery temperature during vehicular operations. A vast quantity of real-time voltage monitoring data was collected in the National Service and Management Center for Electric Vehicles (NSMC-EV) in Beijing to verify the effectiveness of the presented method. The results show that the proposed method can accurately forecast both the time and location of the temperature fault within battery packs. Furthermore, a temperature security management strategy for thermal runaway is proposed on the basis of the *Z*-score approach and the abnormity coefficient is set to make real-time precaution of temperature abnormity.

Keywords: thermal runaway; big-data platform; battery systems; electric vehicles; National Service and Management Center for Electric Vehicles.

1. Introduction

Battery systems are a key component that strongly influences the driving performance and cost-effectiveness of Electric vehicles (EVs). The travel distance, acceleration performance and security requirement of EVs cannot be satisfied by the energy density and power density of the single-cell, so the cells need to be assembled into a small battery module according to certain forms, then a battery system can be composed of a number of battery modules in series or parallel connecting mode, which can satisfy the driving requirement of EVs [1]. When the heating-rate exceeds dissipation-rate, the thermal runaway may occur with extreme phenomena such as battery leakage, smoking or gas venting. With continuous market penetration of EVs in recent years, a spectrum of fatal fire accidents takes place around the world, which forms great challenges for system safety and durability. Generally, thermal runaway occurs when an exothermic reaction goes out of control, that is the reaction rate increases due to an increase in temperature causing a further increase in temperature and hence a further increase in the reaction rate, which possibly resulting in an explosion [2]. Battery degradation and failure are strongly account of the abnormality in cell temperature. Many electric vehicle applications employ thermal management strategies to keep the health state and extend the battery life [3].

A preeminent battery thermal management system (BTMS) is extremely necessary and critical because extreme temperatures can affect the driving performance and safety of EVs. In some extreme cases, fire and explosions might be triggered by thermal runaway if battery temperature is not within the safety scope. The effectiveness of a BTMS depends on the design of battery systerm and the operating conditions. Daowd et al. [4] proposed an intelligent battery management system (BMS) including a battery pack charging and discharging control with a battery pack thermal management system. Finally an experimental step-up has been implemented for the validation of the proposed balancing system. Lan et al. [5] developed a novel design of BTMS based on aluminum minichannel tubes and applied it on a single prismatic Li-ion cell under different discharge rates. To investigate the thermal performance of lithium-ion battery pack, Qian et al. [6] established a three-dimensional numerical model using a type of liquid cooling method based on mini-channel cold-plate and. Though simplified approaches, Mastali et al. [7] developed the simplified electrochemical multi-particle model and homogenous pseudo two-dimensional model to decrease the computational time, the speed and simplicity of three-dimensional electrochemical-thermal models are still of concern. The second kind of models is the equivalent circuit model (ECM), where the battery is usually regarded as a mass point [8, 9]. Therefore, they are suitable to be implanted in the battery management system (BMS) for the state of charge (SOC) or the state of health (SOH) estimation [10-13]. Lin et al. [14] and Forgez et al. [15] added lumped-parameter thermal models to ECM to predict the thermal characteristics of the cell, which made the model more comprehensive. The results showed this method could effectively control the battery temperature at 5℃ discharge and the temperature uniformity was obviously improved. Through the studies metioned in these literatures, apart from a few of study monitored temperature changes through the temperature sensor, no effective and systematic theory or method concerns the accurate and timely temperature fault detection and early detecting and warning of thermal runaway during real operation.

Menwhile, in order to reach higher energy density, the size and complexity of the battery cell is growing, which may lead to the potential temperature imbalance and the risk of various battery faults. So many fault diagnosis methodologies have been presented to prevent and reverse the thermal runaway of battery system. For external short-circuit detection, Chen et al. [16] presented a two-layer model-based a fault diagnosis algorithm, which can give a precise model-based diagnosis. Seo et al. [17] proposed a high accuracy model-based switching model method (SMM) to detect the internal short circuit (ISCr) in the Li-ion battery, which helping the battery management system to fulfill early detection of the ISCr. Zhang et al. [18] proposed a novel method is to perform online and real-time capacity fault diagnosis for a parallel-connected battery group (PCBG) and the fault simulation and validation results demonstrate that the proposed methods have good accuracy and reliability. Due to the inconsistent and varied characteristics of lithium-ion battery cells, Gong et al. [19] and Liu et al. [20] proposed the data-driven biascorrection-based modeling method and model-based sensor fault diagnosis method, which can significantly reduce the computation work and remain good model accuracy. Bai et al. [21] applied a combined power generation system (CPGS) to achieve a reliable evaluation of a distribution network with microgrids combined with fault duration. In addition, many model-based diagnostic algorithms such as extended kalman were presented that diagnoses thermal faults in Lithium-ion batteries [22-25]. The simulation and experimental studies were also presented to illustrate the effectiveness of the proposed schemes. However, all these mentioned researches have applied on online detection and prediction on the SOH of battery systerm. But few of them study on early fault warning for battery system based on experimental data and big data platform of EVs. Futhurmore, these applications can not accurately detect, not to mention predict where and when the faults occurred in the batteries.

However, there are few literatrues dealing with temperature fault diagnosis and prognosis issues of battery systems directly for EV applications. The conventional threshold methods lack the ability of identifying the time and location the abnormity occurs if the abnormal data still remain within the permitted limits together with the safety data. At present, the existing BMS technology cannot achieve early warning effect of battery thermal runaway. This paper mainly studied a prognosis method for the thermal runaway of battery systems caused by the temperature fault during vehicular operations. For addressing these mentioned issues, the entropy method was employed and the results showed that the abnormal data can be diagnosed based on the entropy values. Furthermore, the abnormity coefficient was set up using the Z-score method to evaluate the fault severity. Accordingly, homologous management strategies were put forward to handle detected temperature fault problems and make real-time assessment of the fault levels. To validate the proposed method in our research, a vast quantity of real-time voltage monitoring data was collected from the NSMC-EV in Beijing. The results show that the proposed method can accurately forecast both the time and location of the temperature fault within battery packs.

The remainder of this paper is structured as follows: Section 2 gives a brief introduction of the proposed prognosis method. Sections 3 describes the big data platform for data acquisition. Sections 4 present the detailed prognosis analysis and discussions about temperature faults for battery systems. Section 5 summarized the key conclusions.

2. Diagnosis and prognosis method

Information entropy has been widely used to judge the degree of system disorder in thermodynamics, information science and other fields snce it was proposed, which was firstly introduced by Laude Elwood Shannon in 1948 [26]. It has been widely used to judge the degree of system disorder in a wide range of scientific fieldss since it was proposed and still an important method nowadays [27]. Its capability of measuring the information content for a given sequence, combined with the ease of information processing, makes it a very useful and popular tool. The typical calculation process of the Shannon entropy is shown as follows:

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$$H(X) = -\sum_{i=1}^{n} p(x_i)\log p(x_i) \tag{1}$$

where $H(X)$ is the Shannon entropy, $p(x_i)$ is the data probability density in the ith region and n is the number of the regions.

Z-score is also called the standard score, which has the function of risk prediction in the fields of statistics and finance. For instance, Nanayakkara [28] developed a financial distress prediction model for the Sri Lankan companies using the Z-score model. Chadha and Aloy et al. [29, 30] used Altman's Z-score model to evaluate the financial performance and avoided the high cost that is associated with distress in predicting bankruptcy. However, the Z-score method has not demonstrated the ability and potential of risk prediction of mechanical or electrical fault, especially electric vehicles. In this paper, the Z-score method is used to quantitatively evaluate the temperature fault within battery packs, which can make real-time detection and prognosis of abnormal temperature by setting abnormal coefficient. The voltages and temperatures of different cells are always different due to the inconsistency of battery pack. The formula of Z-score is expressed as:

$$Z = \frac{x-\mu}{\delta} \tag{2}$$

where x is a specific score, μ is the average score and σ is the standard deviation.

In order to find a reasonable real-time detection and evaluation standard, we set the abnormity coefficient based on Z-score as follows:

$$A = \frac{|E\text{-}E_{ave}|}{\sigma_E} \tag{3}$$

where E is the Shannon entropy, E_{ave} is the average Shannon entropies and σ_E is the standard deviation of entropy.

It is worth mentioning that there are multiple iterations of the past data in the entropy calculation. However, the monitoring and diagnosis are required in real-time to predict the state of the battery and connection failure, thus the Shannon entropy calculation needs to be appropriately modified to accommodate the online implementation requirement of EVs. The diagnosis and prognosis algorithm flowchart based on the different extreme value selections for the Shannon entropy is shown as Figure 1.

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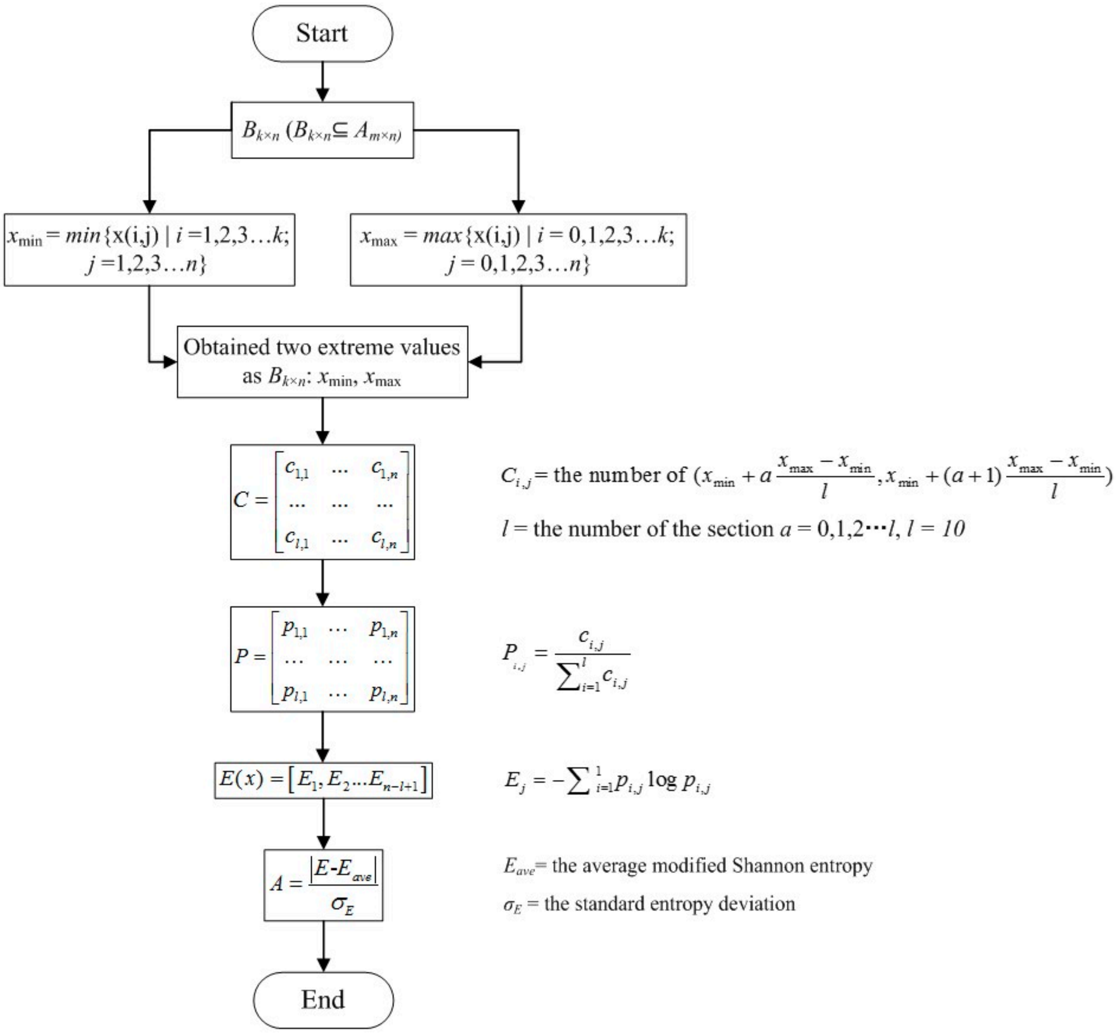

Figure 1. The diagnosis and prognosis algorithm flowchart

3. Data acquisition platform

The temperature and voltage data in this study was collected from the NSMC-EV [31], which has the functions of monitoring and collecting the real-time running data of EVs such as voltage and temperature of battery systems, conducting in-depth analysis and research through big-data techniques. The monitoring and management process of the NSMC-EV is as shown in Figure 2. The data acquisition frequency from the monitored vehicles ranges from 0.03Hz to 1Hz. In addition, the failure statistics of vehicle running state are classified into six levels by failure types, the first level of which is the most dangerous. When anomalous information such as over-temperature is detected, a corresponding fault alarm would be immediately dispatched to the relevant vehicle according to the established response protocols. Eventually, the statistical statements about the vehicle running characteristic and fault statistics will be formed in the forms of daily, weekly and annual report.

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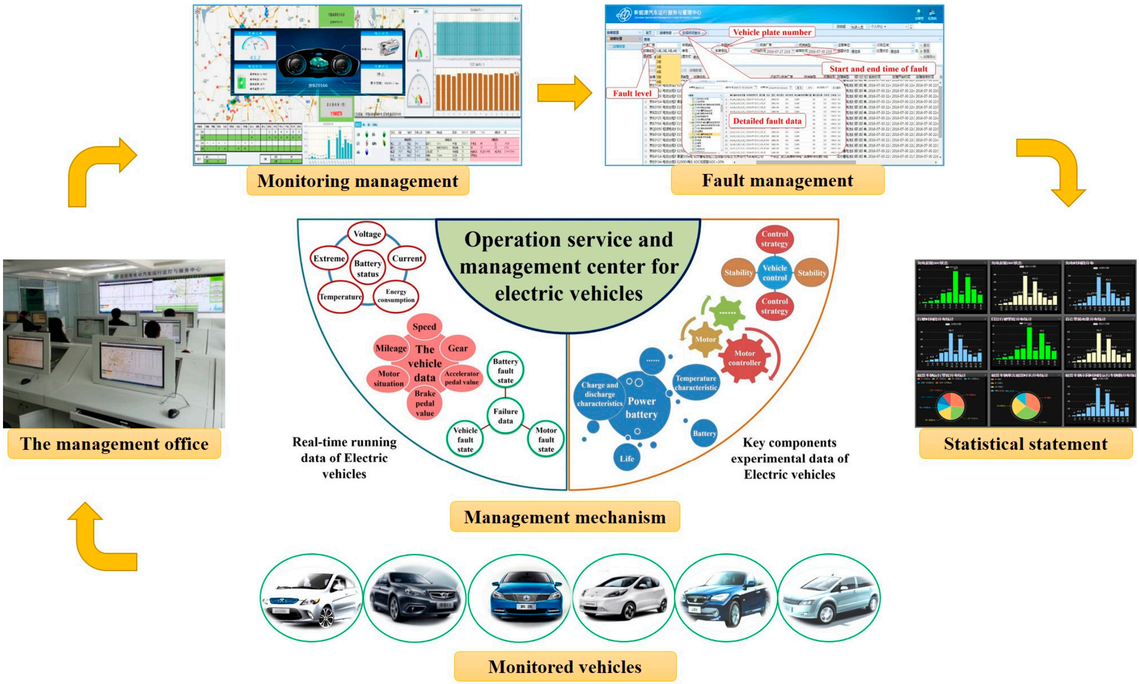

Figure 2. The monitoring and management process of the NSMC-EV

Through the big data platform, almost all kinds of running information and the key components states of the monitored vehicles can be obtained using the vehicle-to-platform communication. The main monitoring objects and purposes of NSMC-EV is as shown in Table 1, from which we can see that there is a potential thermal runaway risk once the battery temperature beyond the maximum threshold. That also means that it needs human intervention of identifing potential problems to safeguard the vehicle operation and keep the battery cycle life. The logical topological management structure of NSMC-EV is sketched in Figure 3, which is a multi-level structure of "acquisition/access-storage-analysis-application", implementing the fusion and centralized supervision multi-source information, one-stop query and service as well as based data support for the whole series of models. Up to now, this center has provided round-the-clock monitoring service for over 7000 units of EVs mainly consisted of public vehicles such as taxis, buses and sanitation vehicles, etc.

Table 1. The main monitoring objects and purposes of NSMC-EV

Order number	Monitoring object	Monitoring purpose
1	Battery voltage	To confirm whether there is a value beyond the range. The low voltage will lead to insufficient capacity, and the high voltage will cause high temperature, gas precipitation, water losses and grid corrosion of battery.
2	Cell voltage	
3	Battery temperature	To identify potential problems and optimize the vehicle operation and cycle life of the battery. Once beyond the maximum value means that there is a potential thermal runaway and it needs for human intervention.
4	Ambient temperature	Too high ambient temperature will shorten battery life and too low ambient temperature will lead to battery capacity decline.
5	Temperature difference	Large temperature difference is because of the inconsistency of the battery, which will cause endurance deterioration.
6	Charge and discharge current	Provide the health state information of the battery to users, which can be used to indicate the operating state and the integrity of the battery connection.

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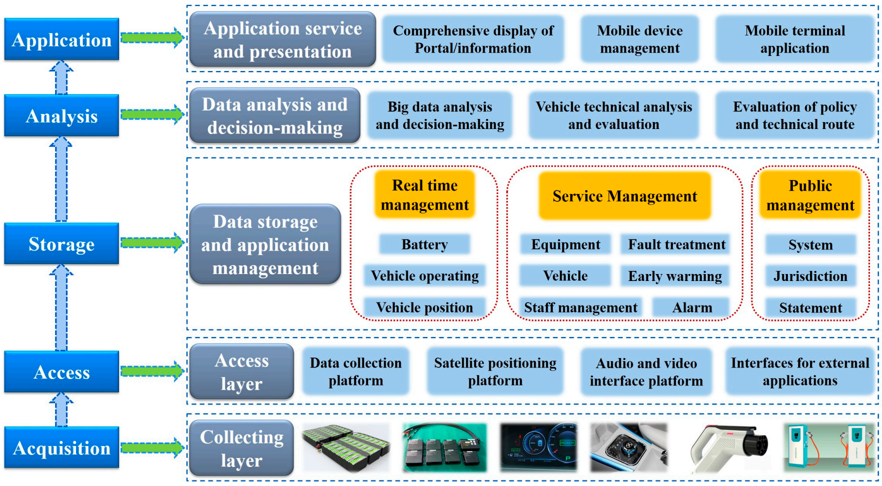
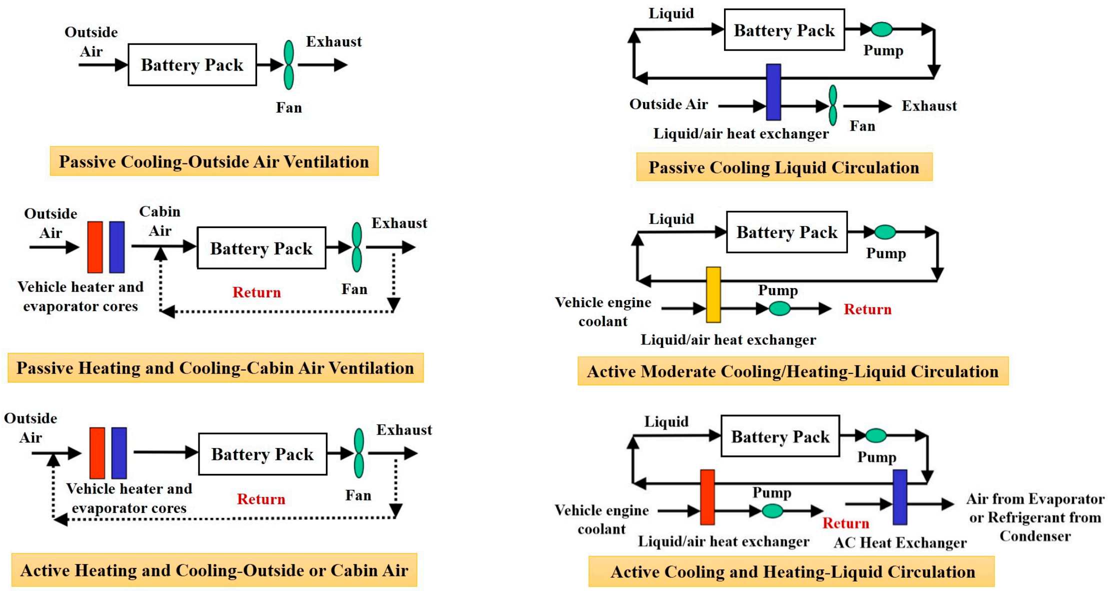


Figure 3. The logical topological management structure of the NSMC-EV

4. The thermal fault prognosis analysis and discussions

4.1. Thermal management schematic

A well-designed thermal management system is required to regulate EV and HEV battery pack temperatures evenly, keeping them within the desired operating range. Proper thermal design of every module has a positive impact on overall pack thermal management with corresponding thermal behavior. In general, a battery thermal management system (BTMS) with a small amount of battery modules using air as the heat transfer medium is less complicated, effective than that using liquid for cooling/heating, but for a battery thermal management system with a large amount of battery modules is just the opposite. General schematics of BTMS using air and liquid are respectively as shown in Figure 4, from which we can see three different heating/cooling schemes using air and another three different heating/cooling schemes using liquid. The thermal management system may be passive (i.e., only the ambient environment is used) or active (i.e., a built-in source provides heating and/or cooling at cold or hot temperatures). The thermal management control strategy is settled through the electronic control unit. A thermal management system may use air for heating/cooling ventilation or use liquid as cooling/heating insulation layer. In addition, phase change materials can also be used as another kind of scheme for cooling/heating as a thermal storage. Whereas, a combination of these three methods is the most common in current BTMS.



(a) (b)

Figure 4. General schematic of BTMS using air and liquid

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Generally, for parallel HEVs, an air thermal management system is adequate, whereas for EVs and series HEVs, liquid-based systems may be required for optimum thermal performance. NiMH batteries require a more elaborate thermal management system than Li-ion and Valve Regulated Lead Acid (VRLA) batteries. Li-ion batteries also need a good thermal management system due to the concerns of safety and low temperature performance. Furthermore, the location of the battery pack may also have a strong impact on the type of BTMS and whether the pack should be air cooled, liquid cooled or others.

In addition to considering the temperature of a battery pack, uneven temperature distribution in a pack should be also considered. Temperature variation from module to module in a pack could lead to different charging/discharging behavior for each module. This, in turn, could lead to electrically unbalanced modules or packs and reduced pack performance. Higher temperatures degrade batteries more quickly, while low temperatures reduce power and energy capabilities, resulting in cost, reliability, safety, range, or drivability implications. Therefore, battery thermal management is needed for EVs to keep the cells in the desired temperature range, minimize cell-to-cell temperature variations, prevent the battery from going above or below acceptable limits, maximize useful energy from cells and pack and use little energy for operation.

A perfect BTMS can not only heat and cool the battery system as soon as possible, but also control the system's thermal safety to prevent thermal runaway. The typical types of temperature faults in NSMC-EV are over-temperature and excessive temperature difference (TD), which are usually caused by abnormal temperature variation. Detecting when and where the abnormal temperature occurs will play an extremely important role in safety battery management. The normal operating temperature range of Lithium-ion battery is -20℃~ 60℃, which is generally controlled at 15℃~60℃ for the safe operation of the vehicles. The maximum permissible TD is 5℃, that is to say the TD should be controlled within TD<5℃. There are a certain amount of temperature probes in different locations of the battery pack for different vehicles, the monitoring platform of NSMC-EV will send a over-temperature alarm when any temperature probe exceed 45℃ and a excessive TD alarm when TD>5℃.

4.2. The fault prognosis of over-temperature

In order to verify the prognosis feasibility and reliabilityof the proposed prognosis method for temperature anomaly. The cell data of Vehicle 1 (vehicle plate: Jing Q6S772, a Fukuda electric sanitation truck) in 2017-03-06 was retrieved from NSMC-EV and the work period of monitoring vehicle was 09:48:39-16:07:52, which occurred alarm of over-temperature of T>45℃ at 11:07:20. There are 16 temperature probes in the different locations of the battery pack and the data acquisition frequency of 0.05Hz. The temperature and SOC curves of Vehicle 1 is as shown in Figure 5, from which we can see that the temperature of Probe 1 and Probe 9 has different fluctuation with the vehicle running, and Probe 1 occurs over-temperature fault. However, although the abnormity appeared early, it cannot be identified before the alarm occurs by the conventional temperature sensor because it is still in the normal temperature range of T<45℃.

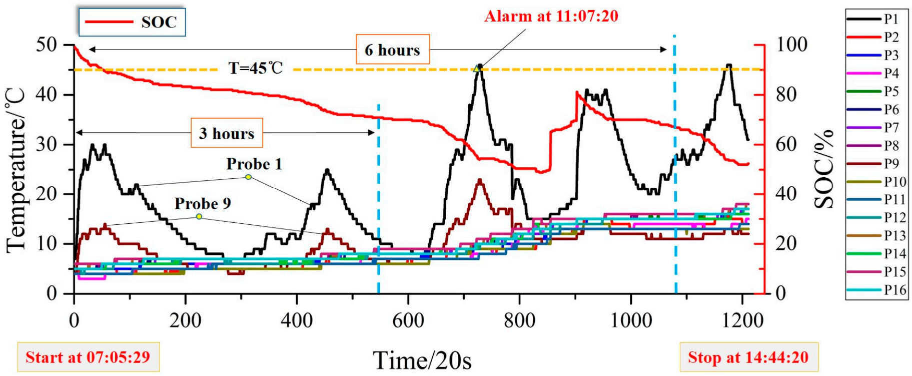

Figure 5. The temperature and SOC curves of Vehicle 1

As for the presented entropy method in Section 2, the length of computation window *K* has significant influence on the accuracy of entropy. If *K* is too small, temperature fluctuations would not be fully revealed. On the contrary, the iterations would become too few to pick the abnormal temperature fluctuations out. Furthermore, because of the graduality and stability of temperature, the temperature fluctuations are relatively small and the position of abnormal temperature is hard to be detected in a short period of time, so K=100 was selected as the length of computation window in this study through the trial-and-error method.

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With the vehicle operation and the rising of battery temperature, the temperature of all probes will be gradually stable. It is difficult to detect the abnormal temperature fluctuations after temperature stability or failure, so the monitoring data should st be processed from the the vehicle starting every day. Figure 6(a) shows the abnormal coefficients of Vehicle 1 at the first 6 hours, from which we can see that Probe 1 and Probe 9, especially Probe 1, have obviously bigger abnormal coefficients than others. This fluctuation of abnormal coefficients is consistent with with the temperature fluctuation shown in Figure 5, which verifies that the proposed method can accurately identify the time and location of the abnormal temperature. In order to verify the prognosis performance of the proposed method, we furtherly choose the first 3 hours as the calculation unit, during when the over-temperature has not been triggered. The abnormal coefficient in the first 3 hours of Vehicle 1 is as shouwn in Figure 6(b), which shows that Probe 1 and Probe 9 with abnormal temperature can also be detected out. So the proposed method can accurately predict where the over-temperature fault will occur in advance.

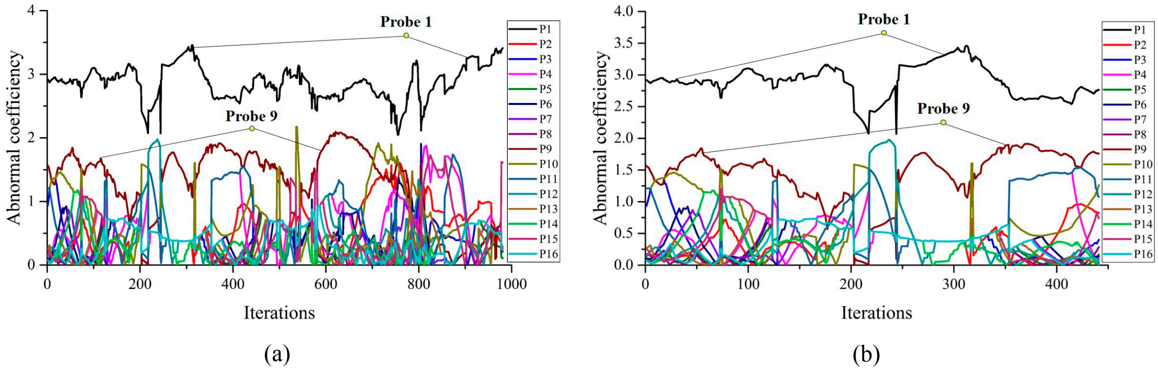

Figure 6. The abnormal coefficient at the (a) first 6 hours and (b) first 3 hours of Vehicle 1

As shown in Figure 6, the anomaly coefficient curves has crosses and accidental extreme, which is is not conducive to quantify and evaluate the level of abnormal coefficient. In order to make the anomaly coefficient more readable and to facilitate horizontal comparison and evaluation between different temperature probes, boxplot was applied to expressing the abnormal coefficient to forecast the temperature faults in this section, which can also be expressed as A_b. Boxplot can reflect the center and spread scope of the data distribution. With by drawing the boxplots of multiple sets of data on the same coordinates, the distribution difference can be clearly displayed. The structure diagram of boxplot is as shown in Figure 7. Boxplot requires the statistical concept of quartile, which means the position numbers of three segmentation points. Q1 is called the lower quartile, which is equal to the number of the 25% of all values from small to big. Q2 is also called median, which is equal to the number of the 50% of all values from small to big. Q3 is also called upper quartile, which is equal to the number of the 75% of all values from small to big. The abnormal coefficient A_b is median of the boxplot in this paper.

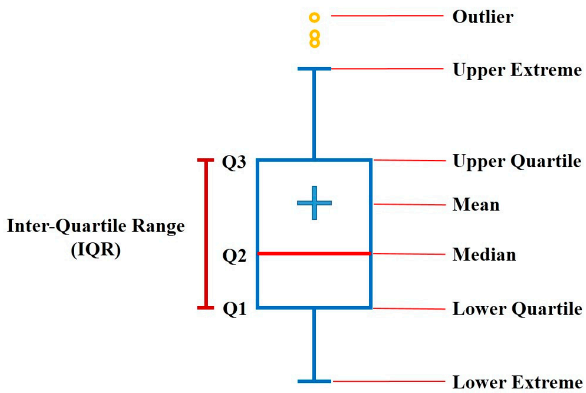

Figure 7. The structure diagram of boxplot

The abnormal coefficient boxplot at the (a) first 6 hours and (b) first 3 hours of Vehicle 1 is as shown in Figure 8. The results shows that Probe 1 and Probe 9 can be easily detected out and the A_b of Probe 1 is much

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bigger than that of Probe 9 and others. By applying a certain detection threshold as A_b=1 and A_b =1.2, the over-temperature fault alarm can be avoided if the abnormal temperature is detected in advance by this method. Actually, for accurate over-temperature fault prognosis, much more monitoring data were retrieved from NSMC-EV and analyzed by the proposed method. The evaluation strategy of abnormal temperature was attained by the trial-and-error method through a large amount of analytical results, which is feasible, reliable and can accurately forecast both the time and location of over-temperature fault within battery pack. Thus, this method can effectively prevent the over-temperature fault by detecting the abnormal temperature in real-time.

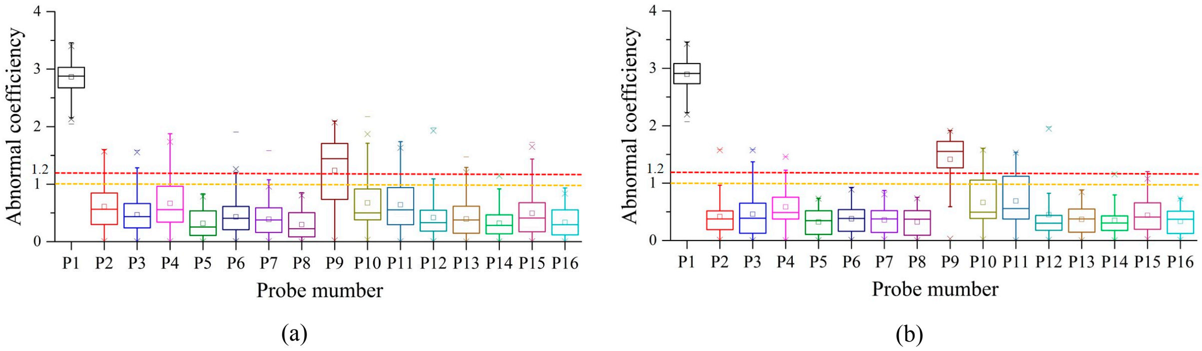

Fig. 8. The abnormal coefficient boxplot at the (a) first 6 hours and (b) first 3 hours of Vehicle 1

4.3. The fault prognosis of temperature difference

The other typical thermal fault in NSMC-EV is excessive temperature difference (TD). The cell data of Vehicle 2 (vehicle plate: Jing B1Y163, CA E30 electric taxi) in 2016-11-02 was retrieved from NSMC-EV and the work period of monitoring vehicle was 07:55:57-23:59:54, which occurred alarm of excessive TD fault of TD>5℃ at 18:14:55, after the tesed vehicle traveled for more than 9 hours. There are 16 temperature probes in the different locations of the battery pack and the data acquisition frequency is 0.1Hz. The temperature curves of Vehicle 2 is as shown in Figure 9, from which we can see that the temperature of Probe 11 has abnormal fluctuation with the vehicle running, which directly leads to the generation of TD fault. However, this abnormity can not detected by the conventional temperature sensor because it is still in the normal temperature range of 0℃~30℃.

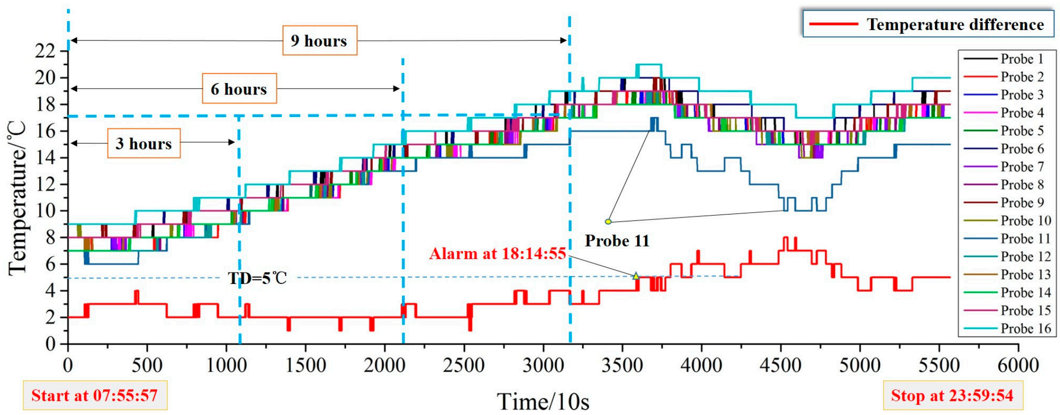

Figure 9. The temperature curves of Vehicle 2

The SOC, speed and TD curves of Vehicle 2 in 2016-11-02 is as shown in Figure 10, from which we can see that this car charged twice with parking severally at 14:58:03 and 21:47:46. In addition, the curves of speed and TD shows that the TD curves rise slowly with the increase of speed and vehiculor running.

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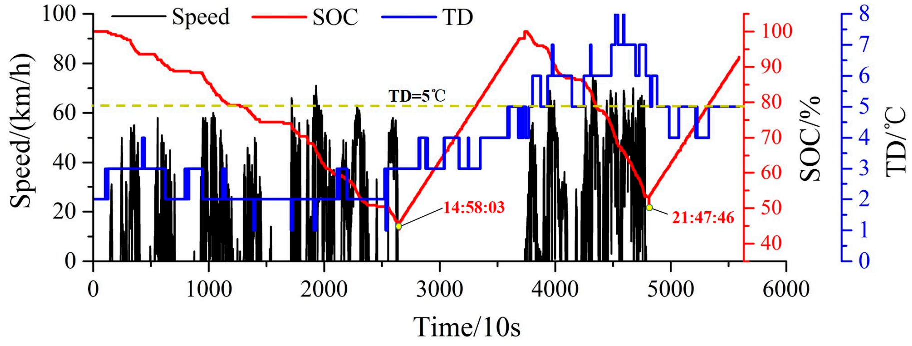
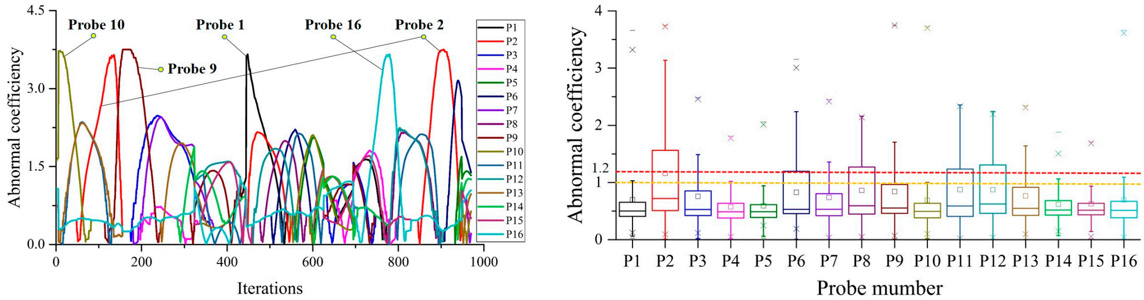


Figure 10. SOC, speed and TD curves of Vehicle 2

The abnormal coefficient and boxplot of Vehicle 2 at the first 3 hours in 2016-11-02 is as shown in Figure 11(a) and Figure 11(b). From Figure 11(a) we can see that there are some probes have anomalous extremum points but no probe has obvious bigger abnormity coefficiency than others. Figure 11(b) shows that the median position of all probes are also confirmed to A_b<1, which is consist with the temperature curves in Figure 9. So all probes are in safety temperature status and no abnormal temperature will be detected at the first 3 hours.



(a) (b)

Figure 11. The abnormal coefficient and boxplot at the first 3 hours of Vehicle 2

Due to the design flaws of battery box or thermal runaway of batteries, the temperature change trend of different temperature probes will have certain difference. With the vehicle operation and the rising of battery temperature, the temperature of the temperature probes will be gradually stable. It is difficult to detect the abnormal temperature fluctuations after temperature become stable or failure, so we choose 3 hours from the starting work as the initial calculation window, if the abnormal temperature probe can not be detected in the first 3 hours, then continue to calculate for another 3 hours. The abnormal coefficient and boxplot of Vehicle 2 at the first 6 hours and the first 9 hours in 2016-11-02 is as shown in Figure 12 and Figure 13. Figure 12(a) shows that Probe 11 has abnormal temperature fluctuation but is difficult to be detected out. Figure 12(b) shows that the median position of Probe 11 is bigger than those of other probes and the abnormal coefficient A_b>1. From Figure 13(a) we can see that Probe 11 has distinct abnormal fluctuation and easier to be detected out. Figure 13(b) shows that the median position of Probe 11 is far with those of another probes and the abnormal coefficient A_b>1. The results are consist with previous temperature curves in Figure 9. The excessive TD fault of Vehivel 2 occurred after it traveled for more than 9 hours. So the proposed prognosis method can detecet the abnormal probe in real time and dentify the fault location in advance.

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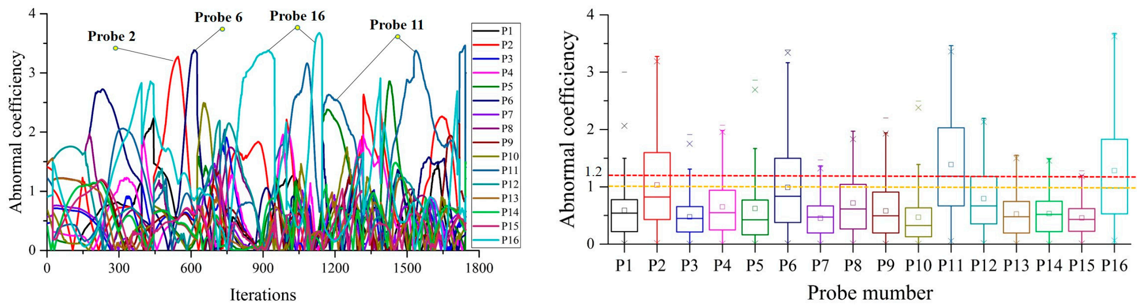
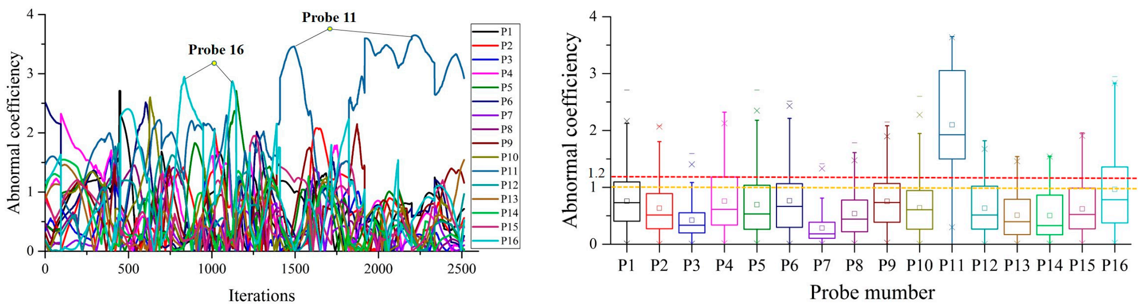


(a) (b)

Figure 12. The abnormal coefficient and boxplot at the first 6 hours of Vehicle 2



(a) (b)

Figure 13. The abnormal coefficient at the first 9 hours of Vehicle 2

In order to verify the stability of this method, the cell data of Vehicle 2 in 2016-11-01 was retrieved from NSMC-EV and the period of monitoring data was 10:51:05-23:36:38. Vehicle 2 occurred alarm of excessive temperature difference of TD>5℃ at 17:12:15, after the tesed vehicle traveled for more than 9 hours. The temperature curves of Vehicle 2 are as shown in Figure 14, from which we can see that the temperature of Probe 11 has different fluctuation with the vehicle running. However, we can not identify the abnormal temperature as long it is still in the safe temperature range.

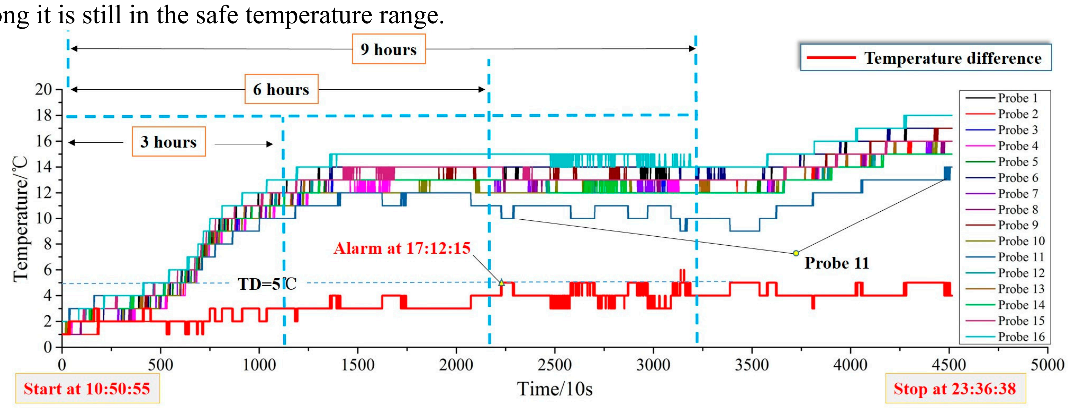


Figure 14. The temperature curves of Vehicle 2

The abnormal coefficient and boxplot at the first 3 hours of Vehicle 2 is as shown in Figure 15. The results shows that Probe 11 can be easily detected out and the A_b of Probe 11 A_b>1, and the excessive TD fault can be avoided if the abnormal temperature is detected in advance using this method. Actually, for accurate excessive TD fault prognosis, much more monitoring data were retrieved from NSMC-EV and analyzed by the proposed method, which shows this mehod is feasible, reliable and stable to accurately forecast the the time location of excessive TD fault within battery pack in advance. Thus, this method can effectively prevent the excessive TD fault by detecting the abnormal temperaturee in real-time.

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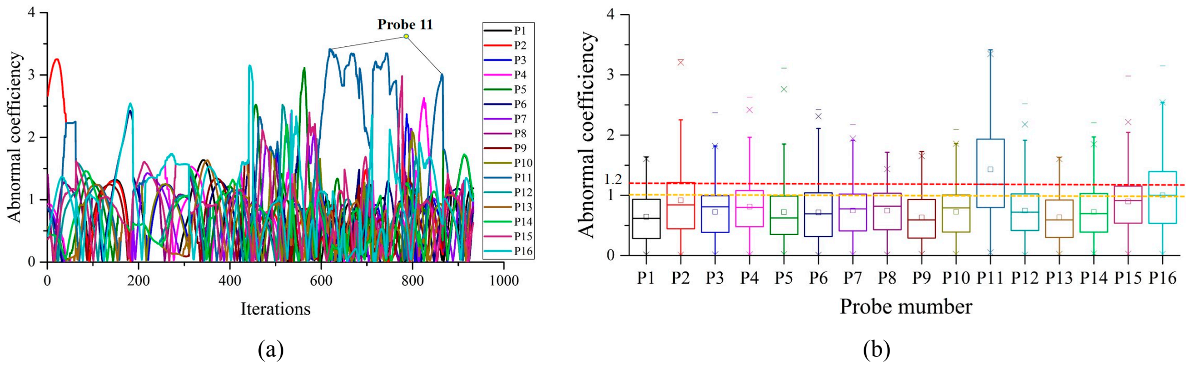

Figure 15. The abnormal coefficient and boxplot at the first 3 hours of Vehicle 2

4.5. The security management strategy and discussion

Through the above analysis, the over-temperature fault and excessive TD fault can both be predicted using the proposed method and it has good reliability and stability. By applying a certain detection threshold as A_b=1 and A_b=1.2, the cell with abnormal temperature can be detected before the thermal faults occur using the proposed method, which has vital significance for the future prognosis and safety management of the battery fault, especially for the prevention of thermal runaway. The prognosis strategy of thermal fault can be attained through analysing much more monitoring data retrieved from NSMC-EV using the trial-and-error method. The prognosis strategy flowchart of thermal fault is as shown in Figure 16.

NSMC-EV currently provides round-the-clock monitoring service mainly for public vehicles apart from private cars, such as taxis, buses and sanitation vehicles, which always have a relatively little number of cells. But, according to the analysis and discussion of different sets of monitoring data, by setting a suitable value of calculation window K, this technique is still valid even if the EV have a larger number of cells (i.e., Tesla, with 6000+ cells). So it has a strong timeliness and will have greater application prospects if some private cars with more cells are monitored and managed by NSMC-EV in the future, which will also provide a foundation for safety precaution mechanism establishment of battery thermal runaway.

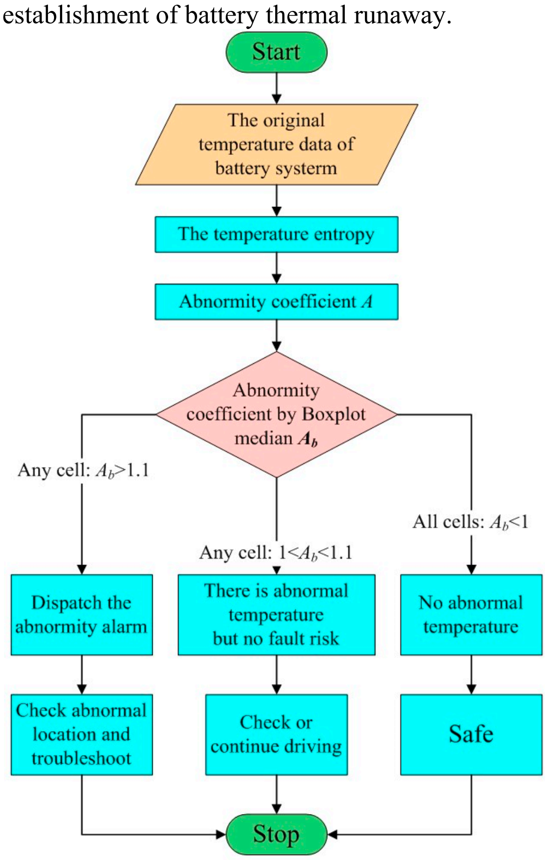

Figure 16. The prognosis strategy flowchart of thermal fault

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5. Conclusions

This paper presented a real-time thermal fault diagnosis and prognosis method based on the NSMC-EV in Beijing. A vast quantity of real-time voltage monitoring data was collected from this big data pltform to verify the effectiveness of the presented prognosis method. The Shannon entropy was applied to analyze the monitoring data. The analysis results showed that the proposed mrthod can detect probes with abnormal temperature, which can also effectively predict the occurrence time and location. These were achieved with relatively small calculation effort, which makes it implementable in real safety BMS. The feasibility, reliability and stability of the prognosis capability were also separately discussed and verified by analyzing large amounts of monitoring data. Furthermore, the prognosis and safety management strategiy for thermal fault of battery system were also developed by applying the Z-score method, and the abnormity coefficients were set to make real-time evaluation on the faulty levels. The presented method can be used in all disorder systems with abnormal fluctuations regardless the data types and application fields, so it can be used in not only electric vehicles but also in other areas in complex abnormal fluctuations environment.

Acknowledgements: The project is supported by the State Key Program of National Natural Science Foundation of China (No. U1564206) and the Special Innovation Methods Program of Science and Technology Ministry of China (Grant No. 2015IM030100).

Author Contributions: Jichao Hong provided algorithms, analyzed the data and wrote the paper; Zhenpo Wang and Peng Liu conceived the structure and research direction of the paper.

Conflicts of Interest: The authors declare no conflict of interest.

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