BATTERY ANOMALY AND DEGRADATION DIAGNOSIS FOR RENEWABLE ENERGY PLANT

Jingjing ZHANG Lu GENG Yuanchen MA
Hitachi (China) Research & Development Corporation
jjzhang@hitachi.cn lgeng@hitachi.cn ycma@hitachi.cn

ABSTRACT

Battery storage is usually applied in the renewable energy (RE) plant for improving RE utilization and integration ability to the power grid. Battery health status detection is essential for plant reliable, safe, and efficient operation. This paper presents a battery anomaly and degradation diagnosis method based on data mining technology. Firstly, battery cell characteristic vectors are set and classified under charging, discharging and standing states respectively. Synthetic Characteristic Vectors (SCV) are formed for abnormal battery cell identification by K-means algorithm. Secondly, battery degradation degree is estimated by searching and comparing with ideal performance curve under the same running status in the historical database. Finally, taking an actual renewable energy plant with battery storage for example, the results verified the correctness and validity of the proposed method.

INTRODUCTION

The upward trend for renewables is being driven by concerns about climate change and energy security. Between 2006 and 2012, global solar photovoltaic's (PV) annual capacity grew 190 percent, while wind energy grew 40 percent. By 2030, solar PV capacity will be nine times and wind power could increase five-fold.

However, large renewable energy integration has adversely impact on power grid because of its fluctuation, randomness and intermittence. Battery storage, for the charging and discharging characteristics, is usually applied in the renewable energy plant. It can smooth RE fluctuation, cut peak and fill valley, track dispatching schedule and real-time order. Battery storage is always made of stacked cells in series and parallel. Although the battery cells are tested and grouped previously, there still exist performance differences which can cause new differences in the long-term running. The abnormal battery cell will decrease battery pack performance, and even cause accidents. Hence, battery cell anomaly and degradation detection is necessary to extend the battery pack life, reduce maintenance cost and ensure RE plant stable and reliable operation.

Battery fault diagnosis technology has made great achievements during these years. Expert system, as one of the common methods, can emulate the decision-making ability of a human expert. However, it has no learning ability and knowledge cannot be expanded.With development of information and communication technology (ICT), data mining techniques make it possible to search large amounts of data for characteristic rules and patterns.

The proposed method uses big data effectively, which can provide advance knowledge of changes to abnormal statuses by exacting significant information from among big data. Firstly, renewable energy plant with battery storage system is introduced. Secondly, battery cell anomaly detection using K-means algorithm is given in details. Thirdly, battery degradation degree is estimated by high speed time-series curve retrieval and distance calculation. Finally, taking an actual renewable energy plant with battery storage for example, the results verified the correctness and validity of the proposed method.

SYSTEM DESCRIPTION

Renewable energy plant

The renewable energy plant with battery storage system structure is presented in Fig.1.

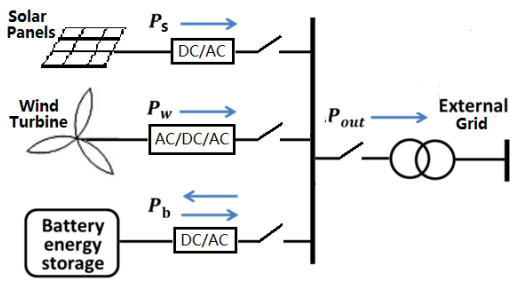


Fig.1 Renewable energy plant with battery storage system

Battery storage system

The structure of battery storage system is presented in Fig.2. Battery pack current and individual cell voltage, temperature are collected on-site.

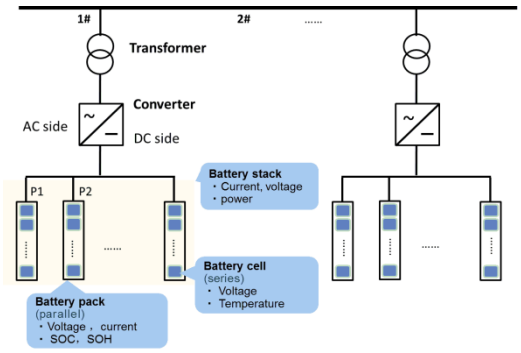


Fig.2 Battery storage system structure

Battery anomaly/degradation diagnosis system

Fig.3 shows the proposed battery anomaly detection and degradation estimation system structure.

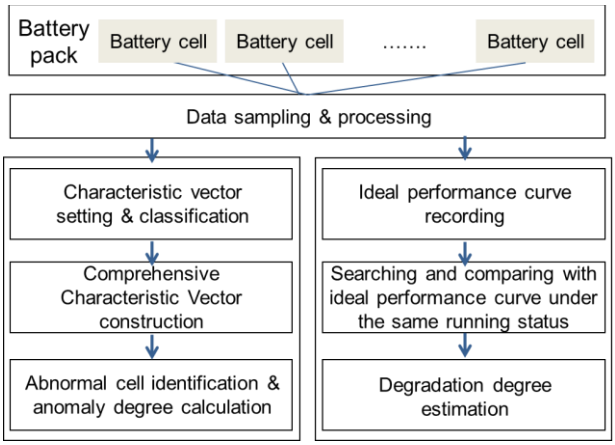


Fig.3 Battery anomaly and degradation diagnosis system structure

BATTERY ANOMALY AND DEGRADATION DIAGNOSIS

Anomaly detection

Battery pack consists of multiple cells which are connected in series. The battery cells in the same pack always run under same control mode and with the same degradation degree. Voltage, temperature, voltage change and temperature change will reflect battery health status. Meanwhile, different symptom expressions under different status such as charging, discharging and standing states will indicate different fault types. For example, discharging voltage decrease fast and charging temperature is high always indicating plate vulcanization fault, charging voltage is very high always indicating inner open-circuit fault. The method adopts relative difference value as characteristic vector. SCV is formed to present the battery cell integral performance for the evaluation period by seeking characteristic vectors centroid under different states. The battery cell with poor/abnormal performance can be identified by the differences with the other cells among the battery pack.

1) Get the real-time monitoring data of battery current, voltage and temperature, calculate voltage change and temperature change. The calculation equations are as follows

$$\Delta U_n(t) = U_n(t+1) - U_n(t) \quad (1)$$

$$\Delta T_n(t) = T_n(t+1) - T_n(t) \quad (2)$$

Where,

t: sampling time.
n: battery cell No.
$I(t)$: battery pack current.
$U_n(t)$, $\Delta U_n(t)$, $T_n(t)$, $\Delta T_n(t)$: battery cell voltage, voltage change, temperature, temperature change.

2) Calculate characteristic vector of each battery cell at each sample point,

$$\overline{X(t)} = \frac{1}{N} \times \sum_{n=1}^{N} X_n(t) \quad (3)$$

$$f(X_n(t)) = \frac{X_n(t) - \overline{X(t)}}{\overline{X(t)} * k_X} \quad (4)$$

$$C_n(t) = [f(U_n(t)), f(T_n(t)), f(\Delta U_n(t)), f(\Delta T_n(t))] \quad (5)$$

Where,

N: total number of battery cells.
X: one kind of characteristic data, refers to U, T, ΔU, ΔT of battery cell.
k_X: relative coefficient.
$\overline{X(t)}$: average value.
$f(X_n(t))$: relative difference value.
$C_n(t)$: characteristic vector of cell n at t point.

3) Classify the vectors under charging, discharging and standing state respectively. Seek centroid of the characteristic vectors under different states and form 12-dimension SCV for each battery cell which can present the integral performance during the period. The flow chart is shown in Fig.4.

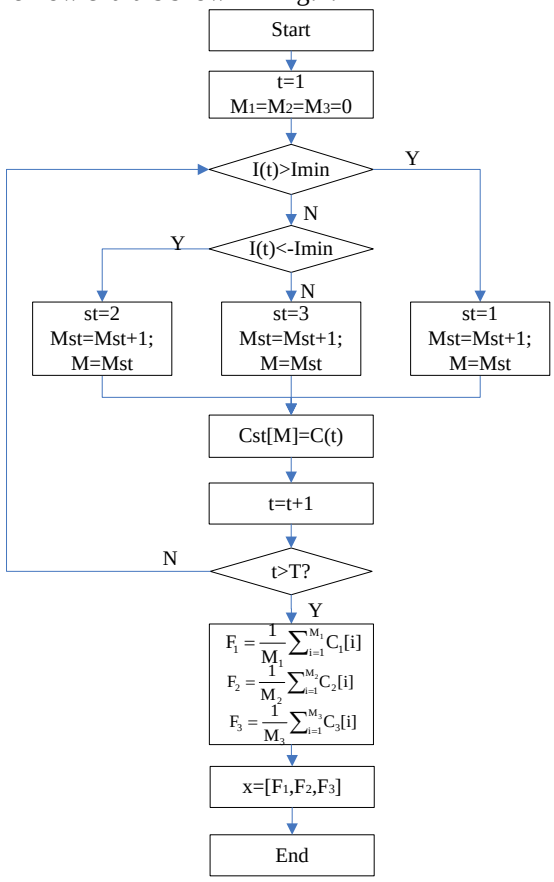


Fig.4 Battery cell SCV construction

Where,

I_{min} : minimum charging/discharging current.

st: 1, 2 and 3 presents charging, discharging and standing state respectively.

M_{st}: total number of characteristic vectors of st state

x: 12-dimentionl Synthetic Characteristic Vector of individual battery cell.

4) Anomaly diagnosis is realized by K-means algorithm which is using SCV of each battery cell as input sample. The logic flow is shown in Fig.5.

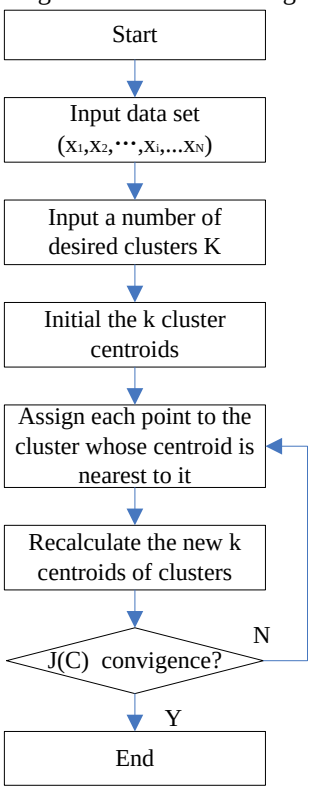


Fig.5 Anomaly detection by K-means method

Where, J(C) is the sum of the squared Euclidean distance from each object to corresponding cluster centroid. The calculation equation is as follows

$$J(C) = \sum_{k=1}^{K} \sum_{i=1}^{N} \|x_i - \mu_k\|^2 \qquad (6)$$

Where,

x_i : battery cell Synthetic Characteristic Vector

μ_k: centroid of k cluster

K: total number of clusters

N: total number of battery cells

By the above definition, J(C) is converged when the assignments no longer change. The K-means clustering run repeatedly with different K setting. The optimal clustering result is considered to identify the abnormal battery cell. Meanwhile, anomaly degree can be calculated by the distance from abnormal point to the normal cluster's centroid.

Degradation estimation

Battery degradation is a normal phenomenon with the power capacity decrease after a certain number of charging and discharging cycles. The degradation degree is estimated based on data-driven approach

1) Ideal performance can be learned from mass historical data of new battery.
2) On real-time operation, the matched time-series data (such as voltage curve) can be searched according to the current status.
3) The degradation degree is estimated by time-series distance calculation with ideal performance curve.

CASE ANALYSIS

Taking an actual renewable energy plant for example, the wind capacity is 100MW, PV capacity is 50MW and the battery storage system capacity is 40MWh. The selected battery stack consists of 10 battery packs. Each pack is 240 cells with 3.3V rated voltage in series. Sampling frequency is 1 minute and the evaluation duration is 2 hours. Voltage resolution is 0.01V and temperature resolution is 1 ℃.

Anomaly detection

Fig.7 shows the real-time monitoring data of battery pack current, battery cell voltage, temperature, and calculated voltage change and temperature change. It can be seen that there are performance differences between battery cells with irregularly charging, discharging and standing operation.

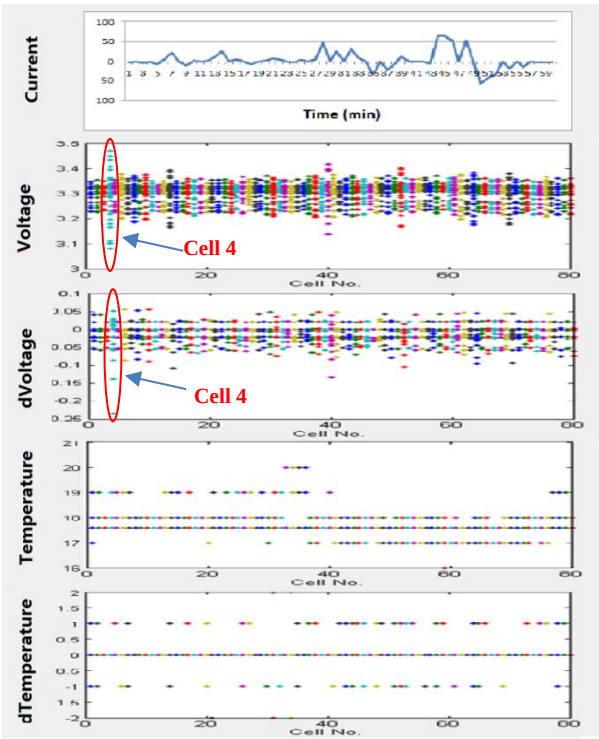
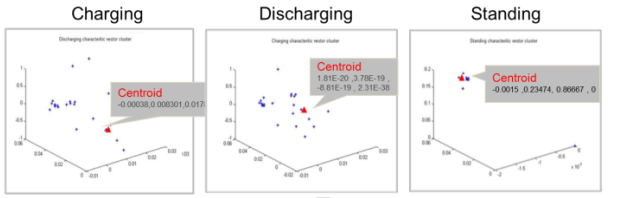


Fig.7 Battery sampling data for 2 hours

According to initial data, relative difference value of each battery cell is calculated as characteristic vector. Seek centroid of characteristic vectors under charging, discharging and standing states and form Synthetic Characteristic Vector for each battery cell. The results are shown in Fig 8.



Cell	F1				F2				F3			
	U	T	ΔU	ΔT	U	T	ΔU	ΔT	U	T	ΔU	ΔT
3	0.000 38	0.008 301	0.017 857	0	1.81E -20	3.78 E-19	8.81 E-19	2.31 E-38	0.001 5	0.234 74	0.086 667	0

Fig.8 Seek characteristic vectors centroid and form SCV

Input 12-dimention SCV of each battery cell as sample of K-means clustering algorithm and the results are shown in Fig.9. Battery cell No.4 is identified as the abnormal cell and the abnormal degree is also given by calculating the distance from abnormal point to the normal cluster's centroid.

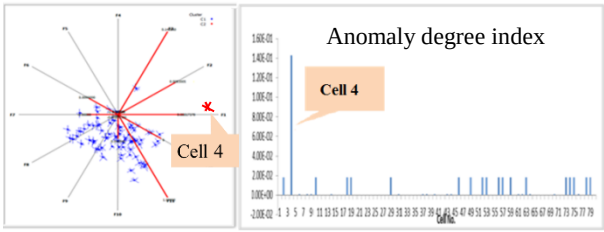
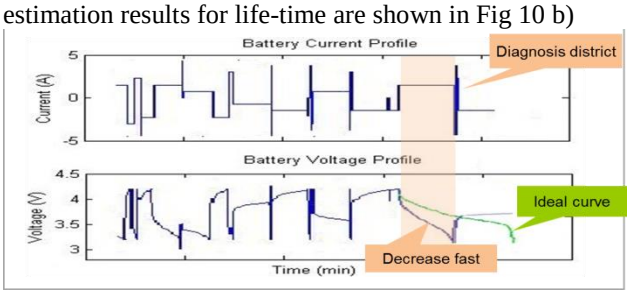


Fig.9 Abnormal battery cell identification by K-means

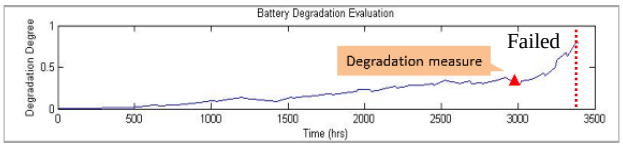
From fig.4, we can see that there are obvious voltage and voltage variation differences between No.4 battery cell and other battery cells which indicates the effectiveness of clustering algorithm for battery anomaly detection

Degradation estimation

Fig.10 a) shows the battery current and voltage curve for a period of time. After full charging, the voltage decreases from maximum voltage under 1A discharging current constantly. Compare the real-time voltage curve with ideal voltage curve under the same running status in the history database. The degradation degree is calculated by time-series distance calculation. The degradation estimation results for life-time are shown in Fig 10 b)



a) Battery real-time operation



b) Battery degradation estimation for life-time

Fig.10 Battery degradation estimation

CONCLUSION

Battery storage is an important part for RE plant operation. Battery cell health evaluation and prognosis can extend the battery pack life and prevent failure loss. This paper presents a battery anomaly and degradation diagnosis method based on data mining technology. Taking an actual renewable energy plant with battery storage for example, the results verified the correctness and validity of the proposed method.

REFERENCES

[1] Cox, D.C.; Perez-Kite, R.; 2000, "Battery state of health monitoring, combining conductance technology with other measurement parameters for real-time battery performance analysis", Twenty-second International Telecommunications Energy Conference, 2000, INTELEC, 342 – 347.

[2] Meissner, E.; Richter, G.; 2003, "Battery Monitoring and Electrical Energy Management - Precondition for future vehicle electric power systems", Journal of Power Sources, vol. 116, no. 1, 79-98(20).

[3] M. A. Roscher, J. Assfalg, and O. S. Bohlen, 2011, "Detection of utilizable capacity deterioration in battery systems", IEEE Trans. Veh. Technol., vol. 60, no. 1, 98–103.

[4] D. P. Abraham, J. Liu, C. H. Chen, Y. E. Hyung, M. Stoll, N. Elsen, S. MacLaren, R. Twesten, R. Haasch, E. Sammann, I. Petrov, K. Amine, and G. Henriksen, 2003, "Diagnosis of power-fade mechanisms in high-power lithium-ion cells", J. Power Sources, vol. 119–121, 511–516.

[5] A. T. Stamps, C. E. Holland, R. E. White, and E. P. Gatzke, 2005, "Analysis of capacity fade in a lithium-ion battery", J. Power Sources, vol. 150, 229–239.

[6] K. W. E. Cheng, B. P. Divakar, H. Wu, K. Ding, and H. F. Ho, 2011, "Battery management system (BMS) and SOC development for electric vehicles", IEEE Trans. Veh. Technol., vol. 60, no. 1, 76–88.