Energy Storage System Health Monitoring and Prognosis

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To enhance the operational safety and stability of energy storage systems (ESS) and address the inherent limitations of conventional single-point monitoring in detecting complex, multivariate anomalies, this study presents a novel health performance indicator (HPI) modeling framework underpinned by the Multivariate State Estimation Technique (MSET). By analyzing historical operational data collected under normal conditions, the framework establishes a memory matrix and a predictive model to generate HPI curves, which serve as real-time indicators of system health. When the HPI drops below a predefined control threshold, the system automatically triggers an anomaly alert, followed by variable contribution analysis to identify the most influential parameters contributing to the deviation. This enables precise fault diagnosis and facilitates proactive, condition-based maintenance strategies. The proposed methodology has been successfully implemented in the ESS infrastructure of China Steel Corporation. Empirical results demonstrate high sensitivity, diagnostic accuracy, and effective visualization capabilities. Overall, this framework significantly improves system reliability and operational intelligence, contributing to the development of smart grid infrastructure and the achievement of carbon neutrality targets.

Keywords: Energy storage system, Multivariate state estimation technique, Health performance indicators

1. INTRODUCTION

The accelerating pace of global climate change and the worldwide push for carbon neutrality have intensified efforts to deploy renewable energy as a replacement for high-emission fossil fuels. Nevertheless, the inherent intermittency and unpredictability of renewable sources—such as solar photovoltaics and wind power—pose serious challenges to grid stability and operational reliability. In response, the integration of energy storage systems (ESS) has emerged as a pivotal strategy to enhance grid resilience and improve the efficiency of renewable energy utilization.

In alignment with Taiwan's national goal of achieving carbon neutrality by 2050, China Steel Corporation (CSC), one of the country's leading industrial enterprises, has initiated a multi-year infrastructure upgrade aimed at strengthening the resilience of its plant-wide power systems. Between 2022 and 2026, CSC is investing NT$1.55 billion (approximately USD 50 million) to implement a suite of advanced energy strategies, with ESS deployment being a core component(1). The ESS installations are designed to mitigate peak electricity demand and address potential supply shortages caused by the electrification of low-carbon industrial equipment. To date, CSC has commissioned three ESS units, totaling 11 MWh in capacity, spanning both front-of-meter (grid-side) and behind-the-meter (user-side) applications. A summary of the system configurations is provided in Table 1.

These ESS deployments not only contribute to CSC's carbon neutrality roadmap but also form the technological foundation for developing smart grids and virtual power plants. Through integration with solar photovoltaics and the application of time-of-use pricing strategies, these systems enhance operational flexibility and energy dispatch efficiency.

Despite their substantial value, ESS deployments are not without risk. Lithium-ion battery systems are susceptible to safety hazards such as thermal runaway, overcharging, and cell imbalance—conditions that are able to escalate into system failures or combustion. Traditional monitoring techniques often rely on single-variable threshold alarms (e.g., voltage, current, or temperature), which lack the capacity to detect complex, multivariate anomalies and provide limited early warning capability.

To overcome these limitations, recent systems—such as daVanci BEMS(2,3)—have introduced health status evaluation models based on six core indicators, including voltage homogeneity, state-of-charge (SOC) consistency, cell voltage distribution, voltage derivative balance, and overall cell balance. While these approaches provide a more comprehensive view of battery conditions,

Table 1 Overview of Energy Storage Systems at China Steel Corporation.

Project Phase	Capacity (MW/MWh)	Application Type	Key Functions
Phase I	1.8/1.8	Front-of-Meter	Participation in Taipower's frequency regulation services (frequency stability)
Phase II	1.5/2.2	Behind-the-Meter	1.Peak shaving and valley filling 2.Offset large user green energy obligations 3.Demand response
Phase III	3.0/7.0	Behind-the-Meter	1.Peak shaving and valley filling 2.Offset large user green energy obligations 3.Demand response 4.Microgrid application

they often lack defined threshold criteria and show weak correlations with actual failure modes, making real-time diagnostics and predictive maintenance difficult to implement effectively.

In this study, we propose a novel health performance indicator (HPI) modeling technique based on multivariate similarity analysis. By constructing a representative memory matrix and a predictive model using historical normal operational data, the system generates HPI curves that assess the similarity between current and baseline healthy states. A sustained drop in the HPI below a predefined threshold indicates a potential abnormal condition, prompting automated alerts and subsequent variable contribution analysis to identify the most influential factors contributing to the deviation. This methodology has been successfully implemented in CSC's ESS infrastructure, demonstrating high sensitivity, diagnostic accuracy, and effective real-time visualization. The results confirm the approach's practical value in enhancing the safety, availability, and intelligent management of ESS, while supporting the broader transition toward smart grid deployment and net-zero emissions.

2. MULTIVARIATE STATE ESTIMATION TECHNIQUE

This study adopts the Multivariate State Estimation Technique (MSET) as the core methodology for modeling the Health Performance Indicator (HPI) of energy storage systems (ESS). By analyzing historical operational data collected under normal conditions, the method constructs an operational behavior model that demonstrates the capability to evaluate the similarity between real-time and baseline healthy states. This enables continuous performance monitoring and early anomaly detection. The overall framework is systematically divided into two stages: Model Construction and State Monitoring, as illustrated in Figure 1.

2.1 Model Construction

The model construction process consists of four key steps:

(1) Data Collection and Preprocessing

Key operational variables—such as voltage, current, temperature, power, and frequency—are recorded during the ESS's stable operation. These parameters are

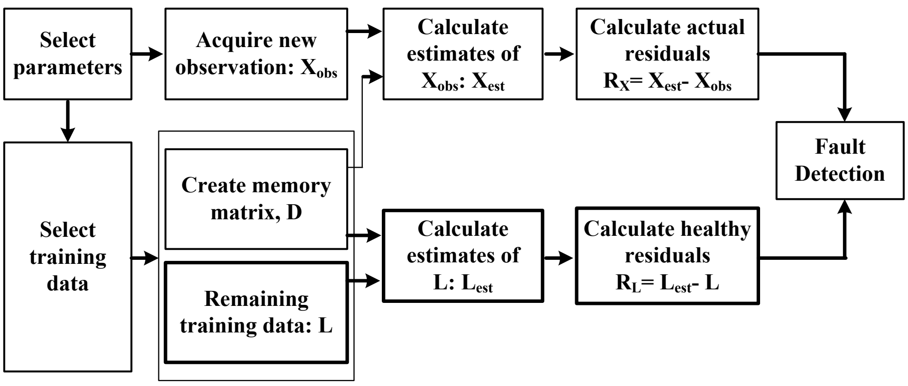

Fig.1. Procedure of HPI Modeling and Fault Detection.

utilized to form a training dataset $X \in R^{n \times m}$, as presented in Equation (1). In this dataset, n represents the number of monitored variables, and m denotes the number of time observations. All data are subsequently normalized to mitigate the impact of scale differences.

$$\begin{array}{lcc} & \begin{array}{ccccc} t_1 & t_2 & t_3 & \cdots & t_m \end{array} & \text{Parameters} \\ \text{Time:} & & \\ & \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1m} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2m} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & x_{n3} & \cdots & x_{nm} \end{bmatrix} & \begin{array}{c} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{array} \end{array} \quad ......(1)$$

Time series signals of one parameter: $x_i(t_j)$

One state (or observation) of system: $X_i(t_j)$

(2) Memory Matrix Construction

From the training data X, d representative samples are selected to form the memory matrix $D \in R^{n \times d}$. Concurrently, the remaining data constitute the residual matrix $L \in R^{n \times (m-d)}$. Sample selection is primarily based on ensuring diversity and comprehensive coverage of typical operational modes to enhance the model's generalizability.

(3) Model Training

Utilizing D as the input features and L as the prediction targets, a predictive model $f(D)$ is constructed. This construction employs advanced artificial intelligence algorithms, including but not limited to XG Boost, random forest, or deep neural networks. The primary objective of this model is to minimize the prediction error between the estimated values $L_{est}=f(D)$ and the actual values L.

(4) Health Performance Indicator Calculation

The similarity between predicted and actual values is computed to derive the Health Performance Indicator (HPI) for each sample using the following equation:

$$\text{HPI} = 1 - \frac{|X_{est} - X_{obs}|}{X_{obs}} \text{.. (2)}$$

Where X_{obs} represents the observed value, and X_{est} is the predicted value. The minimum HPI value among all training samples is selected as the system's control threshold (H_{th}), which serves as the baseline for anomaly detection.

2.2 Fault Detection and Diagnosis

Once the model is established, real-time observations X_{obs} are analyzed as follows:

(1) Similarity Evaluation and Anomaly Detection

The new observation X_{obs} is fed into the model $f(D)$ to compute the predicted value X_{est}, and the HPI is calculated using Equation (2). If the HPI falls below the threshold H_{th}, the system flags it as an anomaly and triggers an alert.

(2) Variable Contribution Analysis

To further diagnose the cause of the anomaly, the relative contribution of each variable is calculated using the following formula:

$$\text{Contribution}_i = \frac{|X_{obj,i} - X_{D,i}|}{\Sigma |X_{obj,j} - X_{D,j}|} \text{.............................(3)}$$

Here, X_D represents the most similar memory sample to the current observation X_{obs}. The contribution values indicate the impact of each variable on the anomaly, providing actionable insights for maintenance personnel to prioritize their response.

(3) HPI Trend Visualization and Early Warning

The system continuously generates HPI trend curves, offering an intuitive visualization of the ESS's health status over time. If the HPI remains below H_{th} across consecutive time intervals, the system automatically activates the fault notification module and identifies the most probable root causes, thereby supporting timely decision-making.

3. RESULTS AND DISCUSSION

To validate the proposed Health Performance Indicator (HPI) modeling technique, this study was applied to the energy storage system (ESS) at CSC as a practical case. The modeling workflow, real-time monitoring mechanism, and actual anomaly analysis results are presented in this section to demonstrate the method's effectiveness in anomaly detection and system state diagnosis.

3.1 Variable Selection and Training Data Preparation

The dataset utilized for model development was collected during stable operating periods of the ESS and comprises multivariate historical time-series data. This dataset includes both electrical characteristics and battery module status indicators, which are closely associated with system performance and reliability. The selected parameters encompass instantaneous voltages and currents across three phases, system frequency, power factor, energy usage, and generation metrics, as well as maximum and minimum battery cell voltages and temperatures. These features were chosen for their diagnostic relevance and representativeness in reflecting the ESS's operational health. The monitored variables are summarized in Table 2.

3.2 Health Model Establishment and Threshold Setting

The MSET algorithm was applied to the training dataset composed of the variables listed above. A subset of representative samples was automatically selected to construct the memory matrix D, which served as the basis for generating the HPI prediction model $f(D)$. Upon completion of training, the model produced a continuous HPI curve that quantifies the similarity between the current system state and the established healthy behavior profile.

The lowest HPI value observed among all training samples (for example, 91.864) was defined as the system's health threshold (H_{th}). This threshold provides a quantitative reference to distinguish between normal and abnormal states in real-time monitoring applications.

3.3 Real-time Health Monitoring Results

During real-time operation, incoming observation vectors X_{obj} are continuously processed by the trained model $f(D)$ to compute the HPI values. A significant and persistent decline in the HPI below the established threshold H_{th} is interpreted as a potential system abnormality. As shown in Figure 2, the drop of the blue HPI curve beneath the red threshold line triggered the system's anomaly alert mechanism.

3.4 Anomaly Diagnosis and Variable Contribution Analysis

Upon detecting an HPI below the threshold, the system automatically initiates diagnostic procedures to identify the primary contributors to the deviation. Table 3 lists the top four abnormal variables of this case, determined by calculating the Variable Contribution Analysis using Equation (3). The details of this case are expressed as follows:

- *Anomalous State Detected*: The HPI dropped to 88.3, significantly lower than the baseline threshold of 91.864.
- *Key Variable Analysis*: The R/S/T phase currents (A_A, A_B, A_C) were all substantially lower than their normal values, indicating they were the dominant contributors to the anomaly.
- *Probable Cause*: The event may have resulted from certain battery modules failing to discharge as expected, or due to an internal circuit malfunction causing abnormally low current.

Table 2 Key Monitored Variables in the Energy Storage System.

Variable	Definition
A_A、A_B、A_C	Instantaneous currents of phases R, S, and T
DMDWH、SUPWH	15-minute cumulative energy consumption and generation
HZ	Instantaneous system frequency
TOT_PF、TOT_VAR、TOT_W	Total power factor, reactive power (input/output), active power (input/output)
V_A、V_B、V_C	Instantaneous voltages of phases R, S, and T
cv_max_sys、cv_min_sys	Maximum and minimum cell voltage in the battery system
ct_max_sys、ct_min_sys	Maximum and minimum cell temperature in the battery system

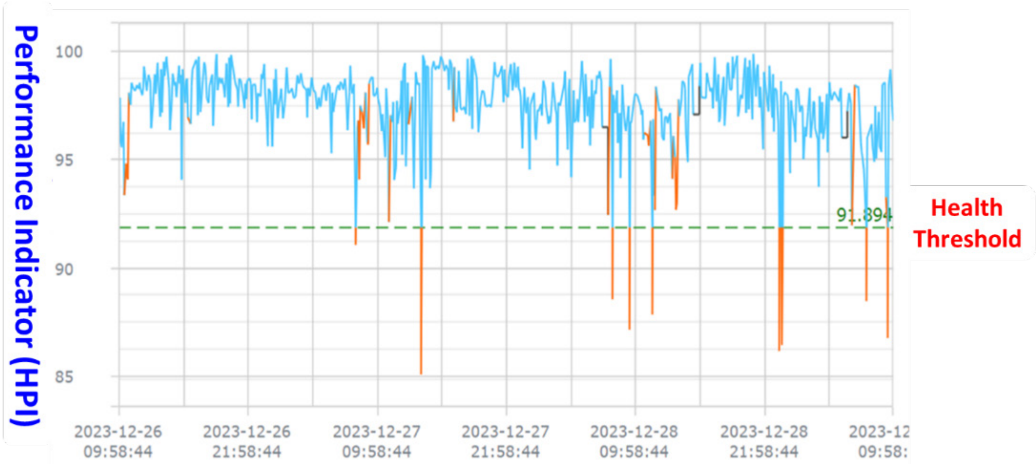

Fig.2. HPI Curve of the Energy Storage System.

Table 3 Variable Contribution Analysis of the Anomaly Case.

Index	Tag Name	Actual Value	Expected Value	Bias
1	W5ESS_AFC_A_C	2328	1904.267	▲
2	W5ESS_AFC_A_B	2377	1951.175	▲
3	W5ESS_AFC_A_A	2304	1847.09	▲
4	W5ESS_AFC_TOT_W	-47774	-32673.365	▼

By integrating similarity-based HPI monitoring with variable contribution analysis, the proposed approach enables fast, accurate identification of root causes. This enhances fault localization efficiency and supports timely and effective maintenance actions, thereby improving the operational resilience and maintainability of the ESS.

4. CONCLUSION

As the penetration of renewable energy accelerates and carbon neutrality goals drive global energy transitions, energy storage systems (ESS) have emerged as essential assets for grid flexibility, power dispatch, and operational stability. However, due to the inherent complexity of ESS operations—characterized by dynamic, multivariate parameter interactions—conventional monitoring approaches based on single-point alarms are insufficient for assessing overall system health or identifying early-stage faults.

To address this critical gap, this study proposed an innovative health performance indicator (HPI) modeling framework underpinned by the Multivariate State Estimation Technique (MSET). By leveraging historical operational data collected under normal conditions, a representative memory matrix and an AI-driven predictive model were constructed to generate real-time HPI curves. These curves enable continuous health assessment, anomaly detection, and early warning.

In a real-world deployment at CSC, the proposed methodology effectively modeled ESS performance and established a robust health threshold for distinguishing between normal and abnormal operational states. When combined with similarity-based diagnostics and variable contribution analysis, the system demonstrated the capability to accurately pinpoint the root causes of anomalies, thereby significantly improving fault response speed and precision.

Empirical results validate the key strengths of the approach:

- *High Sensitivity in Monitoring*: Capable of detecting subtle deviations in system behavior, effectively addressing the limitations of traditional threshold-based alarms.
- *Systematic Diagnostic Capability*: Provides quantifiable contribution metrics that facilitate rapid localization of fault sources.
- *Scalability and Modularity*: The model allows flexible parameterization, making it adaptable to a variety of ESS configurations and other industrial energy assets.

Future research directions include:

- *Integration with Real-Time Data Platforms*: Incorporating SCADA, PI systems, and edge computing to enhance the real-time responsiveness and deployment agility of HPI monitoring.
- *Extension to Multi-System Architectures*: Applying the method to coordinated diagnostics across interconnected systems such as photovoltaics, microgrids, and hybrid energy configurations.
- *Incorporation of Prognostic Models*: Introducing degradation modeling and remaining useful life (RUL) estimation to support predictive maintenance and long-term asset management.

In summary, the proposed HPI-based modeling and intelligent monitoring methodology offers a novel, effective, and scalable solution to improve the reliability, safety, and operational efficiency of energy storage systems. It further lays a robust foundation for intelligent energy system management within the broader context of smart grids and carbon-neutral infrastructure.

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