

# Health Assessment Model for Data Centers Using Environmental Sensor Networks and Uninterruptible Power Supply Telemetry

Jieying Liu,<sup>1</sup> Rui Fan,<sup>2</sup> Napat Harnpornchai,<sup>3\*</sup> and Jianlei Qian<sup>1\*\*</sup>

<sup>1</sup>Cybersecurity and Informatization Office, Shandong University of Finance and Economics, Jinan 250014, China

<sup>2</sup>International Office, Shandong University of Finance and Economics, Jinan 250014, China

<sup>3</sup>Center of Excellence in Econometrics, Faculty of Economics, Chiang Mai University, Chiang Mai 50200, Thailand

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The rapid acceleration of digital transformation has increased the need to maintain the operational integrity of data centers. Conventional monitoring methods rely heavily on isolated threshold-based alarms, often failing to provide a holistic or predictive view of the system's health. By introducing a system-level health index model that integrates multisource data by fusing internal uninterruptible power supply operational logs with external wireless sensor networks, we develop a hierarchical evaluation method using power system health, environmental health, and equipment status as important criteria. To normalize heterogeneous sensor dimensions, a Gaussian mapping function is applied to score industry-standard optimal values. Weight coefficients are derived using the analytic hierarchy process. The results show that power system health (weight of 0.539) and average temperature (0.193) are the most influential factors of systemic stability. The model developed effectively detects transient anomalies, such as a 10 V voltage sag accompanied by an 80 kW load surge, through a sensitive decrease in the health index. The model exhibits strong agreement with expert assessments ( $R = 0.96$ ) and shows a low mean absolute error (0.04). The results of this study contribute to the development of a multimodal sensor deployment strategy and provide a quantifiable, data-driven tool for proactive facility management. Whereas the developed model's applicability is limited by subjective expert weighting and transient data gaps, objective entropy weight methods and deep learning architectures, such as long short-term memory, need to be introduced to enhance long-term predictive accuracy and system resilience.

## 1. Introduction

Data centers are critical infrastructure in the modern information society, serving as vital hubs for data storage, high-performance processing, and global exchange.<sup>(1)</sup> The continuity, reliability, and security of the operations of data centers directly affect the stability of business activities and, more broadly, the resilience of social systems.<sup>(2)</sup> In data center management,

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\*Corresponding author: e-mail: [napateconcmu@gmail.com](mailto:napateconcmu@gmail.com)

\*\*Corresponding author: e-mail: [qianjl@sdufe.edu](mailto:qianjl@sdufe.edu)

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wireless sensor networks (WSNs) and IoT technologies have become indispensable for the real-time acquisition of multimodal data, including temperature, humidity, vibration, and electrical parameters such as voltage and current.<sup>(3)</sup> In addition to them, to ensure operational integrity, uninterruptible power supply (UPS) systems are critical devices, since UPS systems enable continuous, high-quality power delivery and prevent catastrophic data loss or hardware damage during power quality disturbances.<sup>(4)</sup>

The effective monitoring and health assessment of data center rooms are determined by using the parameters of dynamic statuses influenced by electrical loads and ambient environmental conditions.<sup>(5)</sup> Despite the prevalence of sensors used in data center room health assessment and monitoring, reliance on WSN and IoT devices is insufficient. Systems with WSN and IoT devices depend on simple threshold-based alarms that trigger only when parameters deviate from predefined ranges.<sup>(6,7)</sup> While straightforward, the systems suffer from the following deficiencies. First, when environmental sensor data and UPS electrical logs are stored in isolation, data silos occur, hindering the identification of complex system-level correlations. For example, subtle increases in ambient temperature accelerate the degradation of UPS capacitor banks or battery chemistry.<sup>(8)</sup> Second, the response mechanism remains inherently passive, activating only when a failure is imminent and lacking the predictive foresight required for proactive prevention. Recent health assessment models of data centers have adopted deep learning and statistical analysis to enhance their reliability. The models have been applied to evaluate overall data center reliability, energy efficiency, and specific risk factors. In the specific domain of UPS systems, existing studies often emphasize collaborative optimization with energy storage systems or isolated battery life analysis.<sup>(9)</sup> However, the models lack traceability to specific industry benchmarks and mainly focus on optimizing power usage effectiveness rather than holistic operational integrity.<sup>(10)</sup>

To overcome these limitations, sophisticated health assessment models of data center rooms have been developed, employing machine learning, statistical approaches, and advanced analytics.<sup>(11)</sup> The model developed in this study provides a transparent, hierarchical framework that maps multisource data directly to standardized operational setpoints. This ensures that the resulting health index is not only predictive of anomalies but also inherently interpretable for maintenance personnel, allowing them to trace a decline in system health to its specific electrical or thermal root cause.

## 2. Materials and Methods

### 2.1 System structure

The health assessment system proposed for the data center in this study comprises four distinct layers in a hierarchical architecture (Fig. 1).

- Data acquisition layer: This layer serves as the foundation, where sensors, including internal UPS monitoring interfaces and external environmental sensors, form a heterogeneous network with wired or wireless sensors to collect real-time electrical and environmental data.
- Data processing and modeling layer: Raw data is aggregated on the basis of standard network

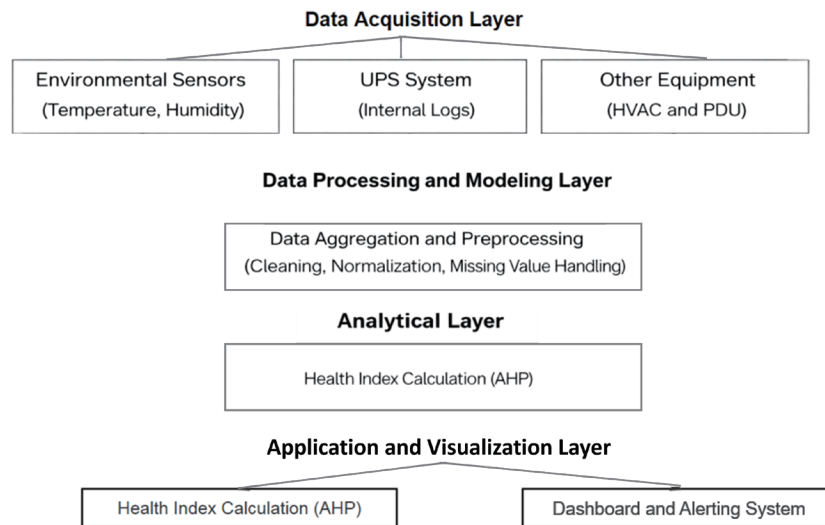


Fig. 1. Hierarchical framework of the data center health assessment system (HVAC: heating, ventilation, and air conditioning, PDU: power distribution unit).

protocols. This layer performs critical preprocessing, including data cleaning, normalization, and handling missing values, to ensure high-quality input for the core analytical models.

- Analytical layer: This layer preprocesses data through the health index model developed in this study. By employing the analytic hierarchy process (AHP), specific weights are assigned to different dimensional indicators, such as power quality (the degree to which the electrical system supports the reliable operation of its loads by maintaining steady and standardized electrical parameters, quantified using UPS telemetry) and thermal stability, to derive a unified, system-level health index.
- Application and visualization layer: The final output is delivered to maintenance personnel through interactive dashboards and situational maps. This layer includes an automated alerting mechanism using email or short message services when the calculated health index falls below safety thresholds.

## 2.2 Sensor network deployment

To ensure visibility, the sensor network was strategically deployed in the functional zones of the data center room (Fig. 2). The sensor data are collected using high-precision industrial-grade sensors. Sensor network-temperature/humidity modular sensors (SN-TH sensor, Vertiv, USA) were used for integrated rack-level monitoring. The sensor is designed for high-density data center environments and provides integrated temperature and relative humidity monitoring. The sensor features a temperature measurement range of 5 to 55 °C with an accuracy of  $\pm 1.1\%$  and a relative humidity range of 10 to 95%.<sup>(12)</sup> These sensors support autoconfiguration and daisy-chaining, allowing for the precise spatial resolution of the data center's thermal profile when connected to the facility's monitoring software via Unity cards. For the electrical telemetry of the UPS system, LEM HASS 50-S current transducers (LEM International SA, Switzerland)

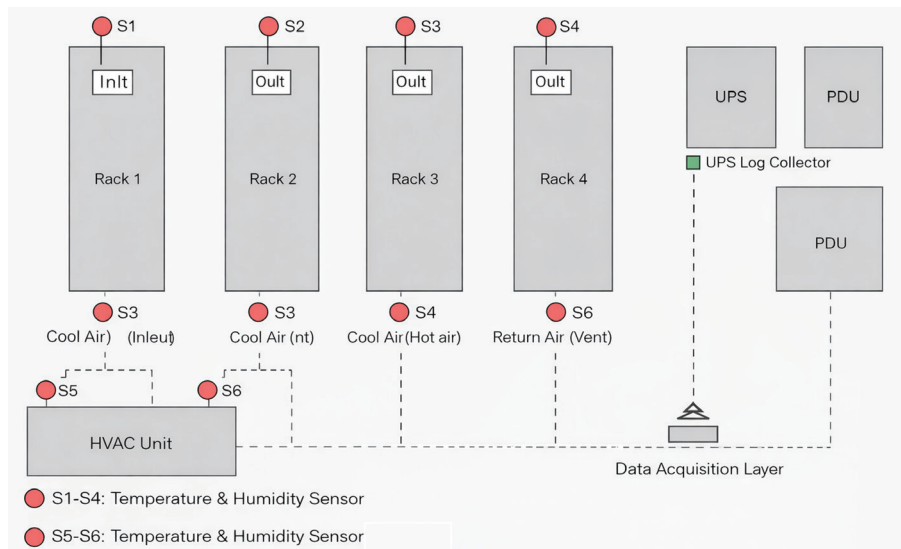


Fig. 2. (Color online) Deployment map of sensor network (S1–S6: temperature and humidity sensors).

were used. The LEM HASS 50-S is an open-loop Hall-effect transducer used for the electronic measurement of DC, AC, and pulsed currents with galvanic isolation between the primary and secondary circuits. It features a nominal primary current of 50 A with a linear measuring range of up to  $\pm 150$  A and a high overall accuracy of  $\pm 1\%$  at 25 °C.<sup>(13)</sup> The transducer's low power consumption and high immunity to external interference make it suitable for the sensitive electrical environments typical of mission-critical data center power systems.

Temperature and humidity sensors S1–S4 were placed at rack inlets and outlets to monitor thermal gradients, while S5–S6 were used to monitor the parameters of the return air in the HVAC system. At the gateway, wireless environmental data and wired UPS log data were aggregated for centralized processing. The technical specifications of the primary sensing units are detailed in Table 1.

### 2.3 Data collection and analysis

Data for this study were collected from the UPS log collector and the environmental sensor network deployed in the data center room. Data were collected from 22:30 on January 29, 2026, to 00:40 on January 30, 2026, with a total of 18 time points and a sampling interval of 5 min. This specific observation window was selected because it encompassed a series of transient power disturbances and load fluctuations required to validate the model's anomaly detection capabilities under varying operational stresses. The dataset included module summaries, electrical characteristic summaries, and bypass attributes of UPS. Electrical parameters were collected from the system-level power logs of UPS, the rack-level consumption data of PDU, and the environmental sensor data of the gateway. The health assessment system interfaces with the UPS internal log data collector to extract high-fidelity electrical metrics. The collected data were categorized into the following groups.

Table 1  
Specifications of sensors used in health assessment system.

Sensor	Parameter	Sensor type	Measurement range	Accuracy
Environmental sensor (SN-TH sensor)	Temperature	Digital CMOSens <sup>®</sup>	−40 to 120 °C	±0.3 °C
	Humidity	Capacitive polymer	0 to 100% RH	±2% RH
Electrical sensor (LEM HASS 50-S)	Voltage (V)	Internal Hall effect	0 to 500 V	±0.5% FS
	Current (A)	Current transformer	0 to 200 A	±1.0% FS
	Frequency (Hz)	Zero-crossing detection	45 to 65 Hz	±0.01 Hz

(RH: relative humidity, FS: full scale range, V: voltage, A: ampere)

- Module summary: output voltage, current, and frequency, which are used to assess the quality of power delivered to the load
- Electrical characteristics: active power and load percentage to evaluate operational efficiency and capacity overhead
- Bypass status: voltage, current, and frequency of the redundancy path to ensure system availability during maintenance or internal faults
- Environmental sensor network: temperature and humidity sensors (S1–S6) deployed near server racks and HVAC units. These sensors help identify thermal hotspots and humidity fluctuations that may lead to hardware degradation or UPS battery failure.

The data were sampled at an interval of 5 min. The log structure was standardized to enable seamless integration into the modeling layer. The data used in this study are described in Table 2.

Raw sensor and UPS log data were collected in long format, in which each row represented a single observation. For time-series analysis and synchronous health index computation, the data were converted into a wide format. In this format, each row corresponded to a unique 5 min timestamp, and columns represented individual sensor readings. During this transformation, electrical readings are aggregated on the basis of the following physical significance.

- Voltage and frequency: Three-phase output voltages ( $V_{out1}$ – $V_{out3}$ ) are mapped to individual columns.
- Power metrics: In the energy control module summary, the three-phase active power components are summed to derive the total active power ( $P_{total}$ ).
- Load dynamics: The three-phase load rates are averaged to determine the comprehensive average load rate ( $L_{avg}$ ).

Data were collected from 22:30 on January 29, 2026, to 00:40 on January 30, 2026, with a total of 18 time points and a sampling interval of 5 min. The dataset included module summaries, electrical characteristic summaries, and bypass attributes of UPS. The structure of reshaped wide-format sensor data is presented in Table 3.

In this study, an optimal operating point was defined for each parameter on the basis of industry standards [the American National Standards Institute/Telecommunications Industry Association-942 (ANSYS/TIA-942)] and manufacturer specifications. Owing to the heterogeneous nature of the parameters, such as voltage and load rate (in percentage), raw values were converted into a single health score that ranges from 0 to 100 using a Gaussian mapping function. In this method, the highest score was used as the optimal value rather than the statistical mean. The health score  $S_{ij}(x)$  for a parameter value  $x$  is computed as follows.

Table 2  
Data field description.

Field name	Description
Location	UPS module or summary name where the data originates
Time	Timestamp of the data record
Value	Sensor reading
Unit	Physical measurement unit

Table 3  
Representative structure of wide-format sensor data.

Timestamp	$V_{out1}$ (V)	$V_{out2}$ (V)	$V_{out3}$ (V)	$V_{out1}$ (Hz)	$P_{total}$ (kW)	$L_{avg}$ (%)
2026-01-29 22:30:00	—	—	—	—	22.4	—
2026-01-29 22:35:00	241.6	241.6	240.7	50.02	22.1	39.23
2026-01-29 22:40:00	242	242	240.9	50.02	22	38.9

$$S_{ij}(x) = 100 \cdot \exp \left[ -\frac{(x - \mu_{opt})^2}{2\sigma_{opt}^2} \right] \tag{1}$$

Here,  $\mu_{opt}$  denotes the optimal value, and  $\sigma_{opt}$  is a sensitivity coefficient that defines the acceptable range before the score begins to degrade. The scoring logic and optimal values for important parameters are summarized in Table 4.

Voltage imbalance was calculated using the following equations.

$$V_{imbalance} = \frac{\max \left[ (V_{out1} - V_{avg}), (V_{out2} - V_{avg}), (V_{out3} - V_{avg}) \right]}{V_{avg}} \tag{2}$$

Here,  $V_{out1}$ ,  $V_{out2}$ , and  $V_{out3}$  are the output voltages of the three phases (A, B, and C), and  $V_{avg}$  is the average of the three-phase output voltage.

### 2.4 AHP weighting criteria

In the model analysis layer, the analytic hierarchy process (AHP) was employed to decompose the complex data center environment into a multilevel evaluation framework. The overall health index was calculated using the weighted sum of two primary dimensions: power reliability and environmental stability. On the basis of expert judgment and the Telecommunications Infrastructure Standard for Data Centers (the American National Standards Institute/Telecommunications Industry Association-942), a pairwise comparison matrix was constructed to assess the relative importance of these criteria.

To establish the weighting hierarchy, structured expert judgment was incorporated through AHP. A panel of five experts, comprising three senior facility managers and two electrical engineers with an average of over 15 years of experience in mission-critical infrastructure, was recruited on the basis of professional certifications and direct involvement in large-scale data

Table 4  
Optimal values and scoring logic for parameters.

Parameters	Optimal value (range)	Scoring logic
Output voltage	240 V (L–N)	Monotonic decrease with deviation from nominal.
Output frequency	50 Hz	Monotonic decrease with frequency shift.
Voltage imbalance	<1%	Penalty-free $\leq 1\%$ ; sharp decay $>3\%$ .
Average load rate	30–80%	Highest score in interval; decline outside range
Bypass current	0 A	Ideal at 0 A; any nonzero value incurs penalty

center maintenance. Each expert performed pairwise comparisons using Saaty's 1–9 scale to evaluate the relative importance of the main criteria. The pairwise comparison matrix was constructed for  $C_1$  as power system health (including voltage stability and battery condition) and  $C_2$  as Environmental Health (including rack-level temperature and humidity). Since power continuity represents the essential function of UPS,  $C_1$  was assigned greater importance than  $C_2$ . Using the eigenvalue method, the corresponding weights were determined as  $w_{C1} = 0.75$  and  $w_{C2} = 0.25$ .

The derived weights reflect the operational priority of maintaining continuous power supply while ensuring environmental stability within the data center.

To ensure the reliability of the weighting process, a consistency check was performed. The consistency ratio ( $CR$ ) was calculated by dividing the consistency index ( $CI$ ) by the random index ( $RI$ ) [Eq. (3)], where the  $RI$  value was obtained from Saaty's standard reference table based on the order of the comparison matrix.

$$CR = \frac{CI}{RI} \quad (3)$$

Here,  $CI = \frac{\lambda_{max} - n}{n - 1}$  ( $\lambda_{max}$  is the maximum eigenvalue of the pairwise comparison matrix) and  $RI$  is the random index that represents the average CI of a large number of randomly generated matrices of a given order  $n$ . If the  $CR$  exceeds a threshold, the pairwise comparisons are re-evaluated to eliminate logical inconsistencies in the ranking of sensor importance. The evaluation hierarchy is presented in three levels (Table 5).

## 2.5 Health index

After obtaining the scores of each parameter at time  $t$  and the final combined weight  $w_j$ , the system health index of the data center room was calculated using the following linear weighted sum method.

$$SHI_t = \sum_{j=1}^n w_j \times Score_{ij} \quad (4)$$

Here,  $SHI_t$  is the system health index at time  $t$ , representing the overall health score of the data center room,  $n$  is the total number of parameters in the assessment, and  $w_j$  is the weight assigned

Table 5  
Assessment hierarchy (AHP model analysis layer).

Level 1 (goal)	Level 2 (criteria)	Level 3 (indicators)	Symbol	Data source	Data unit
Data center room health index	Power system health	UPS output voltage	$V_{out}$	Module summary	V
		UPS output load/imbalance	$L_{avg}$	Electronic control module summary	%
		UPS battery status	$B_{stat}$	Internal logs	—
		UPS battery runtime	$B_{run}$	Internal logs	min
	Environment health	Average temperature (inlet/outlet)	$T_{avg}$	WSN (S1–S4)	°C
		Average humidity	$H_{avg}$	WSN (S1–S4)	%RH
	Equipment status	UPS alarm events	$E_{alarm}$	Event logs	—
		HVAC operational status	$HV_{stat}$	HVAC interface	—

to parameter  $j$ . The weights are derived from the AHP method and reflect the relative importance of each criterion (e.g., power reliability may be weighted more heavily than environmental stability).  $Score_{ij}$  is the health score of parameter  $j$  at time  $t$ . This score is normalized using Eq. (1).

Parameters with higher  $w_j$  contribute more to the overall health index. The resulting  $SHI_i$  is used as a composite measure of system health to monitor the data center's condition in real time. For example, if power reliability is weighted at 0.75 and environmental stability at 0.25, deviations in power-related indicators have a greater impact on the overall  $SHI$  than environmental fluctuations.

### 3. Result

#### 3.1 Indicator system

On the basis of UPS data and operation and maintenance data, we designed a three-tier indicator system (Table 5). The effect of different indicators on the overall health of the computer room varies. Therefore, to determine their relative importance, we employed the AHP method, which integrated qualitative judgment with quantitative analysis to systematically derive indicator weights. Five experts were invited to perform pairwise comparisons of indicators at the same hierarchical level.

The expert group consisted of professionals with experience in data center operations and engineering. One expert contributed over 15 years of leadership in daily operations, capacity planning, and risk management. Another, with more than two decades in a related field, specialized in the reliability, efficiency, and safety of critical power infrastructure. Additional members brought expertise in optimizing thermal environments to maintain stable equipment performance, analyzing the interaction between IT systems and environmental conditions, and ensuring compliance with international standards and regulatory requirements. Collectively, their diverse backgrounds provided a balanced foundation for the pairwise comparison process.

Using Saaty's 1–9 scale, they scored the relative importance of each indicator. The resulting criterion-layer judgment matrix is presented in Table 6.

Table 6  
Criterion layer judgment matrix.

Criteria	Power system health	Environment health	Equipment status
Power system health	1	2	3
Environment health	1/2	1	2
Equipment status	1/3	1/2	1

Then, we normalized each column of the judgment matrix and summed the normalized matrix by row, and then calculated the average value to obtain the initial weight vectors of each indicator. We calculated  $CI$ ,  $RI$ , and  $CR$  to validate the consistency of the results (Table 7). If  $CR < 0.1$ , the judgment matrix is regarded as having satisfactory consistency, and the weights are valid. The order denotes the number of criteria being compared. For example, if three criteria are compared, the matrix order is  $n = 3$ . The calculated  $CR$  (0.008) for the criteria matrix implied that the expert-derived importance levels were mathematically valid and did not have logical contradictions.

To derive the final weights for the health assessment model, pairwise comparison matrices were constructed for both the criteria layer (Level 2) and the indicator layer (Level 3). The combined weight of each indicator was obtained by multiplying its local weight within the indicator layer by the weight of its corresponding criterion.

### 3.2 Weighting results

The weight calculation results are shown in Table 8. Power system health was identified as the most critical factor, since power quality directly affects hardware survival and data integrity. The local weights of the indicators within each criterion reflected the sensitivity of system health to specific sensor readings. For the power system health, output voltage ( $w_L = 0.40$ ) and output load/imbalance (0.30) showed the highest weights, highlighting their role as immediate indicators of electrical stability. For environmental health, average temperature (0.65) is prioritized over humidity (0.35), reflecting the high risk of thermal-induced equipment failure in high-density rack environments. For equipment status, UPS alarm events (0.70) were weighted significantly higher than HVAC operational status, since alarms represent immediate threats to redundancy. The global weights were derived by multiplying each local weight by its criterion weight.

The results of the weight calculation reveal important findings. First, the highest criterion weight of power system health (0.539) indicated the requirement of the data center for a high-quality, uninterrupted electrical supply. Consequently, UPS output voltage was the single most influential indicator overall, contributing 21.56% to the total health index. Second, although environmental health ranked second in the weight, average temperature was the second most important indicator, accounting for 19.31%. This result highlights that thermal stability is as critical as voltage stability in preventing hardware failure, thereby justifying the dense deployment of sensors. Equipment status showed the lowest criterion weight, but UPS alarm events were also significant, contributing 11.48% to the health index. This finding indicates the importance of active prevention, in which a single critical alarm event signals an immediate drop in system health, even when environmental and voltage parameters appear nominal.

Table 7  
Average RI.

Order ( <i>n</i> )	1	2	3	4	5	6	7
<i>RI</i>	0	0	0.58	0.90	1.12	1.24	1.32

Table 8  
Weight calculation results.

Level 1 (goal)	Level 2 (criterion and weight ( <i>w</i> ))	Level 3 (indicators)	Local weight ( <i>w<sub>L</sub></i> )	Global weight ( <i>w<sub>G</sub></i> )	Rank
Data center room health	Power system health ( <i>C</i> <sub>1</sub> ) ( <i>w</i> = 0.539)	UPS output voltage	0.4	0.2156	1
		UPS output load/imbalance	0.3	0.1617	3
		UPS battery status	0.2	0.1078	6
		UPS battery runtime	0.1	0.0539	7
	Environmental health ( <i>C</i> <sub>2</sub> ) ( <i>w</i> = 0.297)	Average temperature (inlet/outlet)	0.65	0.1931	2
		Average humidity	0.35	0.1039	8
		Equipment status	UPS alarm events	0.7	0.1148
	( <i>w</i> = 0.164)	HVAC operational status	0.3	0.0492	9

### 3.3 Time series analysis

We conducted a time-series analysis on the indicators to observe dynamic changes and validate the model's responsiveness to anomalies. As shown in Fig. 3, the three-phase output voltage was monitored for stability. During the observation, a voltage sag region is identified between 36:00 and 37:00 min. In this time window, the voltage decreases from a nominal level of 220 V to a minimum of 210.2 V on Phase B voltage. The voltage sag region was caused by a brief decrease in the root mean square voltage below a threshold, typically between 10 and 90% of the nominal voltage, for a duration of half a cycle to one minute.

Figure 4 shows a significant power or load surge occurring in the same time window. The total active power spiked from a baseline of 20 kW to a peak of 100 kW, while the average load rate rose from 15 to 75%, a threshold value.

Figure 5 shows the time-dependent curve of the health index. The model adopted in this study detected the anomaly, showing a significant decline in health score during the identified event window. This sensitivity was attributed to the AHP weighting results. Because power system health was assigned the highest criterion weight (0.539), and output voltage is the most influential global indicator (21.56%), the observed voltage sag and load surge were related to an immediate and visible decrease in the overall health index. This demonstrates the model's ability to prioritize mission-critical electrical stability over ambient fluctuations.

The model used in this study enables high interpretability, allowing operations personnel to track a decrease in the health index to specific subcriteria, such as the output load, which contributes 16.17% to the final score. To validate the results, we compared the model's output against independent expert assessments. As a result, a high degree of correlation ( $R = 0.96$ ) is observed between the calculated health index and expert scores (Fig. 6).

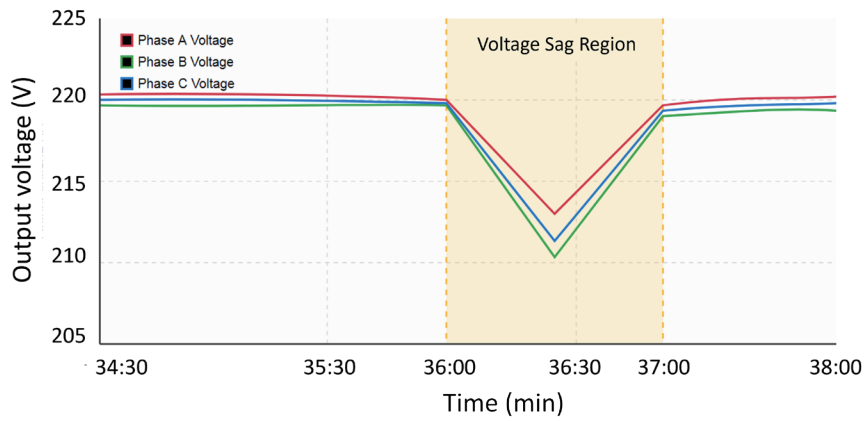


Fig. 3. (Color online) Transient variation of three-phase output voltage highlighting voltage sag region.

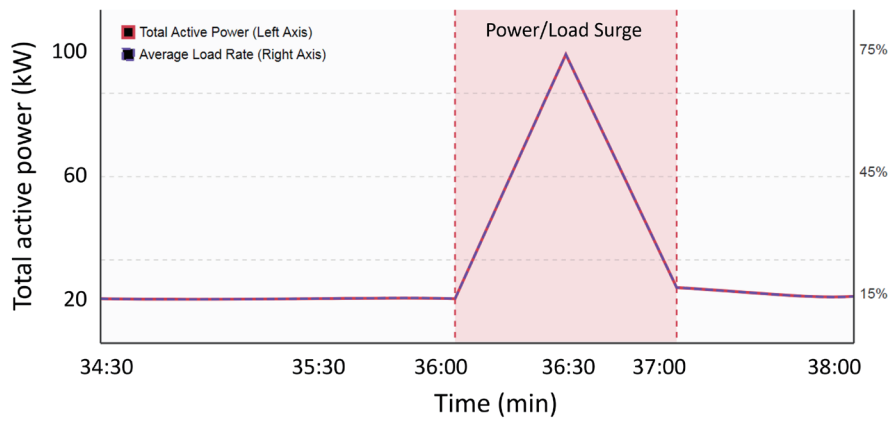


Fig. 4. (Color online) Temporal correlation between total active power (kW) and average load rate (%) during a simulated load surge.

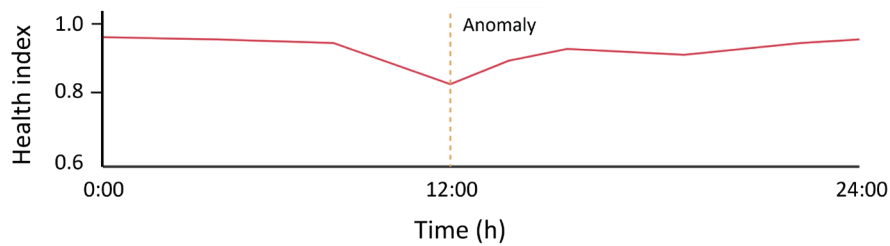


Fig. 5. (Color online) Health index showing anomaly detection and recovery phases.

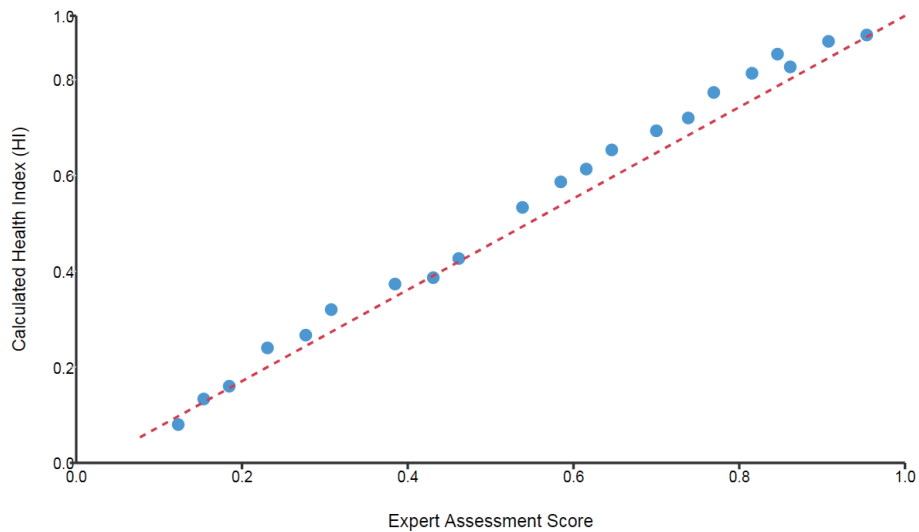


Fig. 6. (Color online) Correlation between AHP-calculated health index and expert assessment scores.

#### 4. Discussion

The health assessment model using the health index for the data center is developed in this study by integrating disparate data streams from internal UPS operational logs and an external WSN. By utilizing AHP to weight heterogeneous data and through the validation of combining internal electrical telemetry with external environmental sensing, the model enables the unified assessment of the operational integrity of the data center.

In traditional data center monitoring models, power systems and thermal management are regarded as silos, neglecting the interdependences between electrical load and heat dissipation.<sup>(14)</sup> However, as validated in this study, the average temperature of the data center room is an influential indicator of the data center's health, following output voltage. This underscores the importance of the sensor deployment strategy in data center rooms.

By placing sensors at the rack inlets and outlets, the model detects the thermal stress of the UPS and IT load during the observed power surges. Such a granularity enables the model to differentiate between a global HVAC failure and localized hotspots caused by electrical imbalances, a distinction that single-point ambient sensors often fail to make.

The model and results of this study can be applied to prognostics and health management. While traditional PHM research focuses on the remaining useful life of individual components, such as UPS batteries or cooling fans,<sup>(15)</sup> the developed model provides a means to construct an appropriate hierarchy to assess system health. For an active prevention of system failure, the health index used in this study reflects minor errors that do not cause higher parameter values than thresholds but indicate a degradation in system redundancy. Such a result can be used for the development of sensor technology from reactive reporting to proactive situational awareness.

The model can also be used to reduce cognitive load for maintenance personnel. By rescaling high-dimensional sensor data into a singular 0–100 score scale, the model provides actionable intelligence based on big data. The health index can be applied to assess power usage

effectiveness and achieve environmentally friendly operational goals.<sup>(14)</sup> A consistently low HI in the environmental criterion in this study indicates cooling inefficiencies that lead to energy waste. Therefore, the appropriate deployment of sensors leads to the enhancement of safety and sustainability and the optimization of cabinet layouts and HVAC setpoints based on real-time health feedback. The generalizability of the developed model is also supported by its reliance on commodity industrial sensors and existing infrastructure. Whereas high-fidelity computational fluid dynamics simulations require significant computational investment, the model processes standard telemetry in real time. This approach significantly lowers the barrier to entry for facility managers, as the smart layer is implemented as a software-based analytical engine on top of existing hardware, rather than requiring a complete infrastructure overhaul.<sup>(16)</sup>

Beyond operational monitoring, the developed health index model provides a basis for the advancement of sensor and material technologies. By quantifying the global weights of system indicators, the physical parameters were identified to increase sensor precision. For instance, the importance of UPS output voltage and average temperature indicates a transition to multimodal sensing units that integrate devices capable of high-frequency electrical sampling and localized thermal detection on a single substrate.<sup>(17)</sup> Cross-system risks, such as thermal impacts following electrical load surges, become targets for the development of intelligent thermal management materials. These include advanced thin-film materials with high thermal conductivity that can be dynamically tuned to respond to the specific load-driven heat signatures identified by the analytical framework.

Despite its potential, the developed model's subjective weighting method needs to be improved. Whereas AHP is a widely used method, the initial pairwise comparisons are subjective. Therefore, it is necessary to integrate entropy weight methods to combine subjective expert knowledge with objective, data-driven weights. For more accurate predictive maintenance, long short-term memory (LSTM) networks or time-series forecasting models must be employed. In addition to this, the model's sensitivity to the voltage sag region must be enhanced by using continuous data packets. Data gaps created by using interpolation algorithms also need to be addressed to enhance the reliability of the assessment results in events causing network latency.

## 5. Conclusions

As digital transformation accelerates, data centers are becoming critical infrastructure. Their continuity, reliability, and efficiency are directly related to the essential functions of institutions and societal stability. Traditional operation and maintenance models, which rely on isolated threshold alarms and passive responses, are insufficient to prevent systemic risks. To address this challenge, we developed a data-fusion-based system-level health index model for effective data center health management.

The model transforms complex operational data into an intuitive and quantifiable basis for decision-making and advances traditional single-point monitoring by fusing internal UPS telemetry with external WSN data. Such an integration enables the detection of cross-system risks, such as thermal impacts associated with electrical load surges, which isolated monitoring approaches often overlook.

A structured indicator model established in this study assesses the health of data centers on the basis of power system health, environmental health, equipment status, and related specific indicators. The AHP method is used to construct a logically consistent weighting hierarchy. The model aligns with expert evaluations ( $R = 0.96$ ) and shows sensitivity to transient anomalies, such as voltage sags. By reducing high-dimensional datasets into a single 0–100 scale, the model simplifies operational decision-making while maintaining traceability to root indicators.

The results of this study provide a basis for the development of intelligent digital twin systems. To more effectively mitigate evolving risks, advanced time-series models, such as LSTM networks, and automated operations platforms must be integrated for closed-loop management across perception, warning, diagnosis, and self-healing.

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