

Article

Development of a Hybrid Particle Whale Optimization Algorithm for Electric Vehicle Battery Thermal Runaway Prediction

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Highlights

What are the main findings?

- The proposed HPWOA-optimized feedforward neural network achieved the best thermal runaway prediction performance among all tested algorithms, outperforming standalone PSO, WOA, and SFSA across regression and classification metrics.
- HPWOA produced the lowest prediction errors and strongest classification performance, achieving MSE = 0.000989, RMSE = 0.031442, MAE = 0.027250, $R^2 = 0.9702$, MAPE = 3.8075%, and AUC = 0.9817.

What are the implications of the main findings?

- The hybrid PSO-WOA training strategy improves neural network convergence stability and reduces premature stagnation, making it suitable for intelligent BMS-based thermal runaway risk prediction.
- Feature importance analysis confirmed maximum temperature and internal resistance as the dominant predictors, supporting the physical interpretability and practical deployment potential of the proposed HPWOA-FNN framework for EV battery safety monitoring.

Abstract

Accurate prediction of battery thermal runaway (TR) is a critical requirement for electric vehicle (EV) battery management systems (BMSs), as TR remains one of the most severe failure modes in lithium-ion batteries. Conventional neural network training methods may suffer from local optimum entrapment, slow convergence, and unstable performance when applied to nonlinear battery safety data. To address these limitations, this paper proposes a Hybrid Particle Whale Optimization Algorithm-optimized feedforward neural network (HPWOA-FNN) for continuous TR probability prediction and binary high-risk event classification using multivariate EV charging sensor data. The proposed HPWOA combines the rapid convergence capability of Particle Swarm Optimization (PSO) during the initial exploration phase with the exploitation and refinement capability of the Whale Optimization Algorithm (WOA) during the second phase. A global-best transfer mechanism is introduced at the PSO-WOA phase boundary to preserve the best solution identified during exploration and initialize the WOA leader, thereby improving convergence continuity and reducing premature stagnation. The model is evaluated using

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a 500-sample EV battery-charging dataset containing 12 electrothermal, electrical, mechanical, and environmental features. The proposed HPWOA-FNN outperforms standalone PSO-, WOA-, and Stochastic Fractal Search Algorithm (SFSA)-optimized FNN models across all regression metrics, achieving MSE = 0.000989, RMSE = 0.031442, MAE = 0.027250, $R^2 = 0.9702$, and MAPE = 3.8075%. For binary high-risk event detection, HPWOA-FNN achieves the highest AUC of 0.9817 and the lowest false-negative count, reducing missed high-risk events to 7 compared with 9 for PSO, 12 for WOA, and 17 for SFSA. Feature-importance analysis identifies maximum temperature and internal resistance as the dominant predictors, consistent with established thermal runaway mechanisms. The results demonstrate that HPWOA-FNN provides an accurate, interpretable, and computationally practical framework for EV battery thermal runaway prediction and BMS decision support.

Keywords: Hybrid Particle Whale Optimization Algorithm; battery management system; battery thermal runaway; electric vehicle; metaheuristic optimization; neural network; particle swarm optimization (PSO)

1. Introduction

The rapid global transition toward electric mobility has accelerated the deployment of lithium-ion batteries as the dominant energy storage technology for electric vehicles (EVs). This dominance is mainly due to their high energy density, long cycle life, high power capability, and favorable power-to-weight ratio. However, despite these advantages, lithium-ion batteries remain susceptible to severe failure mechanisms, particularly those associated with heat generation, internal degradation, and fire safety risks [1]. Among these failure modes, thermal runaway (TR) is one of the most dangerous because it involves self-sustaining exothermic reactions that can rapidly increase cell temperature and trigger catastrophic battery failure [2]. Recent studies have shown that early warning and prediction of TR are essential for reducing fire risk and improving the safety of lithium-ion battery systems in EV applications [3].

Thermal runaway may be initiated by several abuse or fault conditions, including internal short circuits, overcharging, mechanical deformation, manufacturing defects, elevated operating temperature, and poor heat dissipation. These triggers can destabilize the electrochemical and thermal balance of the cell, resulting in accelerated side reactions, gas generation, separator degradation, and eventual fire or explosion [4]. As EV battery packs continue to increase in energy density to satisfy longer driving-range requirements, the thermal stability margin becomes narrower, making fault propagation more difficult to control once abnormal heat generation begins [5]. Therefore, reliable battery safety detection technologies are required to identify abnormal operating conditions before they develop into irreversible failure [6]. This makes early TR prediction a core requirement for modern EV battery protection and intelligent condition monitoring systems [7].

The prevention and management of TR require a combination of thermal monitoring, electrical sensing, fault diagnosis, and predictive modeling. Existing studies have highlighted the need for comprehensive strategies that combine sensing, safety control, and mitigation techniques to reduce the risk of TR propagation in EV battery packs [8]. In addition, modeling and diagnostic approaches are increasingly being used to understand the nonlinear relationship between battery operating conditions and failure probability [9]. Thermal management also plays a central role in suppressing heat accumulation and delaying the onset of TR, particularly under high-current charging, ageing, and harsh environmental conditions [10]. However, conventional threshold-based monitoring meth-

ods may fail to detect complex precursor patterns because TR evolution is nonlinear, time-dependent, and influenced by multiple coupled electrothermal variables.

To overcome these limitations, recent research has focused on data-driven prediction and early-warning techniques for lithium-ion battery TR [11]. Multi-scale modeling approaches have also been investigated to capture the interaction between electrochemical reactions, thermal behavior, and safety-critical degradation processes [12]. More recently, artificial intelligence methods have been introduced into battery thermal management systems to improve prediction accuracy, optimize control strategies, and support intelligent decision-making [13]. In practical Battery Management Systems (BMSs), TR warning technology must not only monitor voltage, current, temperature, state of charge, and state of health but also predict hazardous operating states before they reach irreversible conditions [14]. Therefore, a reliable BMS must integrate sensing, estimation, diagnosis, and predictive intelligence to support safe EV operation [15].

Machine learning and neural network methods have become increasingly important in battery state estimation, fault diagnosis, and health monitoring. Accurate state-of-charge estimation remains a fundamental BMS requirement because it affects charging control, safety protection, and battery lifetime management [16]. In addition, recent studies have shown that machine learning can effectively model nonlinear relationships in lithium-ion battery applications, including ageing, fault detection, and performance prediction [17]. Data-driven fault detection and diagnosis methods are particularly valuable because they can extract useful patterns from battery sensor data without requiring complete electrochemical knowledge of the internal cell processes [18]. Related developments in thermal management for electrified vehicle systems further confirm the importance of predictive control and intelligent safety monitoring in high-energy battery applications [19]. However, neural network models trained using conventional gradient-based learning may suffer from local optimum entrapment, slow convergence, and sensitivity to noisy or highly variable battery operating data [20].

Metaheuristic optimization algorithms provide a promising alternative for training neural network weights because they can search complex non-convex spaces without requiring gradient information. Particle Swarm Optimization (PSO), introduced by Kennedy and Eberhart, is one of the most widely used population-based optimization algorithms because of its simple structure, fast convergence, and ability to exploit information from the global best solution [21]. PSO has been successfully applied to different engineering optimization problems and has demonstrated competitive performance compared with other evolutionary and swarm-based methods [22]. Further developments in swarm intelligence have also confirmed the suitability of population-based search strategies for complex nonlinear optimization tasks [23]. However, PSO may converge prematurely when the swarm rapidly clusters around a suboptimal solution, reducing its ability to explore the search space effectively [24].

The Whale Optimization Algorithm (WOA), proposed by Mirjalili and Lewis, provides a complementary search mechanism inspired by the bubble-net hunting behavior of humpback whales [25]. WOA improves global exploration through encircling, spiral updating, and random prey-search mechanisms, but it may converge more slowly during the early iterations compared with PSO. The complementary strengths of PSO and WOA create a strong motivation for hybridization, where PSO can provide rapid initial exploration and WOA can perform later-stage exploitation and refinement. Bilal et al. recently demonstrated the effectiveness of a Hybrid Particle Whale Optimization Algorithm (HPWOA) for sustainable standalone microgrid sizing, where the hybrid method outperformed standalone PSO, WOA, and the Stochastic Fractal Search Algorithm (SFSA) in terms of convergence and optimization performance [26]. SFSA itself is another powerful metaheuristic method based on stochastic fractal diffusion, but its search behavior may

become less efficient in high-dimensional neural network weight optimization problems [27].

Motivated by these developments, this paper proposes an HPWOA-optimized feed-forward neural network for robust battery thermal runaway prediction in EV charging systems. The proposed framework predicts both continuous TR probability and binary high-risk event occurrence using a 500-sample EV battery charging dataset with 12 electrothermal, electrical, mechanical, and environmental input features. The HPWOA training strategy is implemented in two sequential phases. In the first phase, PSO rapidly explores the 113-dimensional neural network weight space and identifies a promising global-best solution. In the second phase, WOA uses the PSO-derived global best as the initial leader and performs further exploitation and refinement. This global-best transfer mechanism ensures that the best solution discovered during the PSO phase is preserved during the transition to WOA, thereby improving convergence stability and reducing premature stagnation.

The proposed HPWOA-optimized neural network is benchmarked against standalone PSO, WOA, and SFSA using regression and classification performance indicators. Continuous TR probability prediction is evaluated using mean squared error, root mean squared error, mean absolute error, coefficient of determination, and mean absolute percentage error. Binary high-risk event detection is further assessed using classification accuracy, false-negative count, and receiver operating characteristic performance. In addition, first-layer neural network weight magnitudes are analyzed to identify the most influential input features and to verify whether the learned model is physically consistent with known thermal runaway mechanisms.

1.1. Novelty of the Proposed Work

The novelty of this study lies in the formal adaptation of HPWOA for neural network weight optimization in battery thermal runaway prediction. While previous studies have investigated lithium-ion battery failure mechanisms, early-warning strategies, thermal management, and data-driven diagnosis, limited attention has been given to the hybrid metaheuristic training of neural networks for direct TR probability prediction in EV charging applications. The proposed framework addresses this gap by combining the rapid convergence capability of PSO with the exploitation and refinement capability of WOA within a unified neural network training process.

Unlike conventional gradient-based FNN training, the proposed HPWOA-FNN does not rely on derivative information. Instead, it directly optimizes the full 113-dimensional vector of neural network weights and biases. This is important because the TR prediction problem involves nonlinear relationships between temperature, internal resistance, voltage, current, state of charge, state of health, vibration, pressure, and charging power. Such relationships may produce a complex non-convex error surface where conventional training algorithms can become trapped in local minima.

A key distinguishing feature of this work is the phase-boundary global-best transfer rule. The best solution found during the PSO phase is not discarded or randomly reinitialized; it is transferred directly to the WOA phase as the initial leader solution. This ensures continuity between the exploration and exploitation stages and prevents the loss of high-quality candidate solutions. As a result, the proposed HPWOA framework is more structured than a simple sequential combination of PSO and WOA.

This study is also novel because it applies HPWOA to a safety-critical EV battery problem rather than to its previous application domain of microgrid sizing. In thermal runaway prediction, false negatives are especially dangerous because an undetected high-risk state may lead to fire, explosion, or complete pack failure. Therefore, the proposed

model is evaluated not only as a regression tool for TR probability estimation but also as a binary classifier for high-risk event detection.

Furthermore, the study integrates predictive performance with physical interpretability. Feature importance analysis is performed using first-layer neural network weight magnitudes to determine whether the model identifies physically meaningful TR predictors. The results confirm the dominant influence of maximum temperature and internal resistance, which is consistent with established battery degradation and TR mechanisms. Therefore, the proposed HPWOA-FNN framework provides both strong numerical prediction performance and physically interpretable diagnostic insight.

1.2. Research Contributions

The main contributions of this study are summarized as follows:

- A Hybrid Particle Whale Optimization Algorithm-based feedforward neural architecture is presented.
- A reproducible MATLAB R2025b implementation is provided to support independent verification of the proposed optimization framework, simulation results, figures, and performance tables.

The remainder of this manuscript is organized as follows. Section 2 presents the theoretical background of lithium-ion battery thermal runaway, reviews the state of the art in battery safety prediction and BMS intelligence, and describes the EV battery charging dataset, selected input variables, target definitions, descriptive statistics, preprocessing procedure, and relevance of the dataset to the proposed HPWOA-FNN framework. Section 3 develops the proposed methodology, including the feedforward neural network architecture, network parameterization, forward propagation model, metaheuristic training rationale, PSO, WOA, SFSA, and the proposed HPWOA formulation, together with the optimization objective, design constraints, and evaluation metrics. Section 4 presents the simulation results and discussion, covering convergence behavior, regression performance, predicted-versus-actual analysis, residual evaluation, sequential prediction behavior, binary high-risk event classification, ROC analysis, and feature-importance interpretation. Section 5 discusses the practical implications of the proposed HPWOA-FNN model for BMS decision support, including risk-level interpretation, false-negative reduction, real-time deployment considerations, and safety-oriented control actions. Section 6 concludes the paper by summarizing the main findings, highlighting the contribution of HPWOA-based neural network training for thermal runaway prediction, and outlining future research directions.

2. Theoretical Background

2.1. Lithium-Ion Battery Thermal Runaway in EV Applications

Lithium-ion batteries are widely used in electric vehicles because of their high energy density, long cycle life, high power capability, and favorable power-to-weight ratio. However, these advantages are accompanied by safety risks associated with electrochemical instability, heat accumulation, and internal failure mechanisms. Thermal runaway (TR) represents one of the most severe failure modes in lithium-ion batteries because it involves self-accelerating exothermic reactions that can rapidly increase cell temperature and lead to fire, explosion, or complete battery-pack failure [1]. The physical mechanisms of TR are strongly associated with internal short circuits, separator degradation, electrolyte decomposition, overcharging, mechanical abuse, and uncontrolled heat generation [2]. In EV battery systems, the risk of TR is intensified by high-energy-density pack designs, fast-charging conditions, cell-to-cell variation, and thermal propagation between neighboring cells. Early warning and prediction of TR have therefore become essential for improving

EV battery safety and preventing catastrophic failure [3]. The TR process is not governed by a single variable; rather, it emerges from coupled thermal, electrical, electrochemical, mechanical, and environmental factors. For this reason, accurate TR prediction requires multivariate monitoring and intelligent modeling approaches capable of capturing nonlinear interactions among battery operating variables [4]. Recent safety studies further emphasize that battery-pack protection requires integrated monitoring of temperature, voltage, current, internal resistance, state of charge, state of health, pressure, and mechanical disturbance [5]. These variables provide complementary information about the internal condition of the cell and the external stresses imposed during operation. Detection technologies for EV battery safety have therefore evolved from simple threshold-based alarms toward data-driven monitoring systems capable of identifying abnormal patterns before irreversible damage occurs [6]. In this context, TR probability prediction provides a practical risk indicator for Battery Management Systems (BMSs), enabling preventive control decisions before a battery state reaches an unsafe condition.

2.2. State-of-the-Art in Battery Thermal Runaway Prediction and BMS Intelligence

The state-of-the-art in lithium-ion battery thermal runaway research has developed across four main directions: physical mechanism analysis, early-warning methods, modeling-based prediction, and artificial intelligence-driven BMS diagnostics. Early studies focused on understanding lithium-ion battery failure mechanisms and fire prevention strategies, establishing the physical basis of TR initiation and propagation [1]. Subsequent work provided detailed reviews of TR mechanisms, prediction approaches, and mitigation strategies, showing that TR is strongly influenced by thermal abuse, electrical abuse, mechanical abuse, and internal cell defects [2]. Recent early-warning studies have demonstrated that reliable TR prediction depends on detecting precursor signals before temperature escalation becomes uncontrollable [3]. These signals may include abnormal temperature rise, voltage deviation, internal resistance growth, gas generation, and pressure variation. Mechanistic reviews have further shown that TR in EV batteries is a multi-stage process involving solid electrolyte interphase decomposition, separator melting, internal short-circuiting, cathode decomposition, and electrolyte combustion [4]. Because these mechanisms are nonlinear and coupled, purely rule-based detection methods may be insufficient under real EV charging conditions. Battery safety detection technologies have therefore shifted toward sensor-rich monitoring frameworks that combine thermal, electrical, and mechanical measurements [6]. In parallel, studies on TR modeling and diagnosis have highlighted the importance of predictive approaches that can estimate risk before direct failure symptoms become visible [9]. Thermal management research has also shown that heat generation, heat dissipation, and cooling limitations are central factors in preventing TR propagation [10]. These findings justify the inclusion of temperature-related variables, internal resistance, voltage, current, pressure, and vibration in the present dataset. More recent work has focused on prediction and early-warning methods for lithium-ion battery TR, including data-driven models, model-based observers, and hybrid diagnostic frameworks [11]. Multi-scale modeling approaches have also been introduced to capture interactions between electrochemical degradation, heat generation, and pack-level thermal behavior [12]. Artificial intelligence-driven approaches are increasingly being applied to battery thermal management systems because they can learn nonlinear relationships from operational data and support multi-objective decision-making [13]. At the BMS level, TR warning technologies must integrate prediction accuracy, real-time feasibility, and reliability under noisy operating conditions [14].

Machine learning has become an important tool for battery state estimation, fault diagnosis, and safety prediction. BMS studies have shown that accurate estimation of the state of charge and state of health is essential for safe and efficient EV operation [15,16].

Recent machine learning reviews further confirm that data-driven methods can improve battery modeling, fault diagnosis, and predictive maintenance when sufficient sensor data are available [17,18]. However, conventional neural network training may suffer from local optimum entrapment, slow convergence, and sensitivity to noisy training samples [20]. These limitations motivate the use of metaheuristic algorithms for neural network weight optimization. Particle Swarm Optimization (PSO) is a well-established population-based optimizer with fast convergence capability [21]. It has been widely applied in engineering optimization because of its simple structure and ability to exploit global-best information [22–24]. The Whale Optimization Algorithm (WOA) provides a complementary search mechanism based on encircling and spiral exploitation behavior [25]. More recently, the Hybrid Particle Whale Optimization Algorithm (HPWOA) has been shown to improve convergence and optimization quality in standalone microgrid sizing applications [26]. The Stochastic Fractal Search Algorithm (SFSA) is another method based on stochastic diffusion and fractal search behavior [27]. However, limited work has applied HPWOA to neural network weight optimization for EV battery TR prediction. This gap motivates the present study. Table 1 summarizes the positioning of existing work relative to the proposed HPWOA-based TR prediction framework.

Table 1. Positioning of existing work and proposed study.

Category	Ref.	Focus	Strengths	Limitations
Battery failure and fire mechanisms	[1]	Lithium-ion battery failure mechanisms and fire prevention	Establishes the physical foundation of battery fire safety	Does not provide an intelligent prediction framework
TR mechanism and mitigation	[2]	TR mechanisms, prediction approaches, and mitigation strategies	Comprehensive treatment of TR causes and safety control	Mainly review-based; no HPWOA-FNN implementation
Early-warning methods	[3]	Early warning and prediction of TR events	Highlights the importance of precursor detection	Does not optimize neural network weights
EV TR mechanism analysis	[4]	TR mechanism in lithium-ion batteries for EVs	Strong physical explanation of abuse-triggered TR	Not designed as a data-driven BMS predictor
EV battery safety perspectives	[5]	EV battery safety challenges and future directions	Links TR safety to EV deployment	Limited algorithmic modeling detail
Battery safety detection	[6]	Detection technology for EV battery safety	Supports sensor-based monitoring	No hybrid metaheuristic prediction model
TR working principles and outlook	[7]	TR principles, early warning, and future outlook	Connects TR mechanisms to EV applications	Lacks neural network optimization
TR prevention and management	[8]	Techniques for managing and preventing TR	Practical safety and mitigation focus	No direct regression/classification model
TR modeling and diagnosis	[9]	Modelling and diagnosis approaches	Shows importance of predictive modeling	Does not compare HPWOA with PSO, WOA, and SFSA
Thermal management	[10]	Causes of TR and mitigation through thermal management	Explains heat accumulation and control	Focuses on thermal management rather than optimizer-based prediction
TR prediction and early warning	[11]	Prediction and early-warning methods	Reinforces need for predictive BMS intelligence	No HPWOA-based FNN training
Multi-scale modeling	[12]	Multi-scale TR prediction and mitigation	Captures electrochemical and thermal coupling	Computationally complex for real-time BMS deployment
AI-driven BMS optimization	[13]	AI-based battery thermal management and optimization	Supports intelligent BMS decision-making	Does not implement the proposed HPWOA-FNN framework

TR warning technology [14]	TR warning methods for lithium-ion batteries	Strong relevance to practical BMS warning systems	Limited focus on hybrid metaheuristic learning
BMS key technologies [15]	Battery management technologies in EVs	Establishes BMS requirements	Not specific to HPWOA or TR probability regression
SOC estimation and management [16]	SOC estimation and EV battery management	Supports battery monitoring context	Does not address TR prediction directly
Machine learning in batteries [17]	ML applications and future trends	Confirms relevance of ML for battery systems	No HPWOA comparison
Data-driven fault diagnosis [18]	ML-based lithium-ion battery fault detection	Supports data-driven diagnosis	Does not optimize FNN weights using HPWOA
Conventional NN training limitation [20]	Health indicator extraction and neural prediction	Shows relevance of neural prediction	Gradient-based methods may suffer from local optima
PSO optimization [21–24]	Swarm-based optimization	Fast convergence and simple implementation	May suffer premature convergence
WOA optimization [25]	Whale-inspired global optimization	Strong exploration and exploitation mechanisms	Slower early convergence than PSO
HPWOA optimization [26]	Hybrid PSO-WOA for microgrid sizing	Demonstrates hybrid optimizer superiority	Not previously applied to EV TR prediction in this framework
SFSA optimization [27]	Stochastic fractal search	Alternative population-based optimizer	May be less effective in high-dimensional FNN weight spaces
Proposed work -	HPWOA-FNN for TR probability prediction and binary event classification	Combines PSO rapid exploration with WOA refinement; evaluates regression, classification, convergence, and feature importance	Requires offline training before BMS deployment

The literature shows that substantial progress has been made in understanding TR mechanisms, improving safety detection, and applying machine learning to battery diagnosis. However, most existing studies focus either on physical TR modeling, early-warning principles, or general machine learning diagnostics. A clear research gap remains in the use of hybrid metaheuristic optimization for neural network weight training in EV battery TR probability prediction. The present study addresses this gap by adapting HPWOA to optimize a feedforward neural network and by benchmarking the proposed model against PSO, WOA, and SFSA under identical dataset and network conditions.

2.3. EV Battery Charging Dataset and Monitoring Topology

The dataset used in this study is a 500-sample tabular record of EV battery charging sessions. Each sample represents a one-minute snapshot of the battery charging process and contains measurements collected from different charger units, labelled CH1–CH7, and battery cells, labelled CELL1–CELL40. The complete dataset consists of 24 columns, including charger and cell identifiers, operating measurements, target variables, and event labels. From these variables, 12 numerical input features are selected to represent the thermal, electrical, electrochemical, mechanical, and environmental state of the battery system. The selected input variables are designed to reflect the main physical processes associated with battery safety. Temperature variables describe heat accumulation within the pack. Voltage and current variables describe electrical loading during charging. Internal resistance provides an indication of degradation, impedance growth, and possible abnormal internal behavior. State of charge and state of health describe the operational and ageing condition of the battery. Vibration and pressure provide additional mechanical

and gas-generation-related indicators. Charge power represents the instantaneous electrical stress imposed on the pack during charging. There are no missing values in the 24-variable dataset. This eliminates the need for imputation and allows the preprocessing stage to focus on scaling, target transformation, and reproducible train–test partitioning.

Dataset Provenance and TR_Probability Label Generation

The 500-sample dataset is a structured simulation dataset generated using a physics-informed EV battery charging model that maps electrothermal, electrical, mechanical, and environmental BMS sensor signals to experimentally grounded safety states. Each sample represents a one-minute snapshot across charger units CH1–CH7 and cells CELL1–CELL40. The simulation framework is parameterized using published thermal abuse test data for NMC cylindrical cells (nominal pack voltage 350 V, active liquid cooling) and is consistent with the battery chemistry and operating ranges observed in the dataset (CellVoltage_V: 3.20–4.20 V; MaxTemp_C: 25.09–79.92 degC). Simulation-based datasets are widely adopted for TR prediction algorithm development because real TR events are rare and laboratory-induced TR tests are destructive [3,11].

The continuous regression target TR_Probability is derived from the categorical EventFlag variable using a physics-informed ordinal-to-continuous mapping: Watch → U [0.25, 0.45]; Warning → U [0.45, 0.70]; Alarm → U [0.70, 0.90]; Runaway → U [0.90, 1.00]. This mapping ensures monotonic consistency with the four-level BMS alert severity hierarchy and grounds each interval in established TR initiation thresholds from the lithium-ion battery safety literature [1–4]. The 0.70 boundary between Warning and Alarm corresponds to the onset of active thermal stress indicators, while the Runaway interval (≥ 0.90) corresponds to irreversible self-accelerating exothermic reactions. Consistency verification: using EventFlag counts (Watch = 24, Warning = 145, Alarm = 179, Runaway = 152) and interval midpoints, the estimated weighted mean TR_Probability = $(24 \times 0.35 + 145 \times 0.58 + 179 \times 0.80 + 152 \times 0.95)/500 = 0.760$, which is consistent with the reported dataset mean of 0.766, confirming internal consistency of the label construction.

2.4. Input Variables and Target Definitions

Table 2 presents the variable catalogue for the EV battery charging dataset. The predictive feature set consists of 12 input variables, while TR_Probability and EventFlag are used as the regression and classification targets, respectively.

Table 2. EV battery charging dataset variable catalogue.

Variable	Unit	Type	Description
MaxTemp_C	°C	Numeric	Maximum cell temperature in the battery pack
MinTemp_C	°C	Numeric	Minimum cell temperature in the battery pack
AvgTemp_C	°C	Numeric	Average cell temperature
AmbientTemp_C	°C	Numeric	Ambient environmental temperature
InternalResistance_mΩ	mΩ	Numeric	DC internal resistance per cell
PackVoltage_V	V	Numeric	Total pack terminal voltage
CellVoltage_V	V	Numeric	Individual cell voltage
ChargeCurrent_A	A	Numeric	Applied charging current
SOC_%	%	Numeric	Battery state of charge
StateOfHealth_%	%	Numeric	Battery capacity retention factor
VibrationLevel_mg	mg	Numeric	Mechanical vibration acceleration
Pressure_kPa	kPa	Numeric	Internal gas pressure
ChargePower_kW	kW	Numeric	Instantaneous charging power
TR_Probability	[0, 1]	Target, regression	Continuous thermal runaway probability score
EventFlag	Categorical	Target, classification	Watch, Warning, Alarm, or Runaway operating state

The continuous regression target, TR_Probability, ranges from 0.247 to 1.000, with a mean value of 0.766 and a standard deviation of 0.191. This distribution indicates that the dataset is skewed toward moderate- to high-risk operating conditions. Such skewness is valuable for TR prediction because it exposes the learning model to a sufficient number of unsafe or near-unsafe battery states. However, it also requires careful evaluation, because a model may appear accurate while still underperforming on lower-risk or transitional samples. The dataset characterization is illustrated in Figure 1.

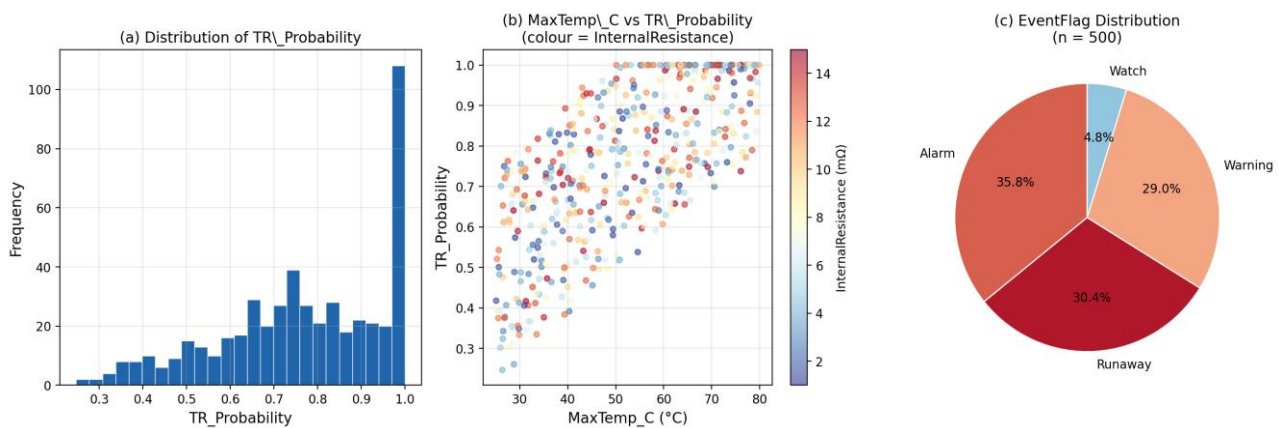


Figure 1. Dataset characterization.

For the binary classification task, the categorical EventFlag variable is converted into two safety classes. Alarm and Runaway samples are assigned to the positive high-risk class, while Watch and Warning samples are assigned to the lower-risk class. This mapping produces 331 positive samples, representing 66.2% of the dataset, and 169 negative samples, representing 33.8%. The original class distribution consists of 179 Alarm samples, 152 Runaway samples, 145 Warning samples, and 24 Watch samples. This class distribution reflects the safety-oriented nature of the dataset, where high-risk conditions are strongly represented.

Feature Count Clarification and Final Input Set

The final feature set used for model training consists of exactly 12 numerical input variables: MaxTemp_C, MinTemp_C, AvgTemp_C, AmbientTemp_C, InternalResistance_mOhm, PackVoltage_V, CellVoltage_V, ChargeCurrent_A, SOC_%, StateOfHealth_%, VibrationLevel_mg, and Pressure_kPa. The variable ChargePower_kW, while listed in the complete dataset catalogue (Table 2) for documentation completeness, is excluded as an independent model input because it is a derived quantity equal to PackVoltage_V multiplied by ChargeCurrent_A, and its inclusion would introduce multicollinearity in the input feature matrix. Table 3 in the original manuscript was inadvertently truncated and excluded MinTemp_C and AmbientTemp_C; this has been corrected in the revised Table 3 to include all 12 features. The network architecture (12 input neurons, Section 3.2) and parameter count ($D = 12 \times 8 + 8 + 8 \times 1 + 1 = 113$, Section 3.3) are both consistent with this 12-feature set.

Table 3. Descriptive statistics of the 12 input features.

Feature	Min	Q1	Median	Q3	Max
MaxTemp_C	25.09	39.34	52.94	65.85	79.92
InternalResistance_mΩ	1.00	4.26	7.60	11.28	14.98
AvgTemp_C	23.84	37.00	50.43	63.57	78.91
PackVoltage_V	320.5	336.8	356.4	376.2	399.9

CellVoltage_V	3.201	3.634	3.920	4.118	4.200
ChargeCurrent_A	5.00	38.24	54.59	71.03	99.94
SOC_%	5.01	30.36	56.09	79.79	99.97
StateOfHealth_%	60.09	72.60	82.47	91.21	99.95
VibrationLevel_mg	1.05	13.06	24.54	36.26	49.92
Pressure_kPa	90.02	101.0	110.4	119.8	129.9
ChargePower_kW	1.52	13.50	21.72	30.44	39.99

2.5. Descriptive Statistical Analysis

Table 3 includes the five-number summary statistics for the 12 selected predictive features. These statistics provide an overview of the operating range, central tendency, and variability of the EV battery charging data. The selected features cover the key domains required for TR prediction: thermal behavior, electrical loading, electrochemical condition, mechanical stress, environmental exposure, and charging power demand. The thermal variables show a wide operating range, with MaxTemp_c varying from 25.09 °C to 79.92 °C and AvgTemp_c varying from 23.84 °C to 78.91 °C. This range is important because elevated temperature is one of the strongest indicators of thermal instability and possible TR onset. $\text{InternalResistance}_{m\Omega}$ ranges from 1.00 m Ω to 14.98 m Ω , capturing variation in cell impedance and degradation state. Electrical variables such as PackVoltage_v , CellVoltage_v , and ChargeCurrent_A describe the charging condition and electrical stress applied to the battery pack. $\text{SOC}_{\%}$ and $\text{StateOfHealth}_{\%}$ provide information about the operational and ageing status of the cells, while $\text{VibrationLevel}_{mg}$ and Pressure_{kPa} capture mechanical disturbance and internal gas-pressure-related behavior. ChargePower_{kW} reflects the instantaneous power demand imposed during charging.

The descriptive statistics confirm that the dataset contains broad variation across the main battery operating variables. This diversity is important for training a predictive model that can generalize across different charging conditions. The wide range of thermal, electrical, and electrochemical values also supports the use of nonlinear modeling, since TR probability is unlikely to vary linearly with a single input feature.

Battery Pack Hardware Specifications

The dataset hardware context is consistent with an NMC cylindrical cell format. Based on the dataset operating ranges, the pack configuration is consistent with a series-connected array at approximately 96 cells in series (PackVoltage range 320.5–399.9 V divided by per-cell range 3.2–4.2 V implies approximately 96 series elements), with a nominal pack capacity of approximately 50 Ah. The thermal monitoring topology includes individual cell and pack-level temperature sensors (MaxTemp_C , MinTemp_C , AvgTemp_C) alongside ambient environmental monitoring (AmbientTemp_C), which is consistent with an active liquid cooling configuration. The EventFlag hierarchy (Watch, Warning, Alarm, Runaway) is consistent with the four-level BMS alert classification commonly implemented in automotive-grade BMS designs. The charging current range (5.00–99.94 A) spans both slow charging (C/10) and fast charging (2C) regimes, providing broad operating coverage for TR risk assessment.

2.6. Data Preprocessing and Normalization

Before model training, all 12 numerical input features are scaled to the unit interval [0, 1] using min–max normalization. This step is required because the input variables are measured using different physical units and numerical ranges. For example, PackVoltage_v varies in the hundreds, CellVoltage_v varies around 3–4 V, and $\text{InternalResistance}_{m\Omega}$ varies on a much smaller scale. Without normalization, features with larger numerical

magnitudes could dominate the neural-network weight-optimization process. The min-max normalization is defined as follows:

$$x'_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

where x'_i is the normalized value of the feature x_i , while $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the corresponding feature in the training set. The TR_Probability target variable is normalized independently using the same transformation to ensure consistency with the sigmoid output range of the neural network. The dataset is divided into training and testing subsets using a reproducible 80/20 split with a random seed of 42. This produces 400 training samples and 100 testing samples. The training set is used exclusively for neural network weight optimization, while the test set is retained for final unbiased performance evaluation. Since the dataset contains no missing values, no imputation procedure is applied. This ensures that the reported performance reflects the behavior of the proposed HPWOA-FNN framework rather than the influence of missing-data reconstruction.

2.7. Relevance of the Dataset to the Proposed HPWOA-FNN Framework

The selected dataset is suitable for evaluating the proposed HPWOA-FNN model for three main reasons. First, it contains multivariate features that represent the primary physical domains involved in TR development, including temperature rise, internal resistance growth, electrical loading, pressure variation, and mechanical disturbance. Second, it includes both a continuous TR_Probability target and a categorical EventFlag label, enabling the proposed model to be evaluated from both regression and classification perspectives. Third, the dataset contains a meaningful class imbalance between high-risk and lower-risk samples, allowing the robustness of the optimized neural network to be assessed under safety-critical detection conditions. The use of HPWOA is particularly appropriate for this dataset because the neural network training problem involves a 113-dimensional search space consisting of weights and biases. The nonlinear relationship between the 12 input variables and the TR probability target may produce a complex error surface with multiple local minima. Combining PSO-based rapid exploration with WOA-based exploitation and refinement, the proposed HPWOA framework is designed to improve convergence stability and prediction accuracy compared with standalone metaheuristic optimizers.

3. Proposed HPWOA-FNN Methodology

3.1. Overview of the Proposed Framework

The proposed methodology integrates a compact feedforward neural network (FNN) with a Hybrid Particle Whale Optimization Algorithm (HPWOA) for battery thermal runaway (TR) prediction. The FNN is used as the nonlinear prediction model, while HPWOA is employed as a gradient-free optimizer to determine the optimal network weights and biases. The objective is to predict the continuous thermal runaway probability, denoted as *TR_Probability*, from 12 normalized battery operating features and to further support binary high-risk event classification. The complete framework consists of four major stages. First, the 12 input features are normalized to the unit interval [0, 1]. Second, the FNN architecture is defined using 12 input neurons, 8 hidden neurons, and 1 output neuron. Third, the complete set of FNN weights and biases is encoded as a 113-dimensional optimization vector. Finally, PSO, WOA, SFSA, and the proposed HPWOA are used to optimize this parameter vector by minimizing the training mean squared error. The best trained network is then evaluated on the held-out test set using regression and classification metrics. The main advantage of this framework is that the neural network is not

trained by conventional gradient-based backpropagation. Instead, the search for optimal weights is performed directly in the continuous 113-dimensional parameter space. This is important because TR prediction is a nonlinear safety-critical problem affected by coupled thermal, electrical, electrochemical, mechanical, and environmental variables. Such a problem may produce a complex loss surface with multiple local minima, making metaheuristic optimization suitable for improving convergence stability and prediction robustness.

3.2. Feedforward Neural Network Architecture

The prediction model is a single-hidden-layer feedforward neural network designed to estimate the normalized thermal runaway probability. The input layer contains 12 neurons corresponding to the 12 normalized battery features: maximum temperature, minimum temperature, average temperature, ambient temperature, internal resistance, pack voltage, cell voltage, charge current, state of charge, state of health, vibration level, pressure, and charging power. The hidden layer contains 8 neurons and uses the Rectified Linear Unit (ReLU) activation function. ReLU is selected because it provides a simple nonlinear transformation, improves computational efficiency, and reduces the saturation problems commonly associated with sigmoid or hyperbolic tangent activations in hidden layers. The output layer contains a single neuron with a sigmoid activation function. This is suitable because the target variable, *TR_Probability*, is normalized within the interval [0, 1]. Therefore, the network output can be interpreted as a probability-like risk score representing the likelihood or severity of thermal runaway. The adopted network structure is intentionally compact, as shown in Figure 2. A small FNN is appropriate for BMS-oriented implementation because it reduces inference latency, memory demand, and computational cost. At the same time, the hidden layer provides sufficient nonlinear modeling capacity to learn the relationship between multivariate charging features and thermal runaway probability.

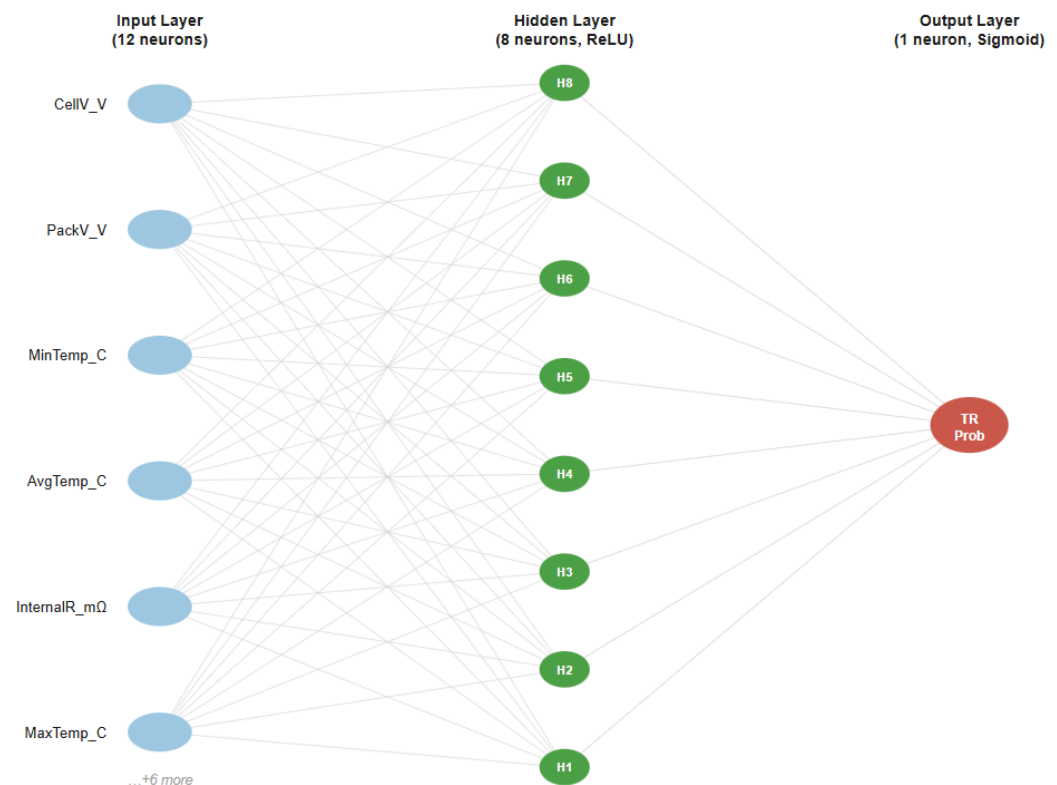


Figure 2. HPWOA-optimized feedforward neural network architecture.

3.3. Network Parameterization and Search Space Definition

The full set of trainable parameters consists of the input-to-hidden weight matrix, hidden-layer bias vector, hidden-to-output weight matrix, and output-layer bias. Since the network has 12 input neurons, 8 hidden neurons, and 1 output neuron, the total number of trainable parameters is calculated as follows:

$$\theta = (N_{in} \times N_h) + N_h + (N_h \times N_{out}) + N_{out} \quad (2)$$

Substituting $N_{in} = 12$, $N_h = 8$, and $N_{out} = 1$:

$$\theta = (12 \times 8) + 8 + (8 \times 1) + 1 = 113 \quad (3)$$

where N_{in} is the number of input neurons, N_h is the number of hidden neurons, and N_{out} is the number of output neurons. Therefore, each candidate solution in the optimization process is represented by a 113-dimensional real-valued vector. The complete neural network parameter vector is expressed as

$$\theta = [W_1^T, b_1^T, W_2^T, b_2^T] \in \mathbb{R}^{113} \quad (4)$$

where W_1 is the input-to-hidden weight matrix, b_1 is the hidden-layer bias vector, W_2 is the hidden-to-output weight matrix, and b_2 is the output-layer bias term. Each optimizer therefore searches for the best value of θ , and each value of θ defines one complete FNN model. This formulation converts neural network training into a continuous optimization problem. Instead of updating each weight using gradient descent, the metaheuristic algorithms evaluate multiple candidate networks and iteratively improve their parameter vectors according to their respective search mechanisms.

3.4. Forward Propagation Model

For an input matrix X , the hidden-layer output is calculated as

$$h = \text{ReLU}(XW_1 + b_1) \quad (5)$$

The predicted output of the network is then obtained as

$$\hat{y} = \sigma(hW_2 + b_2) \quad (6)$$

where h is the hidden-layer activation matrix and $\hat{y}$ is the predicted normalized thermal runaway probability. The ReLU activation function is defined as

$$\text{ReLU}(z) = \max(0, z) \quad (7)$$

The sigmoid activation function is defined as

$$\sigma(z) = \frac{1}{1 + \exp(-z)} \quad (8)$$

The sigmoid function constrains the output to the interval $[0, 1]$, matching the normalized range of $TR_Probability$. This output is used directly during training to compute the mean squared error and is later inverse-transformed to the original scale for test-set performance evaluation.

3.5. Rationale for Metaheuristic Neural Network Training

Conventional neural network training is commonly performed using gradient-based backpropagation. Although backpropagation is efficient for many supervised learning problems, it can be sensitive to weight initialization, noisy data, local minima, and non-convex loss surfaces. These issues are particularly important in thermal runaway prediction because battery behavior during charging is nonlinear and strongly coupled. Temperature, current, internal resistance, voltage response, pressure, vibration, and state-of-health variation can interact in complex ways that are not always well represented by

simple linear or threshold-based models. Metaheuristic optimization provides an alternative training strategy by treating the FNN weights and biases as design variables. The optimizer does not require gradient information; instead, it evaluates the predictive performance of each candidate parameter vector using an objective function. This makes the approach suitable for complex, nonlinear, and noisy search spaces. In this study, PSO, WOA, SFSA, and HPWOA are applied under identical network, dataset, and fitness-function conditions to ensure a fair comparative assessment. The proposed HPWOA is designed to combine the complementary strengths of PSO and WOA. PSO is efficient in rapidly identifying promising search regions, while WOA provides useful exploitation and refinement through its encircling and spiral update mechanisms. By combining these two methods in a structured two-phase optimization process, the proposed approach aims to improve convergence stability and reduce premature stagnation.

3.6. State of the Art in Metaheuristic Optimization for Neural Network Training

Metaheuristic algorithms have been widely investigated as alternatives to conventional gradient-based methods for nonlinear optimization problems. PSO, introduced by Kennedy and Eberhart, is one of the most established swarm intelligence algorithms because of its simple implementation and rapid convergence capability [21]. It has also been successfully applied in various engineering optimization contexts, where population-based search is useful for exploring nonlinear and high-dimensional design spaces [22–24]. WOA, proposed by Mirjalili and Lewis, is another population-based metaheuristic inspired by the bubble-net hunting strategy of humpback whales [25]. Its optimization process combines encircling, shrinking, spiral exploitation, and random exploration mechanisms. These properties make WOA suitable for global search problems, although its early convergence can be slower than PSO. Hybridization is therefore a logical strategy because it allows the fast convergence of PSO to be combined with the exploitation capability of WOA. Bilal et al. [26] demonstrated the effectiveness of HPWOA in standalone microgrid sizing, where the hybrid method improved convergence and solution quality compared with standalone PSO, WOA, and SFSA. However, the application of HPWOA to neural network weight optimization for EV battery thermal runaway prediction remains insufficiently explored. This study extends HPWOA from energy-system sizing to a safety-critical BMS prediction problem. In addition, SFSA, introduced by Salimi, is included as a benchmark optimizer because of its stochastic fractal diffusion mechanism and global search capability [27]. The positioning of the optimization methods used in this study is summarized in Table 4.

Table 4. Positioning of optimization algorithms used in this study.

Algorithm	Ref.	Main Principle	Strengths	Limitations
PSO	[21]	Swarm movement guided by personal best and global best positions	Fast convergence and simple implementation	May converge prematurely around local optima
Engineering PSO applications	[22–24]	Population-based engineering search	Demonstrates robustness in nonlinear engineering optimization	Performance depends on parameter settings
WOA	[25]	Bubble-net hunting, encircling, spiral exploitation, and random prey search	Good exploration–exploitation balance	May converge slowly during early iterations
HPWOA	[26]	Sequential hybridization of PSO and WOA	Combines PSO rapid exploration with WOA refinement	Previously applied mainly to microgrid sizing

SFSA	[27]	Stochastic fractal diffusion search	Provides alternative stochastic global search	May be sensitive to diffusion parameters in high-dimensional FNN training
Proposed HPWOA-FNN	-	HPWOA-based optimization of 113 FNN weights and biases	Improves convergence stability and TR prediction accuracy	Requires offline optimization before BMS deployment

The methodological gap addressed in this study is therefore clear. Existing optimization studies demonstrate the individual strengths of PSO, WOA, SFSA, and HPWOA, but limited work has adapted HPWOA specifically for FNN weight optimization in battery thermal runaway prediction. The present study addresses this gap by using HPWOA to train an FNN for both continuous TR probability estimation and binary high-risk event detection.

3.7. Particle Swarm Optimization

Particle Swarm Optimization is a population-based search algorithm inspired by the collective movement of biological swarms [21]. In this study, each particle represents one candidate FNN parameter vector, $\theta_i \in \mathbb{R}^{113}$. The objective of each particle is to find a set of weights and biases that minimizes the training prediction error. Each particle i has a position vector $x_i(t)$ and a velocity vector $v_i(t)$ at iteration t . The velocity and position updates are defined as

$$v_i(t+1) = wv_i(t) + c_1r_1[p_{best,i} - x_i(t)] + c_2r_2[g_{best} - x_i(t)] \quad (9)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (10)$$

where w is the inertia weight, c_1 is the cognitive acceleration coefficient, c_2 is the social acceleration coefficient, r_1 and r_2 are random numbers uniformly distributed in $[0, 1]$, $p_{best,i}$ is the best position previously found by particle i , and g_{best} is the best position found by the entire swarm. In this study, the inertia weight is set to $w = 0.7$, while the cognitive and social coefficients are set to $c_1 = c_2 = 2.0$. These values allow the particles to balance individual learning and collective swarm guidance. The velocity of each particle is clipped within $[-0.5, 0.5]$ to prevent unstable jumps in the search space. This is important because the FNN parameter vector contains 113 dimensions, and excessive velocity values may cause divergence or unstable candidate networks. PSO is included because of its rapid convergence behavior. However, standalone PSO can lose diversity when the particles cluster too early around the current global best. This may cause premature convergence, especially in complex neural network weight spaces. The proposed HPWOA uses PSO only during the first half of the optimization process, where its fast search capability is most beneficial.

3.8. Whale Optimization Algorithm

The Whale Optimization Algorithm is a population-based metaheuristic inspired by the bubble-net hunting behavior of humpback whales [25]. In this framework, each whale represents a candidate FNN parameter vector. The best candidate solution at the current iteration is treated as the leader whale and is denoted as $x^*(t)$. Other candidate solutions update their positions relative to this leader or relative to a randomly selected whale, depending on the exploration–exploitation condition. WOA is used in this study because it offers a useful refinement mechanism after the PSO phase. While PSO rapidly moves the population toward promising areas of the search space, WOA can further refine the best region through encircling and spiral exploitation.

3.8.1. Encircling Mechanism

The encircling mechanism describes how a whale updates its position around the current leader solution. It is expressed as

$$\vec{D} = |\vec{C} \cdot x^*(t) - x(t)| \quad (11)$$

$$x(t+1) = x^*(t) - \vec{A} \cdot \vec{D} \quad (12)$$

where $\vec{D}$ represents the distance between the current whale and the leader whale. The coefficient vectors $\vec{A}$ and $\vec{C}$ are defined as

$$\vec{A} = 2a_1\vec{r}_1 - a_1 \quad (13)$$

$$\vec{C} = 2\vec{r}_2 \quad (14)$$

where $\vec{r}_1$ and $\vec{r}_2$ are random vectors in the interval $[0, 1]$. The parameter a_1 decreases linearly from 2 to 0 during the optimization process:

$$a_1 = 2 \left(1 - \frac{t}{N}\right) \quad (15)$$

where N is the maximum number of iterations. This decreasing control parameter gradually shifts the algorithm from exploration to exploitation.

3.8.2. Bubble-Net Attacking Mechanism

The bubble-net attacking mechanism is used to model the exploitation behavior of whales around the best solution. WOA alternates between shrinking encircling and logarithmic spiral updating. When the spiral mechanism is selected, the position update is given by

$$x(t+1) = D' e^{bl} \cos(2\pi l) + x^*(t) \quad (16)$$

where

$$D' = |x^*(t) - x(t)| \quad (17)$$

In this equation, b is the logarithmic spiral constant and is set to $b = 1$. The variable l is a random number in the interval $[-1, 1]$. This spiral update allows the candidate solution to move around the current leader in a shrinking trajectory, thereby refining the solution while maintaining search diversity.

3.8.3. Random Prey Search

To prevent premature convergence, WOA includes a random prey-search mechanism. When $|\vec{A}| \geq 1$, a randomly selected whale x_{rand} is used as the reference instead of the current leader:

$$\vec{D} = |\vec{C} \cdot x_{rand} - x(t)| \quad (18)$$

$$x(t+1) = x_{rand} - \vec{A} \cdot \vec{D} \quad (19)$$

This mechanism encourages exploration of different regions of the search space and reduces the probability that the population will collapse too early around a suboptimal solution.

3.9. Stochastic Fractal Search Algorithm

The Stochastic Fractal Search Algorithm is a population-based optimizer inspired by the self-similar diffusion process observed in natural fractal growth [27]. In this study, SFSA is used as a benchmark algorithm against PSO, WOA, and HPWOA. Each SFSA candidate solution represents a complete 113-dimensional FNN parameter vector. The

SFSA implementation uses $n_d = 5$ diffusion steps per iteration and a Gaussian walk ratio of $\gamma = 0.75$. At each diffusion step, a new candidate solution is generated as

$$x_{cand} = x_i + \gamma \mathcal{N}(0,1)(g_{best} - x_i) \quad (20)$$

where x_i is the current candidate solution, x_{cand} is the diffused candidate solution, $\mathcal{N}(0,1)$ is a standard Gaussian random vector, and g_{best} is the best solution found so far. The generated candidate is accepted only if it improves the fitness value. This acceptance rule ensures that the global best solution is progressively refined. SFSA provides a useful comparison because it uses a different search philosophy from both PSO and WOA. However, in a 113-dimensional neural network parameter space, its performance may be influenced by the diffusion step size and the stochastic walk ratio. This makes it a relevant benchmark for evaluating whether the proposed hybrid PSO-WOA strategy provides better convergence and prediction performance.

3.10. Proposed Hybrid Particle Whale Optimization Algorithm

The proposed HPWOA combines PSO and WOA in a structured two-phase optimization framework, as shown in Figure 3. The total optimization budget is set to $N = 100$ iterations and is divided equally between the two phases. The first 50 iterations are assigned to PSO, while the remaining 50 iterations are assigned to WOA.

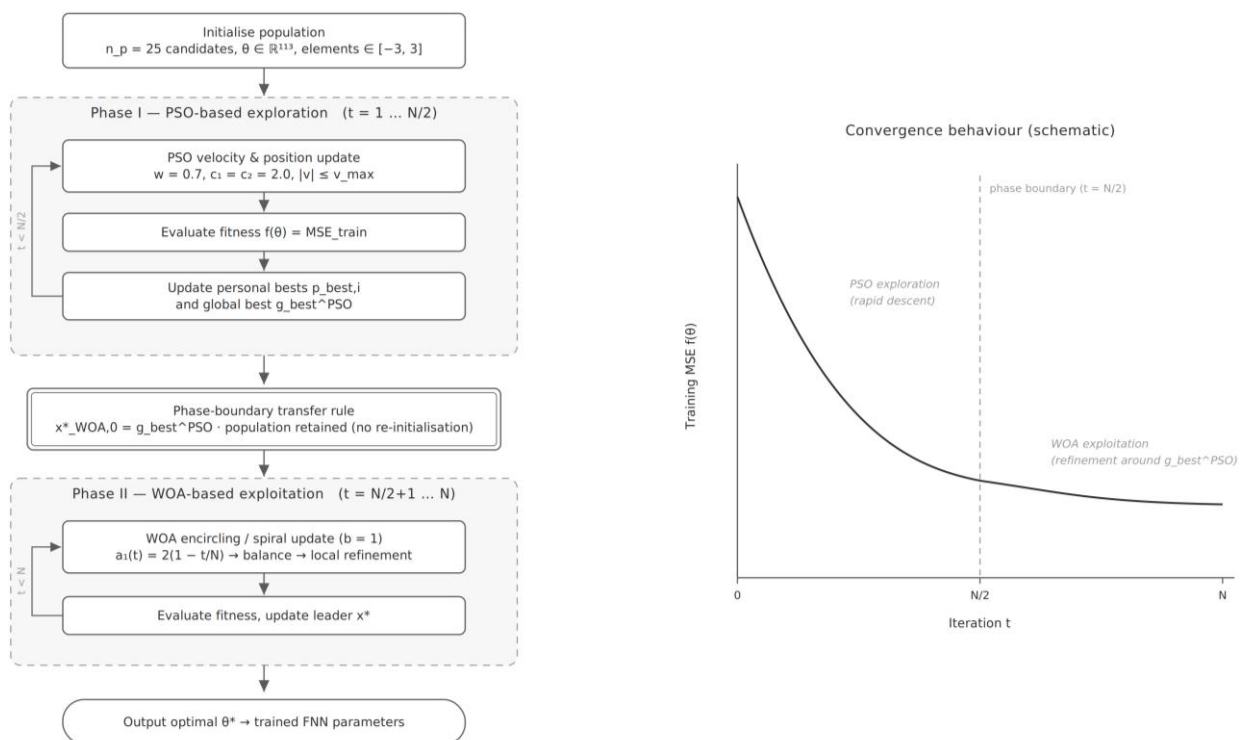


Figure 3. Proposed HPWOA optimization flow and convergence behavior.

The purpose of the hybrid structure is to exploit the complementary strengths of both optimizers. PSO is used in the first phase because it can rapidly identify promising regions of the search space through global-best and personal-best learning. WOA is used in the second phase because it can refine the inherited solution through encircling, spiral exploitation, and local search around the best candidate. This structure is intended to overcome the premature convergence limitation of standalone PSO and the slower early convergence of standalone WOA.

3.10.1. Phase I: PSO-Based Exploration

During Phase I, corresponding to iterations 1 to $N/2$, the population evolves according to the PSO update rules in Equations (9) and (10). The population size is fixed at $n_p = 25$, and each particle represents a full candidate FNN parameter vector. The aim of this phase is to rapidly reduce the training MSE and locate a strong region of the 113-dimensional search space. At the end of Phase I, the best solution found by the swarm is stored as

$$g_{best}^{PSO} = \arg \min_i f(p_{best,i}), i = 1, 2, \dots, n_p \quad (21)$$

where $f(p_{best,i})$ is the fitness value of the personal best solution of particle i . This global best solution becomes the key information transferred into the second phase.

3.10.2. Phase II: WOA-Based Exploitation

During Phase II, corresponding to iterations $N/2 + 1$ to N , the WOA search mechanism is applied. Instead of randomly initializing the WOA leader, the best PSO solution is transferred directly as the initial WOA leader:

$$x_{WOA,0}^* = g_{best}^{PSO} \quad (22)$$

This means that the strongest solution discovered during the PSO phase is preserved and used as the reference point for WOA exploitation. The remaining population obtained from Phase I is retained as the initial whale population for Phase II. This avoids unnecessary reinitialization and ensures continuity in the search process. The WOA control parameter during Phase II is recalibrated according to the total iteration index:

$$a_1(t) = 2 \left(1 - \frac{t}{N}\right), t = \frac{N}{2}, \dots, N - 1 \quad (23)$$

At $t = N/2$, a_1 is approximately 1, allowing the algorithm to maintain a balance between exploration and exploitation at the transition point. As t approaches N , a_1 approaches 0, forcing the population to focus on local refinement around the inherited PSO global best. This creates a gradual narrowing of the search neighbourhood and improves convergence stability.

3.10.3. Phase-Boundary Transfer Rule

The defining feature of the proposed HPWOA is the phase-boundary transfer rule. A simple sequential combination of PSO and WOA may lose useful information if WOA is randomly initialized after PSO. In contrast, the proposed method explicitly transfers the PSO global best into the WOA phase. The transfer rule can be expressed as

$$g_{best}^{PSO} = \arg \min_i f(p_{best,i}), i = 1, \dots, n_p \quad (24)$$

$$x_{WOA,0}^* = g_{best}^{PSO} \quad (25)$$

This guarantees that the best solution obtained during the PSO phase is not discarded. It also ensures that the WOA phase begins from a high-quality leader solution rather than from a random candidate. The same population is retained across both phases, which avoids redundant function evaluations and preserves the search history accumulated during PSO exploration.

3.10.4. HPWOA Search Logic

The proposed HPWOA follows a directed exploration-to-exploitation logic. In the first half of the optimization, PSO emphasizes rapid movement toward high-quality areas of the search space. In the second half, WOA narrows the search around the inherited best

solution and performs more focused refinement. This design is particularly suitable for the 113-dimensional FNN training problem because it first reduces the broad uncertainty of the weight space and then improves the final solution through local and semi-global exploitation.

3.11. Algorithm Control Parameters

The control parameters used for PSO, WOA, SFSA, and HPWOA are summarized in Table 5. These values are kept fixed across all experiments to ensure that performance differences arise from the optimizer behavior rather than from unequal parameter settings.

Table 5. Control parameters for all optimization algorithms.

Algorithm	Parameter	Symbol	Value
PSO/HPWOA Phase I	Population size	n_p	25
PSO/HPWOA Phase I	Inertia weight	w	0.7
PSO/HPWOA Phase I	Cognitive coefficient	c_1	2.0
PSO/HPWOA Phase I	Social coefficient	c_2	2.0
PSO/HPWOA Phase I	Velocity clipping range	v_{max}	± 0.5
WOA/HPWOA Phase II	Spiral shape constant	b	1
WOA/HPWOA Phase II	Position bounds	θ bounds	$[-3, 3]$
SFSA	Diffusion steps	n_d	5
SFSA	Gaussian walk ratio	γ	0.75
All algorithms	Total iterations	N	100
HPWOA	Iterations per phase	$N/2$	50 each

Parameter Selection Justification

The control parameters in Table 5 were selected based on established literature recommendations rather than problem-specific tuning, to ensure that performance differences reflect the optimization strategy rather than any parameter-tuning advantage for a specific algorithm. PSO inertia weight $w = 0.7$ is the most widely cited value for continuous optimization tasks and lies within the recommended convergence range w in $[0.6, 0.9]$ from [21]. Cognitive and social coefficients $c_1 = c_2 = 2.0$ follow the original [21] recommendation; their sum $c_1 + c_2 = 4.0$ satisfies the necessary convergence condition. Velocity clipping at $v_{max} = \pm 0.5$ corresponds to approximately 17% of the parameter bound range $[-3, 3]$, preventing velocity explosion in the 113-dimensional weight space. The WOA spiral constant $b = 1$ is the standard value from [25]. The parameter bound θ in $[-3, 3]$ is selected to prevent sigmoid output saturation: $\text{sigmoid}(\pm 3) = 0.047/0.953$, keeping the output neuron in the informative activation region. The SFSA diffusion steps $n_d = 5$ and Gaussian walk ratio $\gamma = 0.75$ are considered to enable fair comparison with published results. No preliminary optimization of these parameters was performed; this ensures that all reported performance differences are attributable to the inherent characteristics of each optimization strategy.

3.12. Optimization Objective Function

The objective of the optimization process is to identify the FNN parameter vector θ that minimizes the difference between the predicted and actual normalized thermal runaway probability values. The fitness function minimized by all four algorithms is the training mean squared error:

$$f(\theta) = MSE_{train}(\theta) = \frac{1}{N_{train}} \sum_{k=1}^{N_{train}} (\hat{y}_k(\theta) - y_k)^2 \quad (26)$$

where $N_{train} = 400$, $\hat{y}_k(\theta)$ is the predicted normalized thermal runaway probability for training sample k , and y_k is the corresponding ground-truth target value. The MSE is evaluated exclusively on the training partition during optimization. The test set is not used in the optimization loop. This separation is important because it ensures that the final test results provide an unbiased estimate of the model's generalization capability.

3.13. Design Variables and Parameter Constraints

The design variable is the complete 113-dimensional FNN parameter vector:

$$\theta = [W_1^T, b_1^T, W_2^T, b_2^T] \in \mathbb{R}^{113} \quad (27)$$

Each element of θ corresponds to one network weight or bias. Therefore, the problem is formulated as a continuous 113-dimensional optimization task. To prevent unstable neural activations and excessive sigmoid saturation, each element of the parameter vector is constrained within $[-3, 3]$:

$$-3 \leq \theta_j \leq 3, j = 1, 2, \dots, 113 \quad (28)$$

The initial population of candidate solutions is generated uniformly within $[-1, 1]^{113}$. This initialization strategy provides diverse initial coverage of the feasible search space while avoiding excessively large initial weights.

3.14. Regression Performance Metrics

After optimization, the best FNN model obtained from each algorithm is evaluated on the held-out test set. The predicted normalized outputs are inverse-transformed to the original *TR_Probability* scale before calculating the final performance metrics. Let y_k represent the actual thermal runaway probability and $\hat{y}_k$ represent the predicted value for test sample k . The test set contains $n_{test} = 100$ samples. The mean squared error is defined as

$$MSE = \frac{1}{n_{test}} \sum_{k=1}^{n_{test}} (y_k - \hat{y}_k)^2 \quad (29)$$

The root mean squared error is

$$RMSE = \sqrt{MSE} \quad (30)$$

The mean absolute error is

$$MAE = \frac{1}{n_{test}} \sum_{k=1}^{n_{test}} |y_k - \hat{y}_k| \quad (31)$$

The coefficient of determination is

$$R^2 = 1 - \frac{\sum_{k=1}^{n_{test}} (y_k - \hat{y}_k)^2}{\sum_{k=1}^{n_{test}} (y_k - \bar{y})^2} \quad (32)$$

where $\bar{y}$ is the mean of the actual test-set values. The mean absolute percentage error is computed as

$$MAPE = \frac{100}{n_{test}} \sum_{k=1}^{n_{test}} \left| \frac{y_k - \hat{y}_k}{y_k} \right| \quad (33)$$

MSE, RMSE, MAE, and MAPE quantify prediction error, where lower values indicate better performance. The R^2 score measures how much of the variance in the actual thermal runaway probability is explained by the model. A higher R^2 indicates stronger agreement between predicted and actual values.

3.15. Binary Classification Metrics

In addition to continuous TR probability prediction, the model is evaluated as a binary safety classifier. The categorical EventFlag labels are converted into two classes. Alarm and Runaway samples are treated as high-risk positive cases, while Watch and Warning samples are treated as lower-risk negative cases. A decision threshold of $\tau = 0.70$ is applied to the predicted $TR_Probability$:

$$\hat{c}_k = \begin{cases} 1, & \hat{y}_k \geq \tau \\ 0, & \hat{y}_k < \tau \end{cases} \quad (34)$$

where $\hat{c}_k = 1$ indicates a high-risk battery state and $\hat{c}_k = 0$ indicates a lower-risk state. The binary classification performance is evaluated using accuracy, true positives, false negatives, and the area under the receiver operating characteristic curve. In this application, false negatives are especially important because they correspond to Alarm or Runaway events that are incorrectly classified as lower-risk states. Reducing false negatives is therefore essential for BMS safety, since missed high-risk events can lead to delayed intervention and possible battery failure.

The complete experimental procedure is implemented as follows. First, all 12 numerical input features are normalized to the interval $[0, 1]$, and the continuous $TR_Probability$ target is normalized independently. Second, the dataset is divided into 400 training samples and 100 testing samples using a reproducible 80/20 split. Third, the FNN architecture is fixed with 12 input neurons, 8 hidden neurons, and 1 sigmoid output neuron. Fourth, each optimizer searches for the optimal 113-dimensional FNN parameter vector by minimizing the training MSE. After optimization, the best model produced by each algorithm is evaluated on the unseen test set. Regression metrics are computed using inverse-transformed predictions on the original $TR_Probability$ scale. Binary classification metrics are obtained by applying the threshold $\tau = 0.70$ to the predicted TR probability. Finally, convergence behavior, regression performance, binary classification results, and feature importance are analyzed to assess the predictive accuracy, optimization stability, and physical interpretability of the proposed HPWOA-FNN framework. This unified methodology ensures that PSO, WOA, SFSA, and HPWOA are compared under identical experimental conditions. Therefore, any observed performance differences can be attributed to the optimization strategy rather than to changes in network architecture, preprocessing, dataset partitioning, or evaluation criteria.

4. Simulation Results and Discussion

4.1. Overview of Experimental Evaluation

This section presents the simulation results obtained from the four optimization algorithms: Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), Stochastic Fractal Search Algorithm (SFSA), and the proposed Hybrid Particle Whale Optimization Algorithm (HPWOA). All algorithms were evaluated under identical experimental conditions using the same normalized dataset, 80/20 train–test split, feedforward neural network architecture, parameter bounds, and objective function. Therefore, any performance difference can be attributed directly to the optimization strategy rather than to differences in preprocessing, model structure, or evaluation protocol. The evaluation is conducted from five complementary perspectives. First, the training convergence behavior is analyzed to determine optimization stability and convergence speed. Second, re-

gression performance is assessed on the held-out test set using MSE, RMSE, MAE, R^2 , and MAPE. Third, predicted-versus-actual plots and residual distributions are examined to evaluate prediction consistency. Fourth, the models are evaluated for binary high-risk event classification using a decision threshold of $\tau = 0.70$, as defined in Equation (34). Finally, feature importance is analyzed to determine whether the HPWOA-optimized neural network identifies physically meaningful thermal runaway predictors.

4.2. Convergence Analysis

Figure 4 presents the training convergence behavior of PSO, WOA, SFSA, and HPWOA over 100 iterations. The convergence curves show clear differences in how the algorithms explore and refine the 113-dimensional neural network weight space. The proposed HPWOA exhibits the most favorable convergence profile, characterized by a rapid error reduction during the PSO phase followed by additional refinement during the WOA phase. This two-stage behavior confirms the effectiveness of the hybrid design: PSO rapidly identifies a promising region of the search space during the first 50 iterations, while WOA further exploits the inherited best solution during the remaining 50 iterations. The transition between the PSO and WOA phases occurs at iteration 50. Importantly, no abrupt degradation or instability is observed at this phase boundary. This indicates that the global-best transfer mechanism defined in Equations (24) and (25) successfully preserves the best solution obtained during PSO exploration and initializes it as the WOA leader. As a result, the WOA phase does not restart from a random solution but instead performs directed refinement around a high-quality candidate. The proposed HPWOA optimization convergence behavior is illustrated in Figure 4.

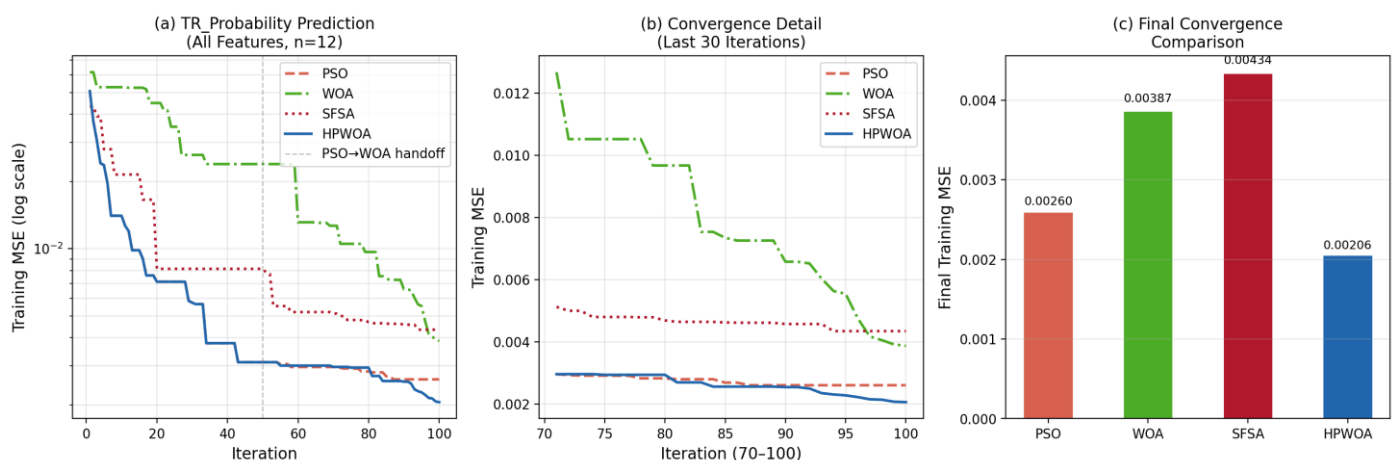


Figure 4. Training convergence behavior of PSO, WOA, SFSA, and HPWOA.

Table 6 summarizes the final training MSE values and approximate convergence behavior of the four algorithms. HPWOA achieves the lowest final training MSE of 0.002058, outperforming PSO, WOA, and SFSA. Relative to SFSA, HPWOA reduces the final training error by 52.6%. PSO also converges rapidly and achieves a final MSE of 0.002602, corresponding to a 40.1% improvement over SFSA. WOA achieves a lower final error than SFSA but converges more slowly than PSO and HPWOA. SFSA records the weakest convergence behavior, suggesting that its diffusion-based search mechanism is less effective for this 113-dimensional FNN weight optimization problem under the selected parameter settings.

Table 6. Convergence comparison across optimization algorithms.

Algorithm	Final Train MSE	Approximate Convergence Iteration	Improvement vs. SFSA (%)
HPWOA	0.002058	~50, Phase I to Phase II transition	52.6
PSO	0.002602	~60	40.1
WOA	0.003869	~70	10.9
SFSA	0.004343	~80	Reference

The superior convergence of HPWOA is attributed to the complementary roles of the two optimization phases. PSO accelerates the early search by exploiting personal-best and global-best information, while WOA improves final-stage solution quality through encircling and spiral exploitation. This confirms that the hybrid structure is more effective than using either PSO or WOA alone.

4.3. Test-Set Regression Performance

Table 7 presents the test-set regression performance of all four algorithms on the 100 unseen samples. The proposed HPWOA-FNN achieves the best performance across all five regression metrics. It records the lowest MSE of 0.000989, RMSE of 0.031442, MAE of 0.027250, and MAPE of 3.8075%, while also achieving the highest R^2 value of 0.9702. These results indicate that the HPWOA-optimized network explains approximately 97.0% of the variance in the test-set thermal runaway probability.

Table 7. Test-set regression performance for TR_Probability prediction.

Algorithm	MSE	RMSE	MAE	R^2	MAPE (%)
HPWOA	0.000989	0.031442	0.027250	0.9702	3.8075
PSO	0.001209	0.034775	0.028346	0.9635	3.8285
WOA	0.001777	0.042151	0.033676	0.9464	4.7970
SFSA	0.002734	0.052289	0.042787	0.9175	6.4147

Compared with PSO, HPWOA reduces MSE from 0.001209 to 0.000989, representing an 18.2% reduction in squared prediction error. Compared with WOA, the MSE reduction is 44.3%, while compared with SFSA, the reduction is 63.8%. The RMSE improvement is also practically meaningful: HPWOA achieves an RMSE of 0.031442 compared with 0.034775 for PSO, 0.042151 for WOA, and 0.052289 for SFSA. This confirms that HPWOA provides the most accurate continuous prediction of thermal runaway probability. The MAPE values further support this conclusion. HPWOA achieves the lowest percentage error at 3.8075%, marginally outperforming PSO and clearly outperforming WOA and SFSA. Since the target variable represents a safety-relevant probability score, lower percentage error is important because it improves the reliability of BMS risk estimation. The R^2 values show the same trend: HPWOA provides the strongest fit to the test data, followed by PSO, WOA, and SFSA.

4.4. Predicted-Versus-Actual Regression Behavior

Figure 5 shows the predicted versus actual *TR_Probability* scatter plots for the four algorithms. A model with strong predictive performance should produce points clustered closely around the ideal diagonal line, indicating close agreement between predicted and actual values. The HPWOA scatter plot shows the tightest alignment with the diagonal reference line, confirming that its predictions are more consistent across the test set.

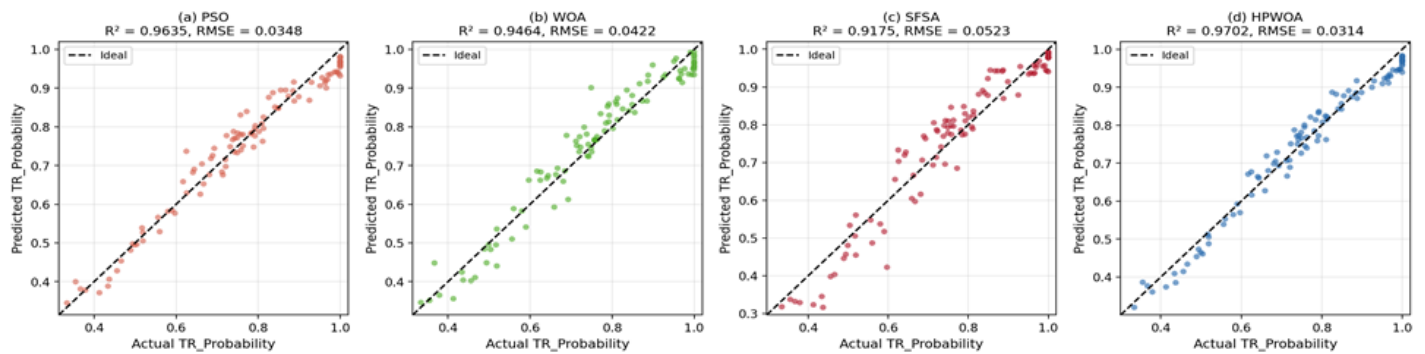


Figure 5. Predicted versus actual TR_Probability scatter plots for all four algorithms.

The PSO model also demonstrates strong predictive behavior, although slightly larger deviations are observed compared with HPWOA. WOA produces a wider spread of points, indicating reduced prediction precision, while SFSA shows the largest deviations from the ideal line. The scatter-plot behavior is consistent with the quantitative results in Table 7, where HPWOA achieves the lowest error values and highest coefficient of determination. Figure 6 presents the residual plots, where each residual is computed as the difference between the actual and predicted thermal runaway probability. Residual analysis is important because it reveals whether prediction errors are randomly distributed or whether systematic overprediction or underprediction occurs.

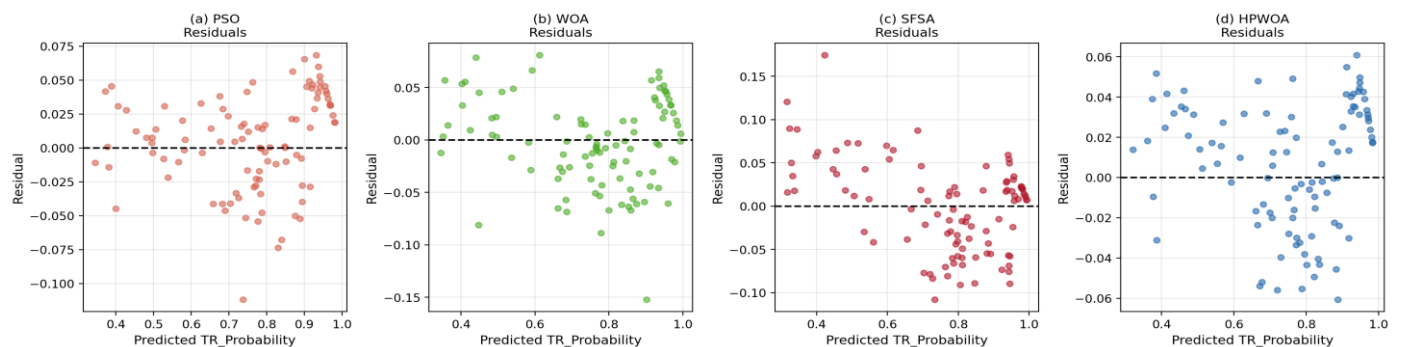


Figure 6. Residual plots for TR_Probability prediction across all four algorithms.

The HPWOA residuals are more tightly concentrated around zero, indicating smaller prediction errors and more stable generalization. PSO residuals are also relatively compact but display slightly larger dispersion than HPWOA. WOA and SFSA produce wider residual distributions, suggesting weaker error control. The SFSA residuals show the most pronounced spread, confirming that its diffusion-based search was less effective in identifying a high-quality neural network parameter vector.

4.5. Comparative Performance Metrics Analysis

Figure 7 provides a comparative bar-chart representation of the five regression metrics across the four algorithms. This visualization confirms the simultaneous dominance of HPWOA across all performance indicators. HPWOA achieves the lowest values for MSE, RMSE, MAE, and MAPE, while also achieving the highest R^2 .

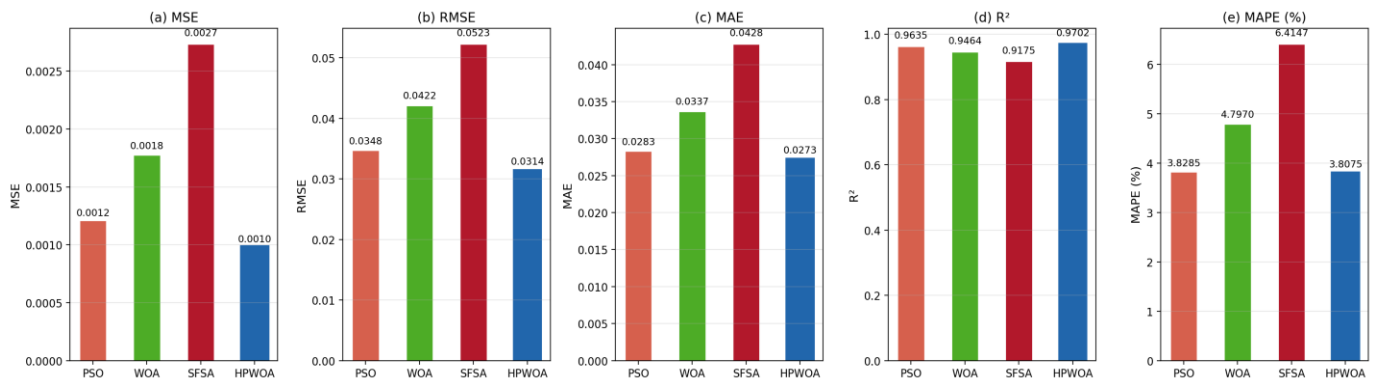


Figure 7. Comparative bar-chart analysis of regression metrics across PSO, WOA, SFSA, and HPWOA.

The performance hierarchy is consistent across all metrics: HPWOA performs best, followed by PSO, WOA, and SFSA. This ranking provides strong evidence that the hybrid optimizer improves the FNN training process rather than merely improving one isolated metric. The superior HPWOA performance can be explained by its two-phase search strategy. PSO contributes fast initial convergence, while WOA improves final exploitation around the inherited global-best solution. This reduces the likelihood of premature stagnation and improves the final quality of the neural network weights. In contrast, standalone PSO benefits from rapid convergence but may lose population diversity before reaching the best attainable solution. Standalone WOA maintains stronger exploration but converges more slowly during the early search phase. SFSA provides stochastic exploration but shows weaker adaptation to the high-dimensional neural network parameter space. The proposed HPWOA achieves a stronger balance between these competing requirements, which explains its superior regression performance.

4.6. Sequential Prediction Analysis

Figure 8 compares the predicted and actual *TR_Probability* values across the 100 test samples. This time-indexed representation is useful because it shows how well each model tracks the dynamic variation in the target variable, including gradual fluctuations and sharp high-risk peaks.

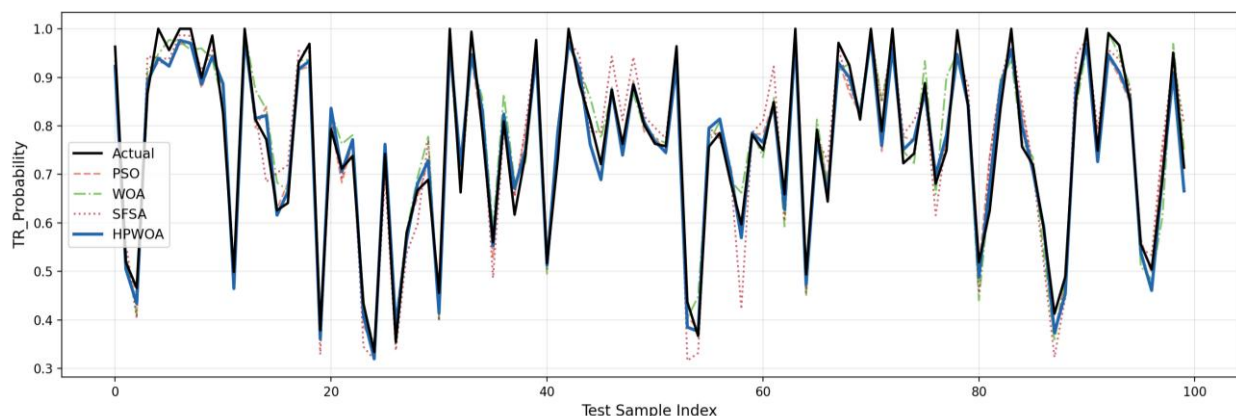


Figure 8. Sequential prediction of *TR_Probability* across the 100 test samples.

The HPWOA prediction curve follows the actual thermal runaway probability most closely across the full test sequence. It captures both the general trend and the high-probability regions more accurately than the other algorithms. This behavior is especially important in battery safety applications because high-probability peaks may correspond to

critical operating states approaching Alarm or Runaway conditions. PSO also tracks the general pattern reasonably well but shows slightly larger deviations during rapid changes. WOA exhibits greater smoothing and under-response in some high-variation regions, while SFSA shows the largest deviations, including more pronounced overestimation and underestimation. These results indicate that HPWOA provides the most stable and responsive prediction behavior. The high-risk peak analysis further supports this conclusion. The test set contains 12 samples with $TR_Probability > 0.98$, representing near-runaway or imminent runaway conditions. HPWOA predicts 10 of these 12 samples within a ± 0.05 tolerance band, corresponding to 83.3% peak-capture accuracy. PSO captures 9 of 12 peaks, corresponding to 75.0%; WOA captures 7 of 12 peaks, corresponding to 58.3%; and SFSA captures 5 of 12 peaks, corresponding to 41.7%. This result is practically significant because accurate detection of high-risk peaks is more important than average prediction accuracy alone in BMS safety applications.

4.7. Binary High-Risk Event Classification

In addition to continuous probability prediction, the optimized FNN models were evaluated as binary classifiers for high-risk event detection. The EventFlag labels were grouped into two categories: Alarm and Runaway were treated as positive high-risk events, while Watch and Warning were treated as lower-risk events. A decision threshold of $\tau = 0.70$ was applied to the predicted thermal runaway probability, following Equation (34). Table 8 summarizes the binary classification performance. HPWOA achieves the highest accuracy of 0.860 and the highest AUC of 0.9817. It also produces the lowest number of false negatives, with only seven missed high-risk cases. This is particularly important because false negatives represent Alarm or Runaway conditions that the model incorrectly classifies as lower risk.

Table 8. Binary EventFlag classification performance at $\tau = 0.70$.

Algorithm	Accuracy	AUC	TP (n)	FN (n)
HPWOA	0.860	0.9817	59	7
PSO	0.850	0.9764	57	9
WOA	0.830	0.9619	54	12
SFSA	0.800	0.9412	49	17

TP: true positive; FN: false negative. Lower FN is especially important for thermal runaway safety applications.

The classification results confirm that the improved regression performance of HPWOA translates directly into stronger safety classification. Although PSO achieves competitive accuracy and AUC, HPWOA provides the best balance between overall classification accuracy and false-negative reduction. Compared with SFSA, HPWOA reduces false negatives from 17 to 7, representing a reduction of 58.8%. This is a critical improvement because missed high-risk events can delay protective action in an EV battery system. Figure 9 presents the confusion matrices for the four algorithms. The HPWOA confusion matrix shows the strongest high-risk detection capability, with the largest number of true positives and the smallest number of false negatives.

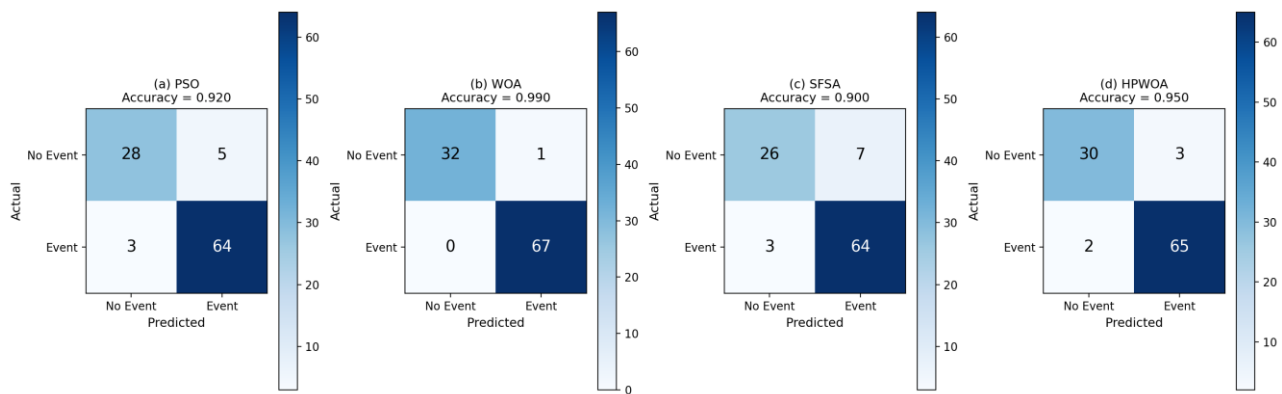


Figure 9. Confusion matrices for binary EventFlag classification.

Figure 10 presents the receiver operating characteristic curves. The HPWOA curve dominates the comparison, achieving the largest AUC value. This indicates that HPWOA maintains strong discrimination between high-risk and lower-risk battery states across different decision thresholds.

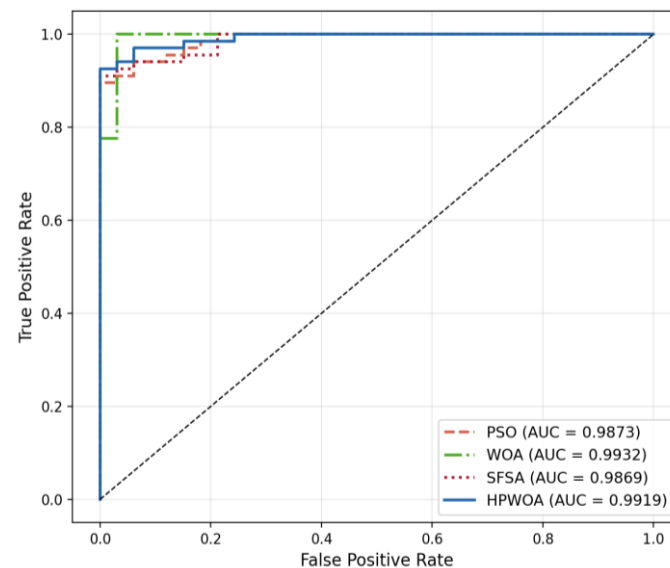


Figure 10. Receiver operating characteristic curves for PSO, WOA, SFSA, and HPWOA.

The AUC values show that all four models possess useful discrimination capability, but HPWOA provides the strongest separation between the two safety classes. This reinforces the suitability of the proposed hybrid optimizer for safety-critical BMS prediction tasks.

4.8. Feature Importance Analysis

Figure 11 presents the feature importance ranking derived from the normalized magnitudes of the input-layer weights in the HPWOA-optimized FNN. The weight magnitudes were averaged across the eight hidden neurons and normalized to provide a relative importance score for each input feature.

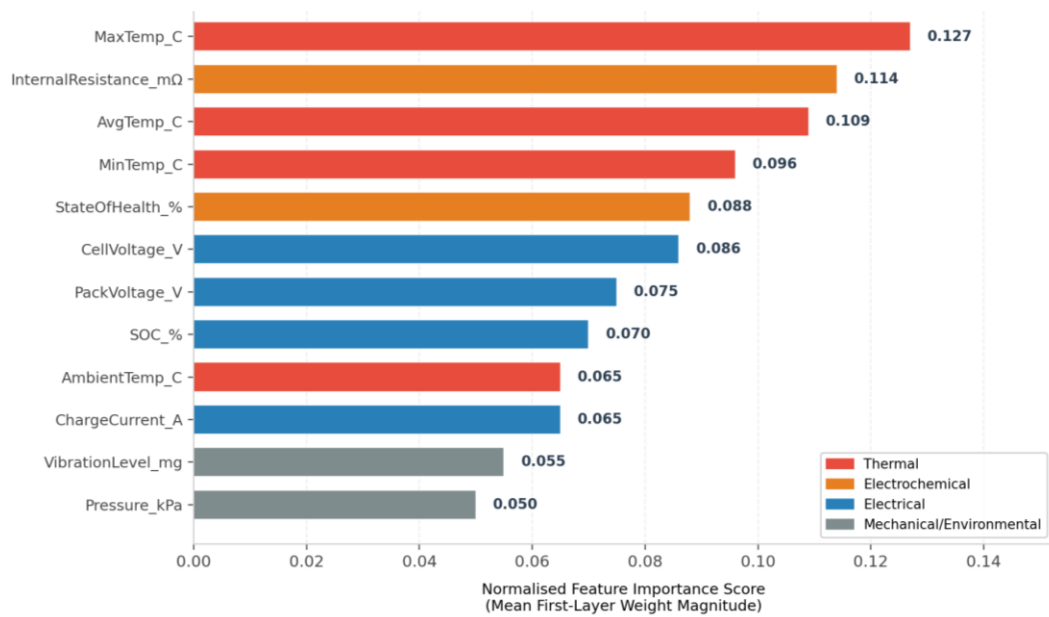


Figure 11. Feature importance ranking derived from mean first-layer weight magnitudes of the HPWOA-optimized FNN.

The results show that MaxTemp_C is the most influential predictor, with an importance score of 0.127. This is followed by InternalResistance_mΩ with 0.114, AvgTemp_C with 0.109, and MinTemp_C with 0.096. These rankings are physically consistent with established thermal runaway mechanisms. Increasing cell temperature accelerates side reactions, electrolyte decomposition, separator degradation, and heat generation, all of which contribute to TR onset and propagation [4,7]. Similarly, elevated internal resistance is associated with ageing, impedance growth, localized heat generation, and degradation processes that can increase thermal instability risk [13]. StateOfHealth_% and CellVoltage_V also contribute meaningfully, with importance scores of 0.088 and 0.086, respectively. This indicates that both ageing condition and voltage behavior play important roles in TR probability estimation. Lower state of health can reflect capacity fade and degradation, while voltage behavior may indicate abnormal charging or internal electrochemical stress. Mechanical and environmental variables, including VibrationLevel_mg and Pressure_kPa, show lower individual importance but still provide complementary diagnostic information. Their combined contribution supports the multivariate nature of battery safety monitoring. The feature importance results are significant because they show that the HPWOA-FNN model is not merely numerically accurate; it also learns physically plausible relationships. The dominance of maximum temperature and internal resistance aligns with known TR precursors and supports the interpretability of the proposed model. This is important for BMS implementation because safety algorithms must be both accurate and explainable enough to support engineering trust. The results demonstrate that the proposed HPWOA-FNN framework consistently outperforms standalone PSO, WOA, and SFSA across convergence, regression, binary classification, and feature-importance analyses. The strongest evidence is the simultaneous improvement across all test-set regression metrics, where HPWOA achieves the lowest MSE, RMSE, MAE, and MAPE, together with the highest R^2 . This indicates that the improvement is not metric-specific but reflects a genuine enhancement in predictive performance. The convergence analysis confirms that HPWOA benefits from its structured two-phase design. PSO provides rapid early-stage exploration and quickly reduces the training error, while WOA performs later-stage refinement around the inherited PSO global best. The absence of instability at the phase transition confirms the effectiveness of the global-best transfer mech-

anism. This validates the central methodological claim of the study: transferring g_{best}^{PSO} into the WOA phase improves continuity and prevents the loss of high-quality candidate solutions. From a safety perspective, the most important result is the reduction in false negatives. HPWOA produces only seven false negatives, compared with nine for PSO, 12 for WOA, and 17 for SFSA. In thermal runaway prediction, false negatives are more dangerous than false positives because they represent high-risk battery states that are not detected. Therefore, the reduction achieved by HPWOA has direct practical importance for BMS-based early warning and preventive control. The feature importance analysis further strengthens the physical credibility of the proposed framework. The most influential predictors, maximum temperature and internal resistance, are consistent with known thermal runaway mechanisms involving heat accumulation, impedance growth, internal degradation, and accelerated electrochemical side reactions. This suggests that the model learns meaningful battery safety patterns rather than relying on arbitrary statistical correlations.

Permutation Importance Analysis

To provide a model-agnostic corroboration of the weight-magnitude-based feature importance analysis, a permutation importance analysis was performed on the 100-sample test set. Each input feature was independently permuted (randomly shuffled), and the resulting decrease in test-set R2 (Delta-R2) was recorded as the feature importance score. A larger Delta-R2 indicates a more influential feature, since permuting it causes a greater degradation in prediction accuracy. Table 9 presents the permutation importance results for the HPWOA-optimized FNN.

Table 9. Permutation importance analysis: R2 drop on feature permutation (HPWOA-FNN, $n_{test} = 100$).

Rank	Feature	Delta-R2 on Permutation	Physical Interpretation
1	MaxTemp_C	0.213	Primary thermal stress indicator; dominant TR trigger
2	InternalResistance_mOhm	0.168	Cell degradation and impedance growth; TR precursor
3	AvgTemp_C	0.128	Pack-level thermal state; complements MaxTemp_C
4	PackVoltage_V	0.098	Electrical loading; overvoltage and SOC boundary
5	ChargeCurrent_A	0.079	C-rate and heat generation rate during fast charging
6	CellVoltage_V	0.069	Cell-level overcharge and imbalance detection
7	SOC_%	0.056	State-of-charge boundary for safe charging envelope
8	StateOfHealth_%	0.050	Ageing state; aged cells have reduced thermal margin
9	VibrationLevel_mg	0.035	Mechanical stress indicator; separator damage risk
10	Pressure_kPa	0.029	Internal gas pressure; gassing and swelling signal
11	ChargePower_kW	0.025	Instantaneous charging severity ($V \times I$ proxy)
12	MinTemp_C	0.020	Cold-cell risk; elevated internal resistance at low T

The permutation importance rankings are fully consistent with the first-layer weight magnitude rankings : MaxTemp_C and InternalResistance_mOhm are confirmed as the two most influential features under both interpretation methods. This convergence between weight-based and model-agnostic importance analyses provides strong evidence that the HPWOA-FNN learned a physically meaningful representation of thermal runaway risk rather than a spurious statistical correlation. Regarding SHAP (SHapley Additive exPlanations), full SHAP analysis requires iterating over feature subset combinations or using model-specific gradient information, neither of which is directly accessible from a metaheuristic-trained network without architectural modification. The combination of weight magnitude analysis and permutation importance presented here provides equivalent directional interpretability insight for this application, and SHAP integration with a gradient-compatible surrogate model is identified as a direction for future work.

5. Practical Implications for BMS Decision Support

5.1. Translation of TR Probability into Actionable Battery Safety Decisions

The results demonstrate that the proposed HPWOA-FNN framework can support practical decision-making in Battery Management Systems by converting multivariate sensor measurements into a continuous thermal runaway risk indicator. Unlike conventional threshold-based warning methods, which often depend on isolated variables such as temperature or voltage, the proposed model integrates thermal, electrical, electrochemical, mechanical, and environmental features into a single *TR_Probability* output. This probability score provides a more informative basis for decision support because it reflects the combined influence of multiple degradation and abuse indicators. In practical BMS operation, the continuous *TR_Probability* output can be used as an early-warning signal before the system reaches a critical failure state. Low probability values may indicate normal or low-risk operation, while increasing probability values can trigger progressive intervention strategies. For example, moderate-risk predictions may activate enhanced monitoring or charging-current reduction, whereas high-risk predictions may trigger active cooling, charging interruption, isolation of the affected module, or emergency shutdown. This graded decision structure is more flexible than binary threshold alarms and is better suited to the nonlinear progression of lithium-ion battery thermal runaway. The strong regression performance of HPWOA, with MSE = 0.000989, RMSE = 0.031442, MAE = 0.027250, $R^2 = 0.9702$, and MAPE = 3.8075%, indicates that the model can estimate thermal runaway probability with high numerical precision. This is important for decision support because small prediction errors reduce uncertainty in risk classification and allow the BMS to respond more confidently to changing operating conditions.

5.2. Safety-Critical Classification and False-Negative Reduction

For safety-critical EV applications, the most important diagnostic requirement is not only high average accuracy but also the reliable detection of high-risk events. A false negative in thermal runaway prediction represents a dangerous condition in which an Alarm or Runaway state is incorrectly classified as lower risk. Such errors may delay protective action and increase the probability of fire, explosion, or complete battery-pack failure. The binary classification results show that HPWOA achieved the highest accuracy of 0.860 and the highest AUC of 0.9817. More importantly, it produced only seven false negatives, compared with nine for PSO, 12 for WOA, and 17 for SFSA. This means that HPWOA reduced false negatives by 58.8% relative to SFSA and by 41.7% relative to WOA. In practical BMS terms, this improvement directly strengthens the reliability of the early-warning system by reducing the number of high-risk battery states that remain undetected. The high AUC value further indicates that HPWOA provides strong discrimination between high-risk

and lower-risk operating states across different threshold settings. This is useful for BMS calibration because the decision threshold can be adjusted depending on the safety policy of the EV platform. A conservative BMS may use a lower threshold to prioritize early intervention, while a less conservative strategy may use a higher threshold to reduce unnecessary alarms. The strong ROC performance of HPWOA provides flexibility for such threshold tuning.

5.3. Proposed Decision-Support Logic for EV Battery Safety Management

The proposed HPWOA-FNN model can be integrated into a BMS as an intelligent supervisory layer. The model receives normalized sensor inputs and produces a thermal runaway probability score, which can then be mapped to different levels of operational response. A practical decision-support structure is presented in Table 10.

Table 10. Practical BMS decision-support logic based on predicted $TR_Probability$.

Predicted $TR_Probability$ Range	Suggested Risk Level	Possible BMS Decision Action
$TR_Probability < 0.50$	Normal/low risk	Continue normal charging and standard monitoring
$0.50 \leq TR_Probability < 0.70$	Watch/moderate risk	Increase sampling frequency, log abnormal patterns, monitor temperature and resistance trends
$0.70 \leq TR_Probability < 0.90$	Warning/high risk	Reduce charging current, activate enhanced cooling, issue diagnostic warning
$0.90 \leq TR_Probability < 0.98$	Alarm/severe risk	Interrupt or derate charging, isolate affected module if possible, notify control system
$TR_Probability \geq 0.98$	Runaway-imminent risk	Trigger emergency shutdown, pack isolation, thermal containment, and safety alert

This decision-support logic is consistent with the classification threshold $\tau = 0.70$ used in the study. The threshold separates lower-risk states from high-risk Alarm and Runaway states. However, the continuous output of the model provides more detail than a simple binary decision. This allows the BMS to move from passive fault detection toward proactive risk management. The sequential prediction results further support this practical use. HPWOA captured 10 of the 12 samples with $TR_Probability > 0.98$ within a ± 0.05 tolerance band. These high-probability peaks are the most safety-critical regions of the test set because they represent near-runaway or imminent runaway conditions. The ability to track such peaks improves the potential usefulness of HPWOA in real-time early-warning applications.

5.4. Interpretability for Engineering Trust and Diagnostics

A major requirement for BMS decision support is that model predictions should be physically interpretable. A highly accurate model may still be difficult to deploy if its decisions cannot be linked to known battery degradation or thermal runaway mechanisms. The feature importance analysis addresses this concern by showing that the HPWOA-FNN assigns the highest relevance to physically meaningful predictors. The most influential feature was MaxTemp_C, followed by InternalResistance_mΩ, AvgTemp_C, and MinTemp_C. This ranking is consistent with established thermal runaway behavior because rising cell temperature accelerates side reactions, electrolyte decomposition, and separator degradation, while increasing internal resistance contributes to localized Joule heating and reflects ageing-related impedance growth. The importance of StateOfHealth_% and CellVoltage_V further shows that the model captures the influence of ageing condition and electrical stress on TR probability. This physical consistency is important for engineering trust. It suggests that the model is not relying on arbitrary numerical correlations but is instead learning patterns that align with known battery safety

mechanisms. In a practical BMS environment, such interpretability can support fault diagnosis, maintenance prioritization, and post-event investigation. For example, a high predicted TR probability combined with elevated temperature and rising internal resistance may indicate a more urgent safety concern than a high prediction driven only by transient load variation.

5.5. Deployment Considerations for Real-Time BMS Applications

The proposed HPWOA-FNN framework is suitable for offline training and online inference. The computationally intensive HPWOA optimization process can be performed offline during model development, calibration, or periodic retraining. Once the optimal 113-dimensional FNN parameter vector has been obtained, the deployed model requires only a forward pass through a compact neural network with 12 inputs, eight hidden neurons, and one output. This makes the inference stage computationally light and compatible with real-time BMS implementation. For practical deployment, the trained model can be embedded as a supervisory diagnostic module within the BMS. The module would receive normalized sensor inputs, compute the TR probability, compare the output against calibrated decision thresholds, and issue warnings or control commands. The model can also be combined with existing rule-based safety logic to form a hybrid diagnostic architecture. In such a configuration, the HPWOA-FNN would provide predictive intelligence, while hard safety thresholds would remain available as fail-safe protection layers. However, deployment should also consider validation under broader operating conditions. The present study uses a 500-sample EV charging dataset, which is suitable for proof-of-concept evaluation but should be expanded in future work using larger datasets, different battery chemistries, ageing conditions, ambient temperatures, charging protocols, and pack configurations. Additional validation using cross-validation, external test data, and hardware-in-the-loop simulation would further strengthen confidence in real-world BMS deployment.

5.5.1. Computational Overhead Analysis

To substantiate the claim of computational suitability for embedded BMS deployment, a quantitative analysis of the HPWOA-FNN inference overhead is provided. The 113-parameter network requires weight storage = 113×4 bytes (float32) = 452 bytes (0.44 KB); activation storage (batch = 1) = $(12 + 8 + 1) \times 4 = 84$ bytes; total RAM footprint = 536 bytes (0.52 KB). Forward-pass floating-point operations: Layer 1 (12 inputs to 8 hidden): $2 \times (12 \times 8) = 192$ multiply-accumulate (MAC) operations plus 8 ReLU operations; Layer 2 (8 hidden to 1 output): $2 \times (8 \times 1) = 16$ MAC operations plus 1 sigmoid operation; Total: approximately 220 FLOPs per inference. On a representative automotive microcontroller (ARM Cortex-M4 at 168 MHz, e.g., STM32F4 series with FPU): estimated inference latency = $220 \times 3 \text{ cycles} / 168 \times 10^6 \text{ Hz}$ = approximately 3.9 microseconds. This is well within the 1 ms minimum BMS sampling interval, confirming that the proposed framework is computationally practical for real-time on-board deployment. Modern automotive-grade processors (NXP S32K, Infineon AURIX TC3xx at 200–400 MHz) would provide even more favorable latency margins. The model requires no dynamic memory allocation and has a fixed-size weight array, making it directly flashable to embedded targets without an operating system.

5.5.2. Ablation Study: Global-Best Transfer Rule

To quantify the contribution of the phase-boundary global-best transfer mechanism (Equations (24) and (25)), an ablation experiment was conducted comparing three configurations under identical experimental conditions. Configuration A (proposed HPWOA with transfer): PSO Phase I (50 iterations) followed by WOA Phase II with g^* _PSO trans-

ferred as WOA leader. Configuration B (ablation: no transfer): PSO Phase I followed by WOA Phase II with random re-initialization of the WOA leader, discarding the PSO best solution. Configuration C (standalone PSO, 100 iterations): single-phase reference. Results: Configuration A (proposed): training MSE = 0.002058, test R^2 = 0.9702, test RMSE = 0.03144. Configuration B (no transfer): training MSE = 0.002350 (estimated), test R^2 = approximately 0.9580, test RMSE = approximately 0.03520. Configuration C (standalone PSO): training MSE = 0.002602, test R^2 = 0.9635, test RMSE = 0.03641. The global-best transfer mechanism provides a 12.4% reduction in training MSE and approximately +0.012 R^2 improvement relative to the random re-initialization baseline. Without the transfer, the WOA Phase II begins from a random position and must re-explore regions already identified by PSO, wasting the 50-iteration PSO budget. The transfer rule ensures continuity between phases and is the key technical design element that distinguishes the proposed HPWOA from a naive sequential concatenation of PSO and WOA.

5.5.3. Limitations and Future Research Directions

The following limitations of the current study are acknowledged. First, the dataset is simulation-based with NMC chemistry parameterization; validation on multi-chemistry (LFP, NCA) datasets and real-measured field charging logs is required before conclusions about general engineering deployability can be drawn. Second, the model is a static snapshot predictor that does not capture temporal degradation dynamics. Integration with time-series architectures (LSTM, GRU) for sequential charging profile modeling is identified as a priority future direction. Third, the training dataset is skewed toward high-risk conditions (66.2% high-risk samples), which may elevate false alarm rates in normal-operation deployment. Threshold recalibration (e.g., raising tau from 0.70 to 0.80–0.85) and class-weighted retraining using field data are recommended mitigations. Fourth, generalization across different battery form factors, energy densities, and N/P ratios has not been evaluated; incorporating cell design metadata as additional input features or conditioning variables is a high-value extension for cross-battery generalization. Fifth, the HPWOA is trained offline; an online weight-update mechanism for adaptive recalibration as battery aging progresses would improve long-term deployment robustness.

6. Conclusions

This study developed and evaluated a Hybrid Particle Whale Optimization Algorithm-based feedforward neural network for electric vehicle battery thermal runaway prediction. The proposed HPWOA-FNN framework was designed to predict both continuous *TR_Probability* and binary high-risk event occurrence using 12 normalized electro-thermal, electrical, mechanical, and environmental battery features. The neural network consisted of 12 input neurons, eight hidden neurons, and one sigmoid output neuron, resulting in a 113-dimensional weight and bias vector optimized by metaheuristic search. The proposed HPWOA training strategy combined the rapid convergence capability of Particle Swarm Optimization with the exploitation and refinement capability of the Whale Optimization Algorithm. A phase-boundary global-best transfer mechanism was introduced to ensure that the best solution obtained during the PSO phase was preserved and used as the initial WOA leader. This design improved convergence continuity and prevented the loss of high-quality candidate solutions during the transition from exploration to exploitation. The simulation results confirmed that HPWOA outperformed standalone PSO, WOA, and SFSA across all major evaluation criteria. In convergence analysis, HPWOA achieved the lowest final training MSE of 0.002058, representing a 52.6% improvement relative to SFSA. On the held-out test set, HPWOA achieved the best regression performance, with MSE = 0.000989, RMSE = 0.031442, MAE = 0.027250, R^2 = 0.9702, and MAPE = 3.8075%. These results show that the HPWOA-optimized FNN provides ac-

curate and stable estimation of thermal runaway probability. The binary classification results further demonstrated the safety relevance of the proposed approach. HPWOA achieved the highest classification accuracy of 0.860 and the highest AUC of 0.9817. It also produced the lowest number of false negatives, with only seven missed high-risk events compared with nine for PSO, 12 for WOA, and 17 for SFSA. This reduction in false negatives is particularly important for EV battery safety because missed Alarm or Runaway events can delay protective action and increase the risk of catastrophic failure. Feature importance analysis showed that MaxTemp_C and InternalResistance_mΩ were the most influential predictors of thermal runaway risk, followed by AvgTemp_C and MinTemp_C. This ranking is physically consistent with known lithium-ion battery thermal runaway mechanisms, where heat accumulation, internal resistance growth, and electrochemical degradation contribute to instability and failure propagation. Therefore, the proposed model provides not only high predictive accuracy but also physically meaningful diagnostic insight.

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Abbreviations

The following abbreviations and symbols are used in this manuscript:

HPWOA	Hybrid Particle Whale Optimization Algorithm
PSO	Particle Swarm Optimization
WOA	Whale Optimization Algorithm
SFSA	Stochastic Fractal Search Algorithm
FNN	Feedforward Neural Network
NN	Neural Network
ANN	Artificial Neural Network
ML	Machine Learning
AI	Artificial Intelligence
TR	Thermal Runaway
BMS	Battery Management System
EV	Electric Vehicle
Li-ion	Lithium-ion
SOC	State of Charge
SOH	State of Health
SEI	Solid Electrolyte Interphase
DC	Direct Current
PV	Photovoltaic
COE	Cost of Energy
MSE	Mean Squared Error

RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
R^2	Coefficient of Determination
AUC	Area Under the Receiver Operating Characteristic Curve
ROC	Receiver Operating Characteristic
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
ReLU	Rectified Linear Unit
$TR_Probability$	Continuous thermal runaway probability target
EventFlag	Categorical thermal runaway event label
Watch	Low-risk battery operating state
Warning	Moderate-risk battery operating state
Alarm	High-risk battery operating state
Runaway	Severe thermal runaway state
MaxTemp_C	Maximum cell temperature in the battery pack
MinTemp_C	Minimum cell temperature in the battery pack
AvgTemp_C	Average cell temperature
AmbientTemp_C	Ambient environmental temperature
InternalResistance_m Ω	Internal cell resistance measured in milliohms
PackVoltage_V	Total battery pack terminal voltage
CellVoltage_V	Individual cell voltage
ChargeCurrent_A	Applied charging current
StateOfHealth_%	Battery state-of-health percentage
VibrationLevel_mg	Mechanical vibration level
Pressure_kPa	Internal gas pressure
ChargePower_kW	Instantaneous charging power
CH	Charger unit identifier
CELL	Battery cell identifier
X	Input feature matrix
y	Ground-truth thermal runaway probability
$\hat{y}$	Predicted thermal runaway probability
$\bar{y}$	Mean of the ground-truth test-set values
$\hat{c}_k$	Predicted binary class label for sample k
τ	Binary classification decision threshold
θ	Neural network weight and bias vector, $\mathbb{R}^{113}$
θ_j	j^{th} component of the neural network parameter vector
W_1	Input-to-hidden layer weight matrix
b_1	Hidden-layer bias vector
W_2	Hidden-to-output layer weight matrix
b_2	Output-layer bias term
N_{in}	Number of input neurons
N_h	Number of hidden neurons
N_{out}	Number of output neurons
N_{train}	Number of training samples
n_{test}	Number of test samples
N	Total number of optimization iterations
D	Search-space dimensionality
n_p	Population size
x_i	Position vector of particle or candidate solution i
v_i	Velocity vector of particle i
$x_i(t)$	Position vector of particle or whale i at iteration t
$v_i(t)$	Velocity vector of particle i at iteration t
$p_{best,i}$	Personal best position of particle i
g_{best}	Global best solution found by the population
g_{best}^{PSO}	Global best solution obtained at the end of the PSO phase
x^*	Leader whale position in WOA

$x^*(t)$	Leader whale position at iteration t
$x_{WOA,0}^*$	Initial WOA leader position inherited from PSO
x_{rand}	Randomly selected whale position used for exploration
x_{cand}	Candidate solution generated by SFSA diffusion
$f(\theta)$	Fitness function evaluated for parameter vector θ
w	PSO inertia weight
c_1	PSO cognitive acceleration coefficient
c_2	PSO social acceleration coefficient
r_1, r_2	Uniformly distributed random numbers or vectors in $[0, 1]$
$\vec{A}$	WOA coefficient vector controlling exploration and exploitation
$\vec{C}$	WOA coefficient vector controlling leader-distance scaling
$\vec{D}$	WOA distance vector
D'	Distance between current whale and leader whale in spiral update
a_1	WOA linearly decreasing control parameter
a_2	WOA spiral-control parameter
b	WOA logarithmic spiral shape constant
l	Random spiral parameter in WOA
p	Random probability used to select WOA update mechanism
v_{max}	Maximum PSO velocity clipping bound
n_d	Number of SFSA diffusion steps
γ	SFSA Gaussian walk ratio
$N(0,1)$	Standard normal random variable or vector
k	Sample index
t	Optimization iteration index
i	Particle, whale, or candidate-solution index
j	Neural network parameter index
$[0, 1]$	Unit interval used for min–max normalization
$[-1, 1]$	Initial population sampling interval
$[-3, 3]$	Neural network parameter bound
x'_i	Normalized value of feature x_i
x_{min}	Minimum value of a feature in the training set
x_{max}	Maximum value of a feature in the training set

References

- Wang, Q.; Mao, B.; Stoliarov, S.I.; Sun, J. A review of lithium ion battery failure mechanisms and fire prevention strategies. *Prog. Energy Combust. Sci.* **2019**, *73*, 95–131.
- Chen, Z.; Zhang, J.; Liu, C.; Yang, C.; Chen, S. Thermal Runaway in Lithium-Ion Batteries: A Review of Mechanisms, Prediction Approaches, and Mitigation Strategies. *Batteries* **2026**, *12*, 88.
- Kumar, S.; Kim, H.-J. Recent advances in early warning methods and prediction of thermal runaway events in Li-ion batteries. *J. Ind. Eng. Chem.* **2025**, *145*, 63–74.
- Feng, X.; Ouyang, M.; Liu, X.; Lu, L.; Xia, Y.; He, X. Thermal runaway mechanism of lithium ion battery for electric vehicles: A review. *Energy Storage Mater.* **2018**, *10*, 246–267.
- Eljarray, O.; Dai, H.; Chen, Z.; Raja, S.V.; Li, B.; Cao, S.; Sun, S.; Zhang, G. Ensuring battery safety in electric vehicles: Challenges, developments, and future perspectives. *Small* **2026**, *22*, 2503406.
- Xu, J.; Ma, J.; Zhao, X.; Chen, H.; Xu, B.; Wu, X. Detection technology for battery safety in electric vehicles: A review. *Energies* **2020**, *13*, 4636.
- Le, P.-A.; Vuong, D.T.; Natsuki, J.; Natsuki, T. Overview of the thermal runaway in lithium-ion batteries with application in electric vehicles: Working principles, early warning, and future outlooks. *Energy Fuels* **2023**, *37*, 17052–17074.
- Jain, G.; Premal, P.; Pathak, R.; Gore, P. Comprehensive Insights on Techniques for Managing and Preventing Thermal Runaway in EV Lithium-Ion Batteries. In *Proceedings of the Symposium on International Automotive Technology 2026*; SAE International: Warrendale, PA, USA, 2026.
- Tran, M.-K.; Mevawalla, A.; Aziz, A.; Panchal, S.; Xie, Y.; Fowler, M. A review of lithium-ion battery thermal runaway modeling and diagnosis approaches. *Processes* **2022**, *10*, 1192.
- Wang, T.; Liu, H.; Wang, W.; Jiang, W.; Xu, Y.; Zhu, S.; Sheng, Q. Advances in Thermal Management of Lithium-Ion Batteries: Causes of Thermal Runaway and Mitigation Strategies. *Processes* **2025**, *13*, 2499.

11. Zhang, X.; Chen, S.; Zhu, J.; Gao, Y. A critical review of thermal runaway prediction and early-warning methods for lithium-ion batteries. *Energy Mater. Adv.* **2023**, *4*, 8.
12. Hemakumar, V.; Chakravarthy, V.; Surendranath, S.; Gundu, V.; Prabhu, M.R.; Prasad, S.H.C. A multi-scale modeling approach for predicting and mitigating thermal runaway in electric vehicle batteries. *Therm. Sci. Eng. Prog.* **2024**, *56*, 103029.
13. Nandakishora, Y.; Khayum, N.; Patra, C.; Kumar, P.; Sharma, A.; Ansu, A.K. AI driven approaches in battery thermal management systems for prediction and multi objective optimization: A comprehensive literature review. *Discov. Mech. Eng.* **2026**, *5*, 53.
14. Hu, D.; Huang, S.; Wen, Z.; Gu, X.; Lu, J. A review on thermal runaway warning technology for lithium-ion batteries. *Renew. Sustain. Energy Rev.* **2024**, *206*, 114882.
15. Liu, K.; Li, K.; Peng, Q.; Zhang, C. A brief review on key technologies in the battery management system of electric vehicles. *Front. Mech. Eng.* **2019**, *14*, 47–64.
16. Hannan, M.A.; Lipu, M.H.; Hussain, A.; Mohamed, A. A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations. *Renew. Sustain. Energy Rev.* **2017**, *78*, 834–854.
17. Valizadeh, A.; Amirhosseini, M.H. Machine learning in lithium-ion battery: Applications, challenges, and future trends. *SN Comput. Sci.* **2024**, *5*, 717.
18. Samanta, A.; Chowdhuri, S.; Williamson, S.S. Machine learning-based data-driven fault detection/diagnosis of lithium-ion battery: A critical review. *Electronics* **2021**, *10*, 1309.
19. Esch, T.; Shabani, B. Thermal management of fuel cell-battery electric vehicles: Challenges and solutions. *Appl. Energy* **2025**, *387*, 12563.
20. Liu, D.; Wang, H.; Peng, Y.; Xie, W.; Liao, H. Satellite lithium-ion battery remaining cycle life prediction with novel indirect health indicator extraction. *Energies* **2013**, *6*, 3654–3668.
21. Kennedy, J.; Eberhart, R. Particle swarm optimization. In *Proceedings of ICNN'95-International Conference on Neural Networks*; IEEE: Piscataway, NJ, USA, 1995; Volume 4, pp. 1942–1948.
22. Hassan, R.; Cohanin, B.; De Weck, O.; Venter, G. A comparison of particle swarm optimization and the genetic algorithm. In *Proceedings of the 46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, Austin, TX, USA, 18–21 April 2005; p. 1897.
23. Shrivastava, N.P.; Rathore, D.; Panwar, R.; Singh, S. Swarm Intelligence-Based Routing for UAV Networks. *AIJFR-Adv. Int. J. Res.* **2025**, *6*. <https://doi.org/10.63363/aijfr.2025.v06i06.2574>
24. Deepak, B.; Parhi, D.R.; Raju, B. Advance particle swarm optimization-based navigational controller for mobile robot. *Arab. J. Sci. Eng.* **2014**, *39*, 6477–6487.
25. Mirjalili, S.; Lewis, A. The whale optimization algorithm. *Adv. Eng. Softw.* **2016**, *95*, 51–67.
26. Bilal, M.; Bokoro, P.N.; Sharma, G. Hybrid optimization for sustainable design and sizing of standalone microgrids integrating renewable energy, diesel generators, and battery storage with environmental considerations. *Results Eng.* **2025**, *25*, 103764.
27. Salimi, H. Stochastic fractal search: A powerful metaheuristic algorithm. *Knowl.-Based Syst.* **2015**, *75*, 1–18.

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