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Robust SVM optimization using PSO and ACO for accurate lithium-ion battery health monitoring

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Highlights:

- The dataset comprises 1000 lithium-ion battery cycles collected under laboratory conditions.
- Accurate State of Health (SOH) prediction is essential to prevent performance degradation and safety risks.
- The findings aim to extend battery lifespan, enhancing reliability and cost-effectiveness in various applications.

Abstract

The increasing demand for reliable lithium-ion battery in various applications is focused on the need for accurate State of Health (SOH) predictions to prevent performance degradation and potential safety risks. Therefore, this research aimed to improve the accuracy of SOH prediction by integrating Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) with Support Vector Machine (SVM) to overcome the overfitting problem in traditional machine learning models. The dataset used consisted of data from 1000 cycles of lithium-ion battery, collected under laboratory conditions. Data from lithium-ion battery cycles were analyzed using optimized PSO-SVM and ACO-SVM models. These models were evaluated using Mean Square Error (MSE) and Root Mean Square Error (RMSE) metrics, showing significant improvements in prediction accuracy and model generalization. The results showed that although both optimized models were superior to the baseline SVM, PSO-SVM had higher generalization performance during testing. The higher performance was due to the effective balance between exploring the search space and exploiting optimal solutions, making it more suitable for real-world applications. In comparison, ACO-SVM showed superior performance in training data accuracy but was more prone to overfitting, suggesting the potential for scenarios prioritizing high training accuracy. These results could be applied to extend the lifespan of lithium-ion battery, contributing to enhanced reliability and cost-effectiveness in applications.

Keywords: State of Health; Particle Swarm Optimization; Ant Colony Optimization; Support Vector Machine; Lithium-ion Battery Performance

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1. Introduction

Lithium-ion battery is foundational to modern energy storage systems due to the high energy density, long service life, and low self-discharge rates. These characteristics make lithium-ion battery very important for various applications, from electronic appliances such as cell phones, smart and laptops to vehicles, increasing electricity popularity among the public [1], [2]. Furthermore, lithium-ion battery is essential in internal components in the storage energy scale, which is large and used for supporting a more efficient and environmentally friendly electrical network [3]. With the increasing adoption of technology in various sectors, the need for accurate and reliable predictions of battery State of Health (SOH) becomes more crucial. Due to high usage time, battery will experience a decline in performance, reducing output power and potentially causing accidents [4], [5], [6].

SOH prediction is an important aspect of battery management systems. This is because SOH is the indicator that mainly reflects the capacity battery remainder compared to the capacity initially [7]. Information regarding accurate SOH is essential to maintaining performance in optimal conditions, preventing unexpected failures, and optimizing timetable maintenance [8]. With precise SOH prediction, users can plan for battery replacements before total failure occurs, thereby extending the end-to-end service life and minimizing operational risks in critical applications.

In recent years, SOH has been predicted using various methods such as real data from vehicle usage [9], [10] and others using laboratory data [11]. Each method has used different algorithms, including Artificial Neural Network (ANN) [12], Support Vector Machine (SVM) [13], Convolutional Neural Networks (CNN), dynamic internal resistance [14], random forest, hybrid neural network [15], machine learning [11], deep machine learning [16], extreme machine learning [17], and transfer learning [18]. These methods have shown significant capabilities in catching complex battery data patterns and providing accurate predictions in specific conditions. For example, CNN can extract features important from input data through layers convolution, while ANN has the potential to model non-linear relationships between various battery parameters. XGBoost, one robust ensemble algorithm, is known for its ability to handle imbalanced datasets and provide good predictions in various machine learning competitions.

One of the main weaknesses of AI-based methods is the need for a large and diverse dataset to achieve high accuracy. Despite their strengths, AI-based methods often face limitations, primarily requiring large and diverse datasets to achieve reliable accuracy. Models such as CNN and ANN depend on extensive data for effective training and risk overfitting when the dataset is small or lacks diversity [19], [20]. When trained on a small or insufficient dataset, these models often experience difficulty in generalization, which causes predictions to become unreliable after being applied to new or different data from training data. This becomes a big challenge in real-world applications where data is available, possibly limited or not reflecting actual operation conditions.

SVM offers solutions for some of these challenges [21], [22]. The performance of SVM is optimal particularly when used with smaller datasets because the algorithm focuses on finding the best hyperplane that separates data points into different classes [23]. SVM capabilities handle linear and non-linear relationships through kernel functions [21], making it very profitable in various application predictions, including lithium-ion battery SOH prediction. Due to the ability to work in data-limited conditions, SVM often provides more reliable predictions than traditional AI-based methods, which require more big data. However, SVM models still require further enhancement to address overfitting when applied to high-dimensional data or under aggressive model settings, where overfitting may degrade performance on test data or real-world applications.

To address the issue of overfitting, this research integrates metaheuristic optimization methods, namely Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), with SVM to improve SOH prediction accuracy. The algorithms used are PSO and ACO, both of which have strong optimization capabilities. PSO-SVM has been previously used with successful outcomes in smart home system management [24], water-lubricated transport optimization [25], and battery module cooling [26]. Meanwhile, ACO-SVM has been applied to optimize bug severity classification [27] and forecast slope displacement [28]. Both methods are particularly well-suited for optimizing SVM parameters, reducing the risk of overfitting, and enhancing model generalization.

This research contributes to the field of lithium-ion battery SOH prediction by introducing a novel method that combines SVM with metaheuristic optimization, specifically PSO and ACO. Compared to traditional SVM models, which often struggle with overfitting in high-dimensional datasets, the integrated PSO-SVM and ACO-SVM models offer enhanced accuracy and generalization. By optimizing SVM hyperparameters, the proposed methods deliver significant improvements in SOH prediction performance. The best conditions for each optimization algorithm are also determined, providing insights into the practical application of metaheuristic optimization in predictive modeling. Therefore, this research aimed to develop a more reliable and adaptable model for managing the health of lithium-ion battery, applicable across various real-world scenarios where accurate SOH prediction is essential.

2. Method

2.1. Data Collection and Processing

This research starts by collecting data from cycle lithium-ion battery. The data cover various related parameters, including battery SOH, measured during cycle charging and discharging. Furthermore, dataset used consists of 1000 cycles of lithium-ion battery performance data, sourced from a controlled laboratory experiment, with different 20 sample sets. The use of 1000 cycles is intentional to capture the full spectrum of battery performance, from optimal initial condition to significant degradation. This number of cycles is in line with real-world applications, such as electric vehicles and energy storage systems, where battery experiences several cycles during their lifespan. Additionally, analyzing 1000 cycles ensures the model can identify degradation patterns over time, including early, mid, and late-cycle behaviors, which improves prediction accuracy and generalization for long-term performance. The testing was conducted using a load simulator on 30 cells of 18650 3.2V 1.8Ah batteries, with the aim of assessing the battery's durability and performance over extended cycles. The tests were carried out for 1000 cycles because, theoretically, lithium-ion batteries like the 18650 typically have an average lifespan of 600-700 cycles before experiencing significant degradation or capacity loss. By extending the test to 1000 cycles, we ensure a more comprehensive characterization of the battery, which serves as a solid foundation for the logic of this research and provides a more accurate understanding of the battery's long-term durability. The accuracy and reliability of the experimental cycle data are based on standardized testing procedures and consistent observation of battery performance throughout the cycling process. **Figure 1** shows an overview of the data obtained from the test results.

The dataset is divided into two subsets, namely training and testing. Distribution is performed with a proportion of 80% for training and 20% for testing. The objective of this division is to train the model on the training set and test model performance on unseen data (test set). This ensures that the model can make good generalizations and not only memorize training data.

Figure 1 Overview of lithium-ion battery cycle data. (a) Voltage vs. capacity during charging, showing consistency across cycles, (b) Voltage vs. time during charging for selected cycles, showing degradation trends, (c) Voltage vs. time during discharging for selected cycles; (d) Capacity degradation across 1000 cycles, demonstrating the steady decline in capacity with usage. The state of health (SoH) of the battery was determined based on the remaining capacity relative to the nominal capacity, which was calculated using the formula:

$$SoH = \frac{C_{current}}{C_{nominal}} x100\% \tag{1}$$

where $C_{current}$ is the battery's current capacity at a specific cycle, and $C_{nominal}$ is the battery's initial (or nominal) capacity. These measurements were taken at regular intervals during both charging and discharging processes.

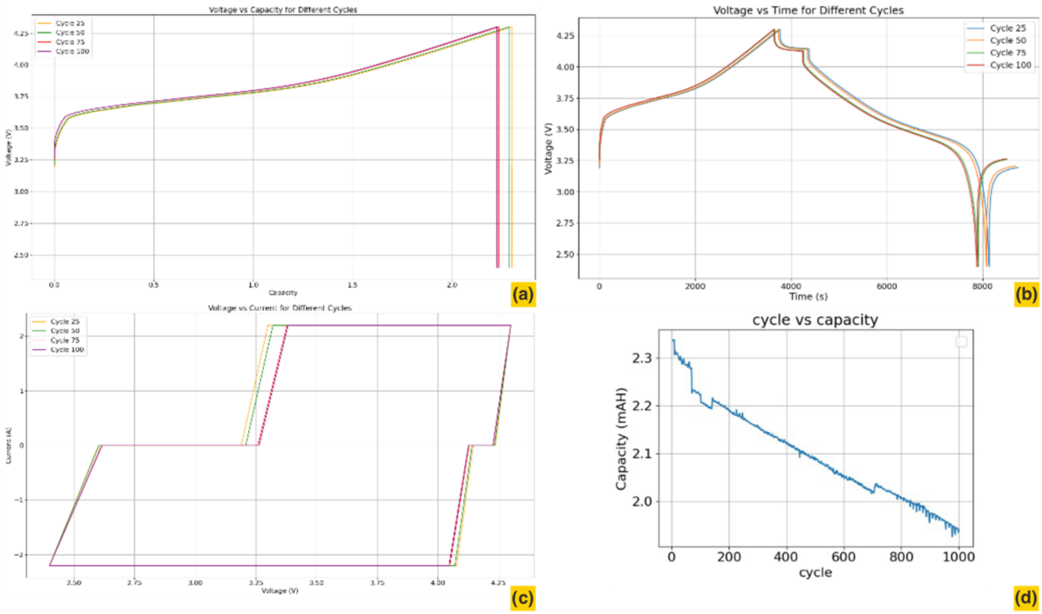

Figure 1. Lithium-ion battery data extraction results testing

Support Vector Machine (SVM) is one of the machine learning methods used for classification and regression. This method operates by finding the optimal hyperplane that separates two classes of room features. Function SVM decisions can be written as follows:

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b \tag{2}$$

where x_i, x is vector feature from training data; y_i is a label or target that corresponds to x_i, x; α_i is Lagrange coefficients obtained from dual SVM solution; $K(x_i, x)$is a kernel function that measures the similarity between two feature vectors x_i, x.

One commonly used kernel is Radial Basis Function (RBF), which maps the input features into a higher-dimensional space to capture non-linear relationships. RBF kernel is defined as:

$$K(x_i, x) = \exp(-\gamma |x_i - x|^2) \tag{3}$$

where *b* is the bias or intercept of the decision function.

In this formula, γ controls the influence of a single training example. A larger γ value focuses on closely fitting the data points, leading to more complex decision boundaries, while a smaller value causes smoother boundaries that generalize better.

Regularization Parameter (C): The parameter C controls the trade-off between achieving a low training error and maintaining a wide margin. When C is large, the model prioritizes minimizing errors in the training data, potentially leading to overfitting as it tries to fit all data points perfectly, including noise or outliers. However, when C is small, the model allows some margin violations (classification errors) to achieve a wider margin, which helps improve generalization.

The main parameters influencing SVM performance are C and γ. The parameter C controls the trade-off between achieving a low training error and maintaining a wide margin. When C is large, the model prioritizes minimizing errors in the training data, potentially leading to overfitting as it tries to fit all data points perfectly, including noise or outliers. However, when C is small, the model allows some margin violations (classification errors) to achieve a wider margin, which helps improve generalization. This trade-off is essential to prevent overfitting of Eq SVM optimization, which contains parameter C as follows:

$$\min_{w,\xi} \left\{ \frac{1}{2} |w|^2 + C \sum_{i=1}^{n} \xi_i \right\} \tag{4}$$

where: w is the weight vector of the hyperplane; ξ_i is slack variable that measures the margin of violation for point data I; C controls how much of a violation against the margin the model allows. A big C will try to minimize the violation against margins, which could lead to overfitting. Meanwhile, a small C allows a wider margin with several violations.

The basic SVM model is trained with default parameters without optimization at this stage. The results obtained will be used as a yardstick measure to compare the performance of the optimized model.

2.2. Particle Swarm Optimization

PSO is algorithm optimization based on behaviorally inspired populations of flock birds or fish looking for food. It functions in a renewed position and accelerates every particle in-room search based on the experience of the best individual and group. PSO optimizes parameters C and γ for SVM models, influencing model performance. The formula used in PSO to update speed $v_i^{k+1}$and the positions $x_i^{k+1}$of the particles are as follows [29]:

$$v_i^{k+1} = w v_i^k + c_1 r_1 \left(p_i^{best} - x_i^k\right) + c_2 r_2 \left(g^{best} - x_i^k\right) \tag{5}$$

where: v_i^k is speed particles on iteration to -k; $x_i^k$is the position of the particle at the kth iteration; p_i^{best} is position best individual particles; $g^{best}$is is the best global position in the herd; w is the inertia factor that controls influence speed previously; c_1, c_2 is coefficient learning, and $r_1, 2$ is number random between 0 and 1.

This research implements PSO to optimize the parameters C and γ from SVM to minimize Mean Square Error (MSE) on the test set. Evaluation of PSO-SVM performance includes comparison results with a basic SVM model, comprising measurement accuracy prediction and efficiency time training.

The hyperparameter search space for this research was defined as follows:

- The regularization parameter C was searched in the range [10^{-3}, 10^{3}] on a logarithmic scale.
- The kernel parameter γ was searched in the range [10^{-3} , 10^{1}] on a logarithmic scale.

The stopping criteria for PSO algorithm included the following:

- A maximum number of 50 iterations was set to balance computational efficiency and accuracy.
- A convergence threshold of 10^{5} for the change in the global best solution across iterations was used to terminate the optimization early if no significant improvements were observed.

2.3. Colony Optimization Support Vector Machine (ACO-SVM)

ACO is algorithm behavior-inspired optimization that searches for the shortest way to source food. Ant puts pheromones on the path taken, which guides more to discover the optimal path. In SVM context, ACO is used to optimize the parameters C and γ, similarly to PSO. ACO process includes iteration where intensity pheromones are updated with the following formula [30]:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{\text{ants}} \Delta\tau_{ij}^{k} \tag{6}$$

where: $\tau_{ij}(t)$ is the pheromone intensity at the edge between nodes i and j at iteration t; ρ is the pheromone evaporation rate; $\Delta\tau_{ij}^{k}$ is the amount of pheromones left by ants k.

This research used ACO to explore parameter space, determining which combination of C and γ is optimal for SVM. After determining the optimal parameters, SVM model is trained and evaluated in the same way as in PSO-SVM, using MSE and RMSE as metric performance. Evaluation of ACO-SVM results includes a comparison against the basic SVM and PSO-SVM models, focusing on accuracy prediction and efficiency. The optimal parameters are used to train SVM model and the results are evaluated using MSE and Root Mean Square Error (RMSE). The formula for MSE and RMSE is:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \tag{7}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2} \tag{8}$$

where: y_i is mark actual; y_i is mark predictions; $n$is the number of samples.

MSE and RMSE were selected as evaluation metrics due to their widespread application for assessing regression models. These metrics are particularly relevant for SOH prediction because of their sensitivity to large errors, interpretability, and relation with optimization objectives. MSE penalizes larger errors more significantly, which is essential for SOH prediction where significant deviations in predictions can lead to incorrect maintenance schedules or costly premature battery replacements. RMSE provides results in the same unit as the target variable, making it easier for engineers and stakeholders to interpret model performance. These metrics also effectively capture cumulative prediction errors across degradation trends over many cycles, ensuring the model's reliability in forecasting battery health. Additionally, both MSE and RMSE are in line with the optimization objectives of PSO and ACO, allowing the models to be tuned for better generalization and predictive accuracy.

3. Result and Discussion

Comparison between the three models, namely PSO-SVM, ACO-SVM, and basic SVM, shows important insights about their effectiveness in predicting SOH during the training and testing stage, as shown in **Figure 2** and **Figure 3**. All models show a strong ability to follow the actual SOH curve, although ACO-SVM and PSO-SVM have a higher sensitivity to data variations, enabling the ability to capture more complex patterns in the training data. This makes ACO-SVM particularly effective in modeling non-linear and varied data structures. In comparison, basic SVM shows more linear predictions, which simplifies the connection between input features and SOH, leading to underpredictions in non-linear regions.

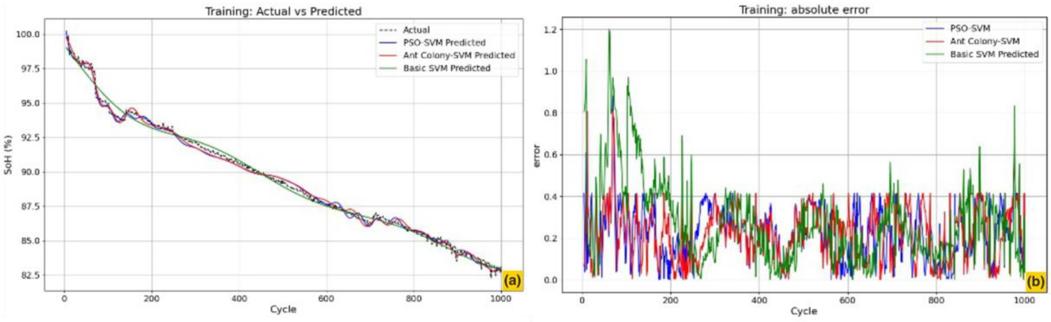

Figure 2. Training results: (a) Actual vs predicted; (b) error predicted

The absolute error graph (**Figure 2b**) shows that ACO-SVM achieves better performance by thoroughly exploring the parameter space and avoiding local optima. However, its higher sensitivity can lead to overfitting. In comparison, PSO-SVM balances exploration and exploitation effectively, causing slightly lower training accuracy with better generalization [31]. Basic SVM, lacking meta-heuristic optimization, struggles to adapt to complex variations in the data, as shown by significant error spikes, particularly around cycle 100. ACO-SVM excels in capturing intricate data patterns during training, showing its advantage in highly non-linear contexts [32].

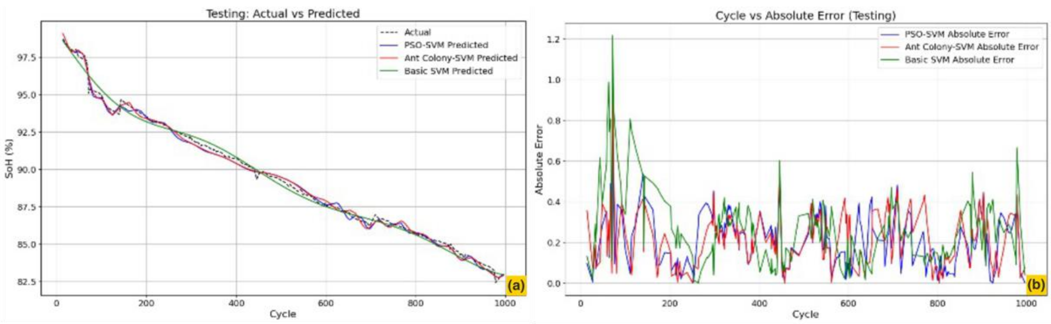

Figure 3. Testing result: (a) Actual vs. predicted SOH; (b) Predicted SOH error

Overfitting in ACO-SVM is primarily caused by the optimization process focusing predominantly on achieving low training errors. This leads to an overly complex model that is finely tuned to the training data such as any noise or outliers, causing poor generalization of unseen data. To mitigate overfitting, cross-validation can be used to evaluate model performance across multiple data splits, ensuring that the model is not overfitting to a specific subset of the training data. Additionally, regularization methods such as adjusting the parameter C in SVM, are capable of penalizing overly complex models and reducing their sensitivity to noise. Balancing exploration and exploitation in ACO algorithm, such as by adjusting pheromone decay rates or limiting the influence of early solutions, can prevent premature convergence to suboptimal parameters and promote better generalization. These strategies collectively enhance the robustness of ACO-SVM and ensure improved performance on unseen data.

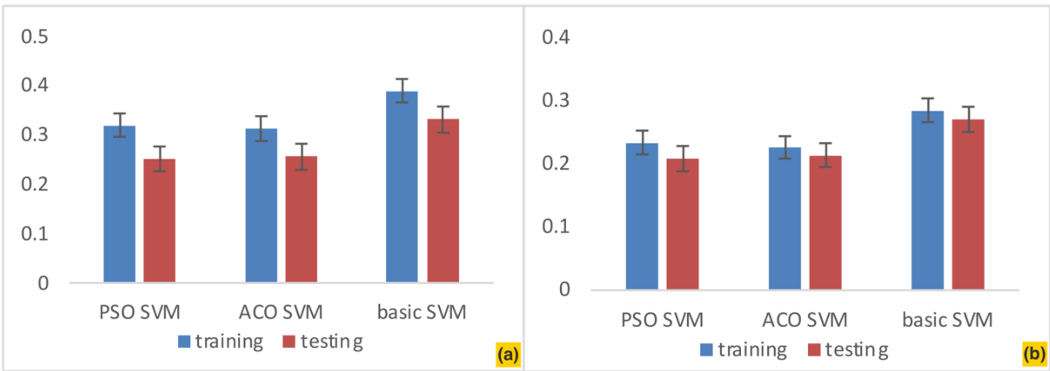

Figure 4. Prediction accuracy: (a) RMSE; (b) MAE

As presented in **Figure 4**, ACO-SVM shows more performance compared to PSO-SVM of 2.06% during training. ACO-SVM shows less performance compared to PSO SVM of 2.04% during testing. This is because PSO-SVM performs better during testing due to its effective global search for hyperparameters, which avoids overfitting and achieves a good balance between model complexity and generalization [33]. Therefore, PSO-SVM generalizes better to unseen data, as shown by lower RMSE in the testing compared to ACO-SVM. Both PSO-SVM and ACO-SVM have approximately the same level of accuracy. A comparison with previous research is shown in Table 1.

Table 1 compares the proposed PSO-SVM and ACO-SVM models with baseline methods such as GBDT (gradient boosting decision tree), LSTM (long short-term memory), and ICNN (incremental convolutional neural network). The methods are selected due to their widespread use in predictive modeling and relevance to SOH prediction. GBDT is robust against overfitting and effective for structured data, while LSTM excels in capturing temporal dependencies, and ICNN leverages feature extraction for non-linear datasets. However, GBDT struggles with high-dimensional data and lacks temporal modeling. LSTM requires large datasets and is computationally expensive, while ICNN risks overfitting on small datasets. In comparison, the proposed PSO-SVM and ACO-SVM address these challenges through hyperparameter optimization. PSO-SVM offers superior generalization in noisy or limited data scenarios and ACO-SVM shows potential to capture complex patterns in highly non-linear datasets. These strengths make the proposed models more adaptable and reliable for diverse SOH prediction scenarios.

Table 1. Analysis methods

SOH Prediction Model Name	MAE	RMSE
GBDT-SSA-FFT [34]	1.03	1.16
FOTILPSO-BPNN [35]		0.47
GBLS-Booster [36]		1.81
GPR [37]	0.74	1.63
LSTM [37]	1.14	2,01
BPNN [37]		0.66
ICNN [38]	0.45	1.1
DGPR [39]	0.47	
ICA-SVR [40]	0.6	1.1
DESGWO-HK-LSSVR [41]	0.32	0.43
PSO SVM (this research)	0.251	0.208
ACO-SVM (this research)	0.256	0.212
SVM (this research)	0.331	0.269

4. Conclusion

In conclusion, this research showed that both PSO and ACO significantly enhanced the performance of SVM in predicting SOH of lithium-ion battery. PSO-SVM provided superior generalization during testing due to balanced exploration and exploitation, making it suitable for deployment in scenarios with limited or noisy data. Meanwhile, ACO-SVM excelled in capturing complex patterns in training data, serving as an ideal option for high-accuracy requirements in controlled environments. These models were found to be particularly applicable in electric vehicles, renewable energy storage systems, and battery health monitoring platforms, where accurate SOH prediction was essential for extending lifespan and optimizing maintenance schedules.

Practical implementation of these methods faced challenges, including the computational cost associated with metaheuristic optimization such as PSO and ACO, which limited real-time applications. Additionally, their performance significantly depended on the availability of high-quality and diverse datasets, which did not show real-world conditions. To address the challenges, future research should focus on optimizing computational efficiency, exploring transfer learning approaches to handle limited datasets, and testing the models in real-world deployment scenarios to validate their robustness under operational constraints.

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Authors' Declaration

Authors' contributions and responsibilities - The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation, and discussion of results. The authors read and approved the final manuscript.

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References

[1] V. Selvaraj and I. Vairavasundaram, "A comprehensive review of state of charge estimation in lithium-ion batteries used in electric vehicles," *Journal of Energy Storage*, vol. 72, p. 108777, Nov. 2023, doi: 10.1016/j.est.2023.108777.

[2] F. Jiang *et al.*, "A comprehensive review of energy storage technology development and application for pure electric vehicles," *Journal of Energy Storage*, vol. 86, p. 111159, May 2024, doi: 10.1016/j.est.2024.111159.

[3] H. Zuo, B. Zhang, Z. Huang, K. Wei, H. Zhu, and J. Tan, "Effect analysis on SOC values of the power lithium manganate battery during discharging process and its intelligent estimation," *Energy*, vol. 238, p. 121854, Jan. 2022, doi: 10.1016/j.energy.2021.121854.

[4] Y. Deng *et al.*, "Feature parameter extraction and intelligent estimation of the State-of-Health of lithium-ion batteries," *Energy*, vol. 176, pp. 91–102, Jun. 2019, doi: 10.1016/j.energy.2019.03.177.

[5] R. Feng, S. Wang, C. Yu, N. Hai, and C. Fernandez, "High precision state of health estimation of lithium-ion batteries based on strong correlation aging feature extraction and improved hybrid kernel function least squares support vector regression machine model," *Journal of Energy Storage*, vol. 90, p. 111834, Jun. 2024, doi: 10.1016/j.est.2024.111834.

[6] Z. Li, S. Shen, Y. Ye, Z. Cai, and A. Zhen, "An interpretable online prediction method for remaining useful life of lithium-ion batteries," *Scientific Reports*, vol. 14, no. 1, p. 12541, May 2024, doi: 10.1038/s41598-024-63160-2.

[7] J. Nan, B. Deng, W. Cao, and Z. Tan, "Prediction for the Remaining Useful Life of Lithium–Ion Battery Based on RVM-GM with Dynamic Size of Moving Window," *World Electric Vehicle Journal*, vol. 13, no. 2, p. 25, Jan. 2022, doi: 10.3390/wevj13020025.

[8] J. Zhu, T. Tan, L. Wu, and H. Yuan, "RUL Prediction of Lithium-Ion Battery Based on Improved DGWO-ELM Method in a Random Discharge Rates Environment," *IEEE Access*, vol. 7, pp. 125176–125187, 2019, doi: 10.1109/ACCESS.2019.2936822.

[9] S. Wen, N. Lin, S. Huang, X. Li, Z. Wang, and Z. Zhang, "Lithium battery state of health estimation using real-world vehicle data and an interpretable hybrid framework," *Journal of Energy Storage*, vol. 96, p. 112623, Aug. 2024, doi: 10.1016/j.est.2024.112623.

[10] E. Ezemobi, M. Silvagni, A. Mozaffari, A. Tonoli, and A. Khajepour, "State of Health Estimation of Lithium-Ion Batteries in Electric Vehicles under Dynamic Load Conditions," *Energies*, vol. 15, no. 3, p. 1234, Feb. 2022, doi: 10.3390/en15031234.

[11] M. Bao *et al.*, "Interpretable machine learning prediction for li-ion battery's state of health based on electrochemical impedance spectroscopy and temporal features," *Electrochimica Acta*, vol. 494, p. 144449, Aug. 2024, doi: 10.1016/j.electacta.2024.144449.

[12] Y. Zhao and S. Behdad, "State of Health Estimation of Electric Vehicle Batteries Using Transformer-Based Neural Network," in *Volume 5: 28th Design for Manufacturing and the Life Cycle Conference (DFMLC)*, American Society of Mechanical Engineers, Aug. 2023. doi: 10.1115/DETC2023-116426.

[13] T. Zhu, S. Wang, Y. Fan, N. Hai, Q. Huang, and C. Fernandez, "An improved dung beetle optimizer- hybrid kernel least square support vector regression algorithm for state of health estimation of lithium-ion batteries based on variational model decomposition," *Energy*, vol. 306, p. 132464, Oct. 2024, doi: 10.1016/j.energy.2024.132464.

[14] Y. Sun, F. Liu, W. Qin, J. Li, X. Cheng, and J. Zeng, "Dynamic internal resistance modeling and thermal characteristics of lithium-ion batteries for electric vehicles by considering state of health," *Journal of Power Sources*, vol. 612, p. 234806, Aug. 2024, doi: 10.1016/j.jpowsour.2024.234806.

[15] B. Chen, Y. Liu, and B. Xiao, "A novel hybrid neural network-based SOH and RUL estimation method for lithium-ion batteries," *Journal of Energy Storage*, vol. 98, p. 113074, Sep. 2024, doi: 10.1016/j.est.2024.113074.

[16] N. Cai, X. Que, X. Zhang, W. Feng, and Y. Zhou, "A deep learning framework for the joint

prediction of the SOH and RUL of lithium-ion batteries based on bimodal images," *Energy*, vol. 302, p. 131700, Sep. 2024, doi: 10.1016/j.energy.2024.131700.

[17] H. Sun *et al.*, "A novel multiple kernel extreme learning machine model for remaining useful life prediction of lithium-ion batteries," *Journal of Power Sources*, vol. 613, p. 234912, Sep. 2024, doi: 10.1016/j.jpowsour.2024.234912.

[18] W. Liu, S. Gao, and W. Yan, "Comparison-Transfer Learning Based State-of-Health Estimation for Lithium-Ion Battery," *Journal of Electrochemical Energy Conversion and Storage*, vol. 21, no. 4, Nov. 2024, doi: 10.1115/1.4064656.

[19] C. F. G. dos Santos and J. P. Papa, "Avoiding Overfitting: A Survey on Regularization Methods for Convolutional Neural Networks," *Computer Vision and Pattern Recognition*, vol. arXiv:2201, 2022, doi: 10.48550/arXiv.2201.03299v.

[20] M. M. Hassan, A. Gumaei, A. Alsanad, M. Alrubaian, and G. Fortino, "A hybrid deep learning model for efficient intrusion detection in big data environment," *Information Sciences*, vol. 513, pp. 386–396, Mar. 2020, doi: 10.1016/j.ins.2019.10.069.

[21] S. Ghosh, A. Dasgupta, and A. Swetapadma, "A Study on Support Vector Machine based Linear and Non-Linear Pattern Classification," in *2019 International Conference on Intelligent Sustainable Systems (ICISS)*, IEEE, Feb. 2019, pp. 24–28. doi: 10.1109/ISS1.2019.8908018.

[22] H. Han, "Analyzing Support Vector Machine Overfitting on Microarray Data," in *Lecture Notes in Computer Science*, 2014, pp. 148–156. doi: 10.1007/978-3-319-09330-7_19.

[23] V. K. Chauhan, K. Dahiya, and A. Sharma, "Problem formulations and solvers in linear SVM: a review," *Artificial Intelligence Review*, vol. 52, no. 2, pp. 803–855, Aug. 2019, doi: 10.1007/s10462-018-9614-6.

[24] A. Althnian *et al.*, "Impact of Dataset Size on Classification Performance: An Empirical Evaluation in the Medical Domain," *Applied Sciences*, vol. 11, no. 2, p. 796, Jan. 2021, doi: 10.3390/app11020796.

[25] M. Abu Gunmi, F. Hu, D. Abu-Ghunmi, and L. Abu-Ghunmi, "A smart home energy management system methodology for techno-economic optimal sizing of standalone renewable-storage power systems under uncertainties," *Journal of Energy Storage*, vol. 85, p. 111072, Apr. 2024, doi: 10.1016/j.est.2024.111072.

[26] M. Alsehli *et al.*, "Insights into water-lubricated transport of heavy and extra-heavy oils: Application of CFD, RSM, and metaheuristic optimized machine learning models," *Fuel*, vol. 374, p. 132431, Oct. 2024, doi: 10.1016/j.fuel.2024.132431.

[27] J. Wang, Z. Wang, P. Guo, X. Hu, J. Zhu, and T. Yu, "Multi-objective optimization of phase change cooling battery module based on optimal support vector machineoptimal support Vector Machine," *Applied Thermal Engineering*, vol. 236, p. 121386, Jan. 2024, doi: 10.1016/j.applthermaleng.2023.121386.

[28] A. Kukkar, Y. Kumar, A. Sharma, and J. Kaur Sandhu, "Bug severity classification in software using ant colony optimization based feature weighting technique," *Expert Systems with Applications*, vol. 230, p. 120573, Nov. 2023, doi: 10.1016/j.eswa.2023.120573.

[29] J. Chen, Y. Wei, and X. Ma, "Forecasting Slope Displacement of the Agricultural Mountainous Area Based on the ACO-SVM Model," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–10, Sep. 2022, doi: 10.1155/2022/2519035.

[30] M. Oszczypała, J. Konwerski, J. Ziółkowski, and J. Małachowski, "A genetic algorithm and particle swarm optimization for redundancy allocation problem in systems with limited number of non-cooperating repairmen," *Expert Systems with Applications*, vol. 256, p. 124841, Dec. 2024, doi: 10.1016/j.eswa.2024.124841.

[31] M. Xie, D. Pi, Y. Xu, Y. Chen, and B. Li, "Path optimization algorithm for mobile sink in wireless sensor network," *Expert Systems with Applications*, vol. 255, p. 124801, Dec. 2024, doi: 10.1016/j.eswa.2024.124801.

[32] B. F. Azevedo, A. M. A. C. Rocha, and A. I. Pereira, "Hybrid approaches to optimization and machine learning methods: a systematic literature review," *Machine Learning*, vol. 113, no. 7, pp. 4055–4097, Jul. 2024, doi: 10.1007/s10994-023-06467-x.

[33] W. Deng, H. Zhao, L. Zou, G. Li, X. Yang, and D. Wu, "A novel collaborative optimization algorithm in solving complex optimization problems," *Soft Computing*, vol. 21, no. 15, pp. 4387–4398, Aug. 2017, doi: 10.1007/s00500-016-2071-8.

[34] Z. Fouad, M. Alfonse, M. Roushdy, and A.-B. M. Salem, “Hyper-parameter optimization of convolutional neural network based on particle swarm optimization algorithm,” *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 6, pp. 3377–3384, Dec. 2021, doi: 10.11591/eei.v10i6.3257.

[35] R. Pan, T. Liu, W. Huang, Y. Wang, D. Yang, and J. Chen, “State of health estimation for lithium-ion batteries based on two-stage features extraction and gradient boosting decision tree,” *Energy*, vol. 285, p. 129460, Dec. 2023, doi: 10.1016/j.energy.2023.129460.

[36] L. Chen *et al.*, “State of health estimation of lithium-ion batteries based on equivalent circuit model and data-driven method,” *Journal of Energy Storage*, vol. 73, p. 109195, Dec. 2023, doi: 10.1016/j.est.2023.109195.

[37] P. Yang *et al.*, “Joint evaluation and prediction of SOH and RUL for lithium batteries based on a GBLS booster multi-task model,” *Journal of Energy Storage*, vol. 75, p. 109741, Jan. 2024, doi: 10.1016/j.est.2023.109741.

[38] H. H. Goh, Z. Lan, D. Zhang, W. Dai, T. A. Kurniawan, and K. C. Goh, “Estimation of the state of health (SOH) of batteries using discrete curvature feature extraction,” *Journal of Energy Storage*, vol. 50, p. 104646, Jun. 2022, doi: 10.1016/j.est.2022.104646.

[39] Z. Bao, J. Nie, H. Lin, J. Jiang, Z. He, and M. Gao, “A global–local context embedding learning based sequence-free framework for state of health estimation of lithium-ion battery,” *Energy*, vol. 282, p. 128306, Nov. 2023, doi: 10.1016/j.energy.2023.128306.

[40] Y. Yang, S. Chen, T. Chen, and L. Huang, “State of Health Assessment of Lithium-ion Batteries Based on Deep Gaussian Process Regression Considering Heterogeneous Features,” *Journal of Energy Storage*, vol. 61, p. 106797, May 2023, doi: 10.1016/j.est.2023.106797.

[41] Y. Zhang, Y. Liu, J. Wang, and T. Zhang, “State-of-health estimation for lithium-ion batteries by combining model-based incremental capacity analysis with support vector regression,” *Energy*, vol. 239, p. 121986, Jan. 2022, doi: 10.1016/j.energy.2021.121986.