JOURNAL OF AUTOMOBILE ENGINEERING AND APPLICATIONS
(VOL.13, ISSUE:2) 2026
E-ISSN: 2455-3360
RECEIVED DATE- 04 February, 2026
ACCEPTED DATE- 10 February, 2026
PUBLISHED DATE- 10 March, 2026
Article Type: Research Article

Particle Swarm Optimization Framework for Accurate Battery State-of-Charge and Remaining Useful Life Estimation

Rupali Sanjay Firke*[1], Mukesh Kumar Gupta [2], Amit Tiwari [3]

[1*] Research Scholar, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur, Rajasthan, India.

[2] Professor, Department of Electrical Engineering, Suresh Gyan Vihar University, Jaipur, Rajasthan, India.

[3] Assistant Professor, Department of Mechanical Engineering, Suresh Gyan Vihar University, Jaipur, Rajasthan, India.

Corresponding author email: firkerupali@gmail.com

Abstract:

Accurate estimation of the State of Charge (SOC) and State of Health (SOH) of a battery is key to safe and efficient management of batteries in electric vehicles and energy-storage systems. However, it is challenging due to high nonlinearity, varying operating conditions, measurement noise, and limited access to comprehensive electrochemical parameters. Traditional data-driven models often generalize poorly and require heavy tuning, which can produce unstable predictions. To address these problems, we have proposed a Particle Swarm Optimization (PSO)-based Support Vector Regression (SVR) framework that estimates SOC and SOH using only easily measured variables, namely ambient temperature, charge current, voltage, and cycle count. Our primary objectives are to improve estimation stability and reduce prediction error through optimal tuning of the SVR hyperparameters using PSO. PSO searches the validation set to find the optimal values of the penalty factor, kernel width, and epsilon-sensitive loss, thereby minimizing the root-mean-square error (RMSE). Convergence plots, residual curves, residual histograms, and confusion-matrix-based classification tests of the resulting SVR models are evaluated. Experimental results indicate that PSO converges reliably, achieving a minimum RMSE of approximately 26.6 for SOC and 9.17 for SOH. The residual analysis shows that SOH errors are predominantly within the range of +15, whereas SOC errors may reach up to +40, reflecting the higher dynamic complexity of SOC. Further analysis using the confusion matrix shows stronger consistency in SOH classification, with 17 of the moderate-SOH samples correctly classified. Overall, the PSOSVR framework is more robust and converges better for battery state estimation. These results indicate that PSO is efficient for hyperparameter optimization and that more time-dependent features are necessary to enhance the accuracy of SOC prediction.

Keywords: Particle Swarm Optimization, State of Charge Estimation, State of Health Prediction, Support Vector Regression, Battery Management System, Machine Learning Optimization

1. Introduction

Adequate State of Charge (SOC) tracking and Remaining Useful Life (RUL) prediction are two key functions of a modern Battery Management System (BMS) [1-2]. SOC is used to make real-time decisions about energy availability, and RUL is used to plan maintenance and avert safety hazards [3-4]. Pronounced nonlinearity, hysteresis, temperature dependence, aging drift, sensor noise, and varying operating profiles simultaneously challenge both functions, making estimators with fixed parameters unreliable and degrading model generalizability [5-6]. This has encouraged the use of metaheuristic optimization methods, and Particle Swarm Optimization (PSO) has emerged as especially useful for tuning model parameters, hyperparameters, and filters to improve precision and robustness [7-10]. In more recent SOC-based studies, PSO has demonstrated the ability to improve estimation accuracy directly by selecting optimal deep model architectures [11-16]. Tiwari, A et al. [17] proposed a PSO-TCN-Attention SOC estimator, in which PSO optimizes the parameters of a temporal convolutional network and an attention mechanism identifies the most informative time steps. The resulting model achieved a root-mean-square error (RMSE) of less than 1%, a maximum absolute error (MAXE) of less than 5.75%, and an R^2 of more than 99.88%, indicating excellent performance under dynamic conditions and across various temperatures [18-22]. However, the methodology still relies on sufficiently diverse training data and may require retraining if there is a major change in battery chemistry or duty-cycle parameters [23-26]. Simultaneously, Jain, R et al. [27] introduced a BP-PSO approach to a sparse-representation-based predictor (BP-PSO-SRP), with an RMSE of 0.355^{-1} and a maximum absolute error of 0.998^{-1}, showing that PSO-enhanced training can minimize error peaks. However, sparse-representation pipelines can be computationally expensive and sensitive to feature scaling and windowing decisions, especially when embedded BMS requirements are considered [28-32]. CL, S et al. [33] compared several hybrid SOC models with optimizers and DNNs, with a PSO-DNN baseline having a mean absolute error (MAE) of 4.3089% and an RMSE of 5.9672, and TLBO-DNN performing better than the PSO-DNN setup [34-36]. These findings suggest that although PSO can be beneficial, it is not always the best metaheuristic; its behavior depends on the tuning of inertia and acceleration coefficients and search space design, and it may fail to perform in a complex hyperparameter space without hybridization or adaptive scheduling [37-41].

In addition to deep learning, PSO combined with filtering methods has been effective in reducing sensor noise and model mismatch. Patni, Y. R et al. [42] proposed a dynamic framework that combines a forgetting-factor recursive least squares (RLS) filter with a PSO-based resampling strategy to enable online SOC estimation. This approach achieved maximum errors of 1.137 and 0.797% in battery-to-battery degradation symptom testing (BBDST) and degradation signal testing (DST) at 25 °C and 35 °C, respectively, demonstrating robustness to temperature changes and drive cycles [43-46]. However, particle estimators still carry computational cost and require careful attention to the number of particles to keep them feasible in real time [47-50]. Patni, Y. R et al. [51] suggested an adaptive PSO-LSSVM SOC estimator using current, voltage, and temperature inputs, with a SOC estimation error of 1.63. This paper indicates that PSO can effectively tune the parameters of the kernel; however, support vector machine-type methods are also sensitive to the choice of kernel and can experience performance deterioration as age-related changes in the feature distribution move outside the training regime [52-54]. Natesh, C. P et al. [55] analyzed a filtering-centric method comprising unscented particle filtering combined with PSO-based resampling (PSO-UPF). They reported accuracy of less than 1% with fewer particles, indicating better accuracy and lower runtime requirements [56-57]. Nonetheless, the assumptions of the methodology must be confirmed on high-power electric vehicle datasets and on cell-to-cell variability, which is a known challenge in practical battery packs [58-59]. The RMSE of a hybrid joint estimator between classical observers and PSO-optimized deep sequence learning (EKF + PSOLSTM) was found to be less than 0.258%, with a maximum error of less than 1.559% in both standard laboratory and road-testing conditions. These findings demonstrate the stabilizing effect of PSO on the LSTM hyperparameters while maintaining dynamic consistency using the extended Kalman filter. Typical weaknesses of these joint approaches include the need for consistent calibration of measurements and the possibility of EKF-based bias in the learning module unless designed with aging-conscious states and periodic re-identification [60-61].

PSO is often used in RUL and state-of-health (SOH) estimation, as well as in hyperparameter optimization and feature engineering for data-driven prognostics, because prediction errors can grow significantly when capacity regeneration, noise, and knee-point behavior occur [62]. Chopra, A et al. [63] proposed Battery-Insight-PSO, in which PSO optimizes XGBoost parameters, yielding extremely high fit scores of $R^2 = 0.9998$ for SOH and $R^2 = 0.9987$ for RUL. This suggests that PSO can greatly improve tree-ensemble prognostics; however, tree models remain prone to overfitting with feature leakage, and under domain shifts (e.g., new temperature or charging regimes) they can lose accuracy unless domain adaptation or uncertainty calibration is added [64]. Patel, V et al. [65] proposed a PSO-optimized multi-model RUL framework based on domain-driven feature engineering and comparisons among machine-learning and deep-learning models. The PSO-tuned LSTM performed best, with MAE = 0.34, RMSE = 0.76, and $R^2 = 0.93$. These findings indicate that PSO-optimized hyperparameters and engineered battery indicators can help minimize error and stabilize training; however, feature quality and consistent preprocessing are important, and computational costs may increase when many models are optimized and ensembled [66]. Tiwari, A et al. [67] introduced a PSO-NN RUL estimator that yields MAE = 2.7708 and RMSE = 4.3468, significantly lower than baselines, including HSA-NN (MAE = 22.0583, RMSE = 34.5154) and ARIMA (MAE = 494.6275, RMSE = 584.3098). These results indicate that PSO can substantially reduce prediction deviation, but the largest error remains substantial (e.g., 104.7381), suggesting that even optimized NNs can perform poorly in late-life nonlinear degradation phases unless knee-point detection or hybrid physics constraints are employed. Xia, F et al. [68] used CEEMD-decomposed capacity series, sample entropy as a measure of complexity, and an enhanced PSO to improve an LSSVM in a signal-processing-based hybrid RUL. They report comparative performance: CEEMDSELSSVM baseline (RMSE = 3.8059, MAPE = 0.1844) and IPSOLSSVM (RMSE = 6.8902, MAPE = 0.2361) outperform other baselines, including SVR (RMSE = 9.3241). This method highlights the advantages of decomposition and PSO tuning in terms of stability, though these pipelines can be sensitive to decomposition environments and difficult to implement online because of multi-stage processing overhead [69]. Lastly, SOH stability can be enhanced to facilitate correct RUL estimation, and ensemble learning can reduce PSO-SVM variance [70]. However, they also recognize that even single-model predictions may drift and that cross-battery adaptability needs to be rigorously validated, particularly when the training data reflect only limited operating conditions. Summarizing these works, the literature shows that PSO is a consistent and reliable method that optimizes the performance of the SOC/RUL system by (i) optimizing the hyperparameters of deep temporal networks (TCN/LSTM), (ii) optimizing the kernel or regression parameters of the LSSVM/SVR system, and (iii) strengthening filtering or particle-resampling mechanisms to ensure robustness.

This paper addresses the critical challenge of reliably estimating the State of Charge (SOC) and State of Health (SOH) of a battery when the dataset is sparse and noisy, with the goal of developing a robust and stable estimation system that captures the battery's nonlinear behavior using only simple, easily accessible inputs: ambient temperature, charge current, voltage, and cycle count. To accomplish this, we propose a Particle Swarm Optimization (PSO)-assisted Support Vector Regression (SVR) model, in which PSO optimizes the SVR hyperparameters to ensure convergence to the global solution and avoid local minima. This approach is novel because it integrates PSO-based hyperparameter optimization with parallel SOC and SOH prediction, as confirmed by convergence curves, residuals, and confusion matrices, in contrast to the conventional approach that uses fixed parameters or complex electrochemical data. Our model converges and produces unbiased predictions with this simple input set, and the research transparently addresses the model's limitations through classification-based evaluation and highlights practical deployment issues. In general, the study provides a computationally effective, interpretable, and optimization-enhanced baseline architecture for a next-generation battery management system.

2. Research gap

1. Joint SOC–RUL coupling is underexplored: Most studies optimize SOC or RUL separately; few build a single unified architecture that propagates SOC uncertainty into RUL prediction.
2. Limited real-world generalization: Many results are strong on specific datasets/temperatures but lack cross-temperature, cross-cell, cross-chemistry validation and domain-shift testing.
3. PSO configuration is not standardized: Inertia/coefficients, swarm size, and stopping criteria vary widely; few papers provide sensitivity analysis or computational budgets for embedded BMS use.
4. Late-life nonlinear “knee-point” handling remains weak: Even PSO-optimized models can show higher peak errors near end-of-life; robust knee-point detection + adaptive retraining/weighting is still missing.
5. Uncertainty and safety metrics are rarely reported: Most works report RMSE/MAE only; few include prediction intervals, calibration, risk-aware thresholds, or decision-ready metrics for safety-critical EV operation.

3. Methodology

Particle Swarm Optimization (PSO) is used as the methodology to enhance the accuracy and strength of battery State of Health (SOH) estimation through a Support Vector Regression (SVR) model. It uses four independent inputs, which are ambient temperature (°C), charge current (A), terminal voltage (V), and cycle count, and one output, battery SOH (%). The data is initially loaded into an excel spreadsheet and it is cleared to eliminate incomplete data. The data are then cleaned and divided into training and testing data sets in a ratio of 75:25 to ensure that the evaluation of the performance is not biased. Since SVR is scale-sensitive, all the inputs are standardized with mean and standard deviation of training data. The reason why an RBF - kernel SVR is selected is that this type of model can adequately explain the nonlinear deterioration of batteries. The performance of the SVR is primarily determined by three hyperparameters, including the penalty parameter (C), the kernel width (γ), and epsilon - insensitive loss (ε). These parameters are determined by finding the optimal values of PSO. A given PSO particle is a candidate set $p = [\log_{10}(C), \log_{10}(\gamma), \log_{10}(\varepsilon)]$. Particles are initially randomly distributed between fixed values: $\log_{10}(C) \in [-1, 5]$, $\log_{10}(\gamma) \in [-6, 2]$, and $\log_{10}(\varepsilon) \in [-4, 0]$. According to the swarm, velocities and positions are updated with inertia $w = 0.72$, cognitive coefficient $c_1 = 1.49$ and social coefficient $c_2 = 1.49$ which balances between exploration and exploitation. Each particle fitness is also assessed at every iteration by the root mean square error (RMSE) on a validation subset selected by sampling the training data. The particles retain their optimal individual scores and converge to the global optimum that is minimizing RMSE. After convergence, the hyperparameters of the optimal SVR are taken as the input to the last SOH estimation model. The trained model is then applied to test data that is not seen. The predicted SOH values are sorted as health states and allow the analysis of performance based on classification and facilitates practical decisions on the management of batteries.

4. Results and Discussion

The optimization behavior of Particle Swarm Optimization (PSO) with RMSE as the fitness criterion is evident in the convergence curves in Fig. (1a) and Fig. (1b) for the SOH and SOC models, respectively. Fig. (1a) (SOH model) starts with a higher mean swarm RMSE (=9.6), which decreases gradually, indicating effective global exploration at the beginning of the iterations. The optimal swarm RMSE decreases rapidly in the initial 5-10 iterations, from approximately 9.45 to approximately 9.18, indicating strong exploitation. Once the number of iterations reaches around 20, the best and mean RMSE curves converge to a similar point and stabilize at about 9.17. This implies that the swarm has converged to a near-optimal point with few oscillations and high convergence stability. Fig. (1b) (SOC model) shows a similar but more erratic trend in the optimization process due to greater nonlinearity in SOC estimation. The mean RMSE starts with a large value (around 27.9) and exhibits oscillations during the initial iterations, corresponding to broader search-space exploration. Nevertheless, the optimal swarm RMSE decreases from an average of 26.75 to about 26.60 during the initial 15-20 iterations. After 40 iterations, the two curves converge and settle around 26.6, indicating satisfactory convergence. In general, these plots validate that PSO is an efficient algorithm that balances exploration and exploitation, attains stable convergence, and minimizes the estimation error of both SOC and SOH models.

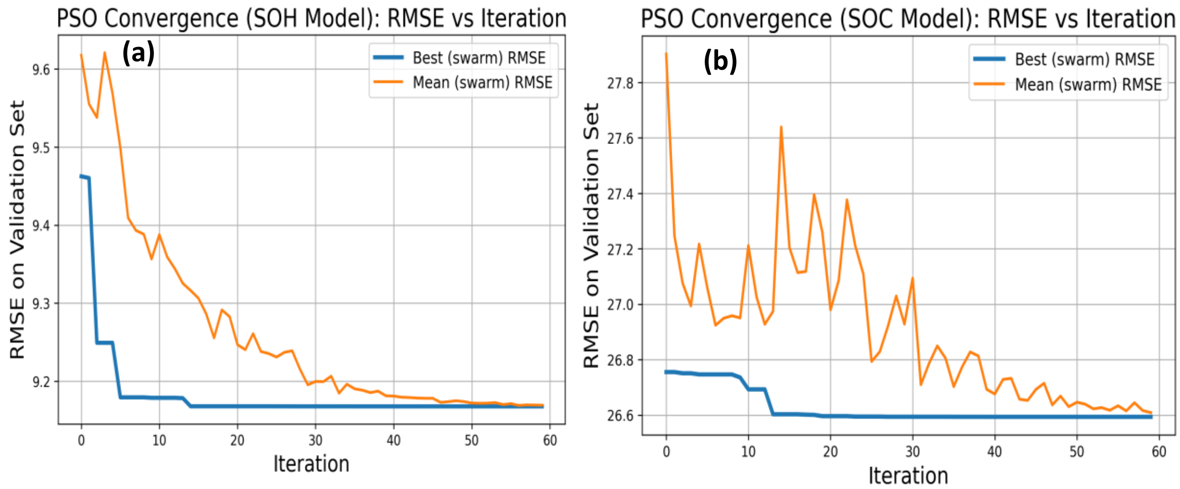

Figure 1. PSO convergence characteristics for SOC and SOH models based on RMSE minimization

The residual plots in Fig. (2a) and (2b) provide a close examination of the errors in the SOH and SOC models' predictions on the test dataset. Fig. (2a) (SOH residual curve) shows residuals distributed around zero, with most values falling within the range of +15 to -15. The narrow error band indicates that the degradation trend is well represented by the PSO-optimized model and that SOH estimation is stable. The absence of systematic drift or monotonic bias with the sample index indicates that the model does not consistently over- or underestimate SOH, a significant attribute for long-term battery health monitoring. Plateau spikes around ±15 may be due to sudden degradation or temperature variations related to the cycle. Conversely, Fig. (2b)

(SOC residual curve) shows that the errors are more dispersed, with a range of approximately -40 to +40. This increased dispersion points to greater nonlinearity in SOC estimation. The higher oscillations, particularly at multiple test indices, indicate sensitivity to instantaneous operating conditions, including current and voltage variations. Nevertheless, the residuals remain around zero, indicating no systematic bias. Overall, these residual patterns indicate that PSO leads to better model stability. They also show that SOC estimation is harder than SOH prediction due to higher short-term dynamics and less information about the inputs.

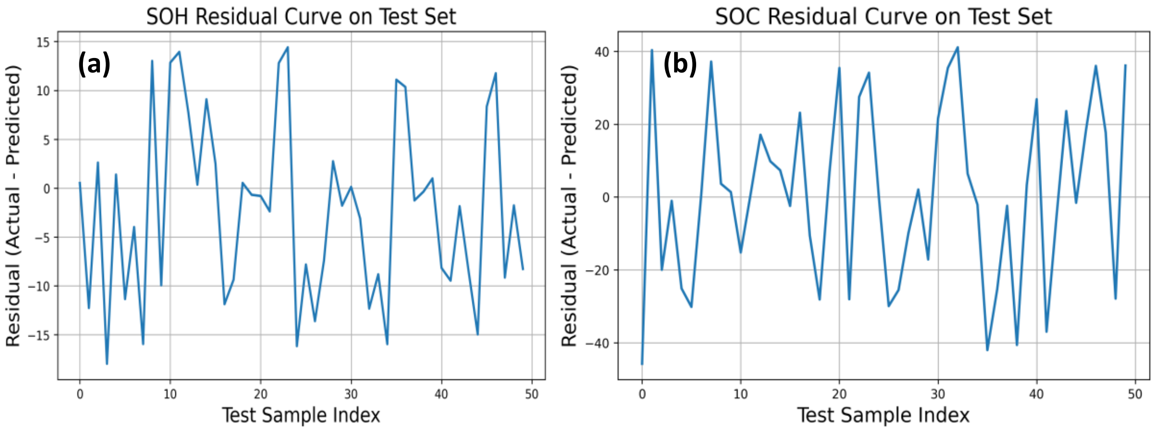

Figure 2. Residual error trends of PSO-optimized SOC and SOH models on test dataset

The residual histograms of Fig. (3a) and Fig. (3b) provide the statistical perspective on prediction errors of the SOH and SOC models, respectively, to determine the error distribution, spread, and symmetry. Fig. (3a) (SOH residual histogram) shows that the residual values lie mostly in a slim band between approximately -15 to +15. Its maximum frequency is close to zero, indicating that a majority of SOH predictions are of close results compared to the actual ones. The fact that this spread is almost symmetrical around zero suggests that there is little systematic bias and this confirms that the PSO-optimized SOH estimation model is valid and consistent. The low dispersion is also an indication of good generalization and predictive consistency in various test samples. On the other hand, Fig. (3b) (SOC residual histogram) presents a far wider distribution of error, with a range of about -40 to +40. Despite the fact that the peak frequency remains close to zero, broader tails indicate greater instantaneous deviation of SOC prediction. The nonlinear and dynamic characteristics of SOC as reflected by this pattern make it more sensitive to sudden changes in current and voltage than SOH. On the whole, the histograms prove the fact that PSO-based optimization provides stable and unbiased estimates. SOH prediction is more consistent whereas SOC prediction is more difficult, thus supporting the importance of more time-series features or dynamic modeling to minimize SOC errors even further.

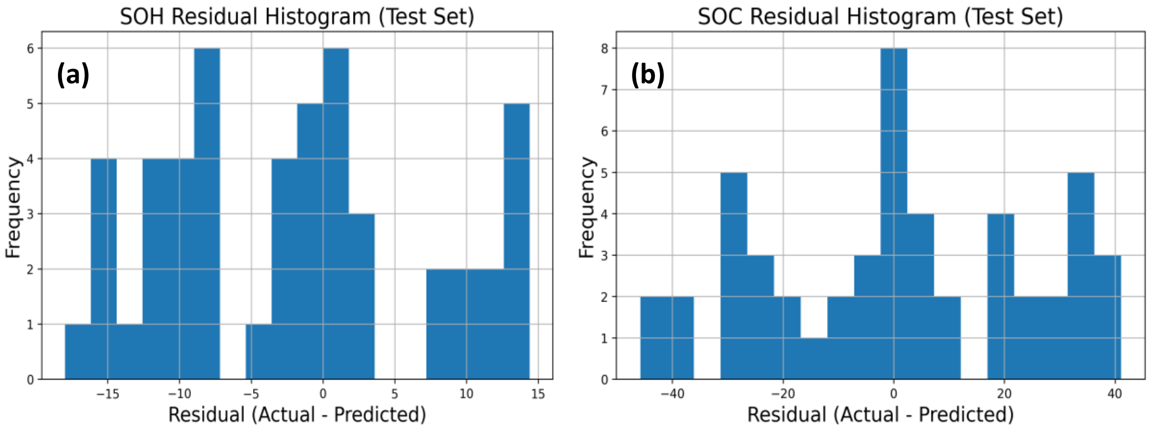

Figure 3. Statistical distribution of residual errors for PSO-based SOC and SOH estimation models

The SOH classification confusion matrix on PSO-SVR model demonstrates the way the model predicts each of the classes as shown in figure 4. The confusion matrix groups the data into three health groups Poor SOH (<80%), Moderate SOH (80 -90%), and Healthy SOH (>90%). The false prediction of the Moderate SOH is complete, with an error of 18 Poor SOH incorrectly predicted. The 13 samples of the Healthy SOH are also predicted to be Moderate SOH. Conversely, 17 samples are properly classified as in the Moderate SOH category, and 2 samples are wrongly identified as Healthy SOH. Since nearly all predictions are collapsed in the Moderate SOH column, the PSO-SVR model favors the middle state of health, which lines the boundaries between the extreme classes. This implies that the input characteristics are not sufficient to offer sufficient separability to differentiate between early degradation (Poor SOH) and conditions that are almost healthy. The absence of predictions in the Poor SOH column indicates that the model avoids extreme low-health predictions, which means that it is conservative. In general, the confusion matrix illustrates that although PSO enhances the stability of regression, more degradation sensitive or temporal capacity degradation data will be needed to distinguish between battery health conditions.

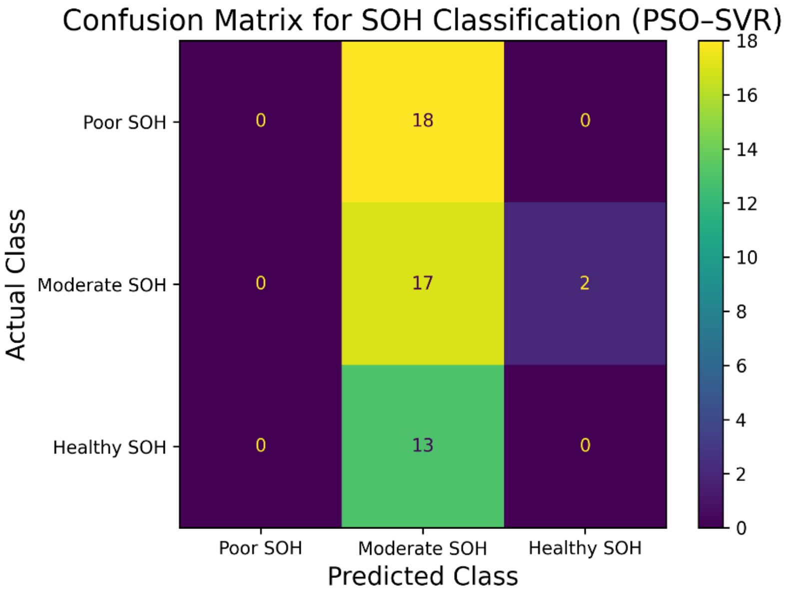

Figure 4. Confusion matrix analysis of PSO–SVR based battery state-of-health classification performance

The PSO-SVR-based confusion matrix for SOC classification shown in figure 5, the distribution of predicted charge states across three categories: Low SOC (< 40%), Medium SOC (40-70%), and High SOC (> 70%). All test samples are predicted as Medium SOC, indicating a strong central bias in the model's decisions. In particular, 14 Low SOC samples, 20 Medium SOC samples, and 16 High SOC samples are assigned to the Medium SOC category, and none belong to either the Low or High predicted classes. This shows that the PSO-optimized regression model tends toward an average SOC value when translating continuous predictions into discrete classes. This behavior implies that the discriminative power of the chosen inputs (ambient temperature, current, voltage, and cycle count) is limited to instantaneous SOC separation. Transient electrochemical dynamics are highly sensitive to SOC, and snapshots of static features are usually unable to capture rapid changes in charge. The absence of noise misclassifications in the Low and High SOC columns indicates that the model is stable, but it does not provide strong separation between classes. System-wise, this conservative prediction tendency can minimize extreme estimation errors but is not appropriate for SOC discrimination. In summary, the confusion matrix indicates that although PSO stabilizes model training, correct SOC classification requires more time-dependent or sequence-based features to enhance boundary demarcation among charge states.

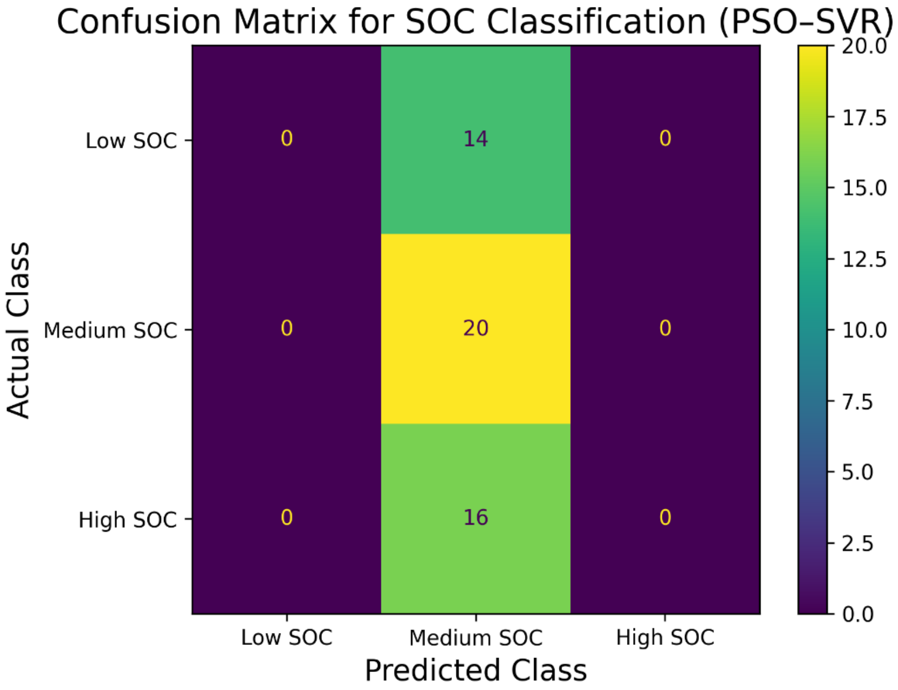

Figure 5. Confusion matrix evaluation of PSO–SVR based battery state-of-charge classification performance

5. Conclusion

This paper discusses a Support Vector Regression (SVR) model aided by Particle Swarm Optimization (PSO) to estimate battery State of Charge (SOC) and State of Health (SOH). The model uses readily available operational data, including ambient temperature, charge current, voltage, and cycle count. PSO achieves steady, effective convergence for both SOC and SOH models. Root-mean-square errors (RMSE) decrease slowly after approximately 40-50 iterations, with stopping points of approximately 26.6 for SOC and 9.17 for SOH. These findings show that PSO can balance global search and local fine-tuning in hyperparameter optimization. Analysis of the residual curve and histogram indicates that SOH prediction errors are maintained within ±15 units. Conversely, SOC residuals increase to a range of 40 units, indicating that SOC is more dynamic and nonlinear. Examination of the confusion matrix shows that most predictions fall within the middle health or charge category. This conservative trend indicates weak class separability when using only static features. The SOH model is also more uniform, and the 17 moderate-SOH samples are correctly classified with less dispersion than SOC predictions. In general, the PSO-SVR model offers a robust, unbiased, and computationally efficient baseline for battery state estimation. PSO increases model robustness, but to achieve greater SOC discrimination accuracy, time-series features or electrochemical indicators will likely need to be included. The article provides useful information on the strengths and weaknesses of PSO-based optimization in the implementation of effective battery management systems.

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