UDC 621.3:620.96 https://doi.org/10.36296/1819-8058.2026.1(84).109-115

STATE OF HEALTH (SOH) ESTIMATION FOR EMBEDDED BATTERY MANAGEMENT SYSTEMS: A COMPARATIVE ANALYSIS OF COMPUTATIONALLY EFFICIENT METHODS

Received Oct. 31, 2025; accepted Mar. 23, 2026
Available online Mar. 31, 2026

Sorochynskyi Ya.[1], Bosak Al.[2], Dubovyk V.[3], Kulakovskyi L.[4], Bosak An.[5]

Author for correspondence: Bosak Alla
e-mail: allabosak@lll.kpi.ua

[1] Postgraduate Student
https://orcid.org/0009-0008-8056-520X

[2] Cand. of Tech. Sciences, Assoc. Prof.
https://orcid.org/0000-0003-0545-9980

[3] Senior Lecturer
https://orcid.org/0000-0001-8884-8222

[4] Cand. of Tech. Sciences, Assoc. Prof.
https://orcid.org/0000-0003-1273-6894

[5] PhD, Junior Researcher
https://orcid.org/0000-0002-4667-9720

[1, 2, 3, 4] National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”, Kyiv, Ukraine.

[5] General Energy Institute of the National Academy of Sciences of Ukraine.

Abstract. *Accurate State of Health (SOH) estimation is critically important for the safe and long-term operation of lithium-ion batteries. However, the implementation of estimation algorithms in embedded Battery Management Systems (BMS) is significantly limited by available computational resources. This paper presents a scientifically grounded comparative analysis of two computationally efficient machine learning methods – Support Vector Regression (SVR) and Random Forest – to determine the optimal algorithm for practical implementation, with a dual focus on prediction accuracy and computational efficiency. Based on an open dataset, systematic hyperparameter tuning with GridSearchCV and cross-validation was conducted for both models. The performance of the final, optimized models was evaluated by accuracy metrics (RMSE, MAE) and indicators of suitability for embedded systems (forecasting time, model size). The results showed that even after thorough optimization, the SVR model demonstrated higher prediction accuracy (RMSE 2.67% vs. 3.08% for Random Forest). An even more significant advantage was found in the efficiency analysis: SVR was found to be almost 170 times faster (forecast time of 0.119 ms vs 20.570 ms) and 200 times more compact (model size 8.6 kB vs 1718.6 kB). It is concluded that, for the problem of estimating SOH based on cyclic data, the SVR model is the optimal candidate for practical implementation in embedded BMS. It offers the best balance of high accuracy and minimal hardware resource requirements, outperforming Random Forest across all key criteria for engineering practice.*

Key words: *Keywords: State of Health, SOH, battery management system, BMS, Battery Energy Storage Systems (BESS), renewable energy, distributed generation, microgrids, lithium-ion batteries, machine learning, embedded systems, Support Vector Regression, Random Forest, computational efficiency.*

ОЦІНКА СТАНУ ПРАЦЕЗДАТНОСТІ (SOH) ДЛЯ ВБУДОВАНИХ СИСТЕМ КЕРУВАННЯ БАТАРЕЯМИ: ПОРІВНЯЛЬНИЙ АНАЛІЗ ОБЧИСЛЮВАЛЬНО ЕФЕКТИВНИХ МЕТОДІВ

Отримано 31 жов. 2025 р.; рекомендовано до публікації 23 бер. 2026 р.
Доступно онлайн 31 бер. 2026 р.

Сорочинський Я. З.[1], Босак А. В.[2], Дубовик В. Г.[3], Кулаковський Л. Я.[4], Босак А. В.[5]

Автор для кореспонденції: Босак Алла,
e-mail: allabosak@lll.kpi.ua

[1] аспірант
https://orcid.org/0009-0008-8056-520X

[2] канд. техн. наук, доц.
https://orcid.org/0000-0003-0545-9980

[3] старший викладач
https://orcid.org/0000-0001-8884-8222

[4] канд. техн. наук, доц.
https://orcid.org/0000-0003-1273-6894

[5] д-р. філософії, мол. наук. співроб.
https://orcid.org/0000-0002-4667-9720

[1,2,3,4] Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського», Київ, Україна.

[5] Інститут загальної енергетики НАН України.

Анотація. *Точна оцінка стану працездатності (State of Health, SOH) є критично важливою для безпечної та довговічної експлуатації літій-іонних акумуляторів. Однак реалізація алгоритмів оцінки у вбудованих системах керування батареями (BMS) суттєво обмежується доступними обчислювальними ресурсами. В роботі проведено науково обґрунтований порівняльний аналіз двох обчислювально ефективних методів машинного навчання – методу опорних векторів для регресії (SVR) та випадкового лісу – а для визначення оптимального алгоритму для практичної реалізації з подвійним фокусом на точності* *прогнозування та обчислювальній ефективності. На основі відкритого набору даних, для обох моделей було проведено систематичний підбір гіперпараметрів за допомогою GridSearchCV з перехресною валідацією. Ефективність фінальних, оптимізованих моделей оцінювалася за метриками точності (RMSE, MAE) та показниками придатності для вбудованих систем (час прогнозування, розмір моделі). Результати показали, що навіть після ретельної оптимізації модель SVR продемонструвала вищу точність прогнозування (RMSE 2.67% проти 3.08% у Випадковий Ліс). Ще більш значуща перевага була виявлена в аналізі ефективності: SVR виявився майже у 170 разів швидшим (час прогнозу 0.119 мс проти 20.570 мс) та у 200 разів компактнішим (розмір моделі 8.6 кБ проти 1718.6 кБ). Зроблено висновок, що для задачі оцінки SOH на основі циклічних даних модель SVR є оптимальним кандидатом для практичної реалізації у вбудованих BMS. Вона забезпечує найкращий баланс високої точності та мінімальних вимог до апаратних ресурсів, перевершуючи Випадковий Ліс за всіма ключовими для інженерної практики критеріями.*

Ключові слова: *стан працездатності, SOH, система керування батареями, BMS, системи накопичення енергії, відновлювана енергетика, розподілена генерація, мікромережі, літій-іонні акумулятори, машинне навчання, вбудовані системи, метод опорних векторів, випадковий ліс, обчислювальна ефективність.*

List of abbreviations and symbols

BMS – Battery Management System

EV – Electric Vehicle

MAE – Mean Absolute Error

RMSE – RMS Error

SOH – State of Health

SVR – Support Vector Method for Regression

RES – Renewable Energy Sources

BESS – Battery Energy Storage Systems

RUL – Remaining Useful Life

Introduction. The rapid transition of the global economy towards carbon-neutral models is predicated on the massive deployment of renewable energy sources (RES). However, the integration of stochastic generation sources, such as solar (PV) and wind power plants, into the general power grid is impossible without high-efficiency buffer systems. In this context, lithium-ion batteries have become a key technological element for ensuring frequency stabilization and peak shaving. According to the IEA's annual report "Renewables 2025. Analysis and forecasts to 2030", the share of RES in the global energy mix is critically dependent on the pace of Battery Energy Storage Systems (BESS) deployment [1].

The efficiency of such systems in the energy sector depends directly on the accuracy of estimating the storage units' remaining useful life. For renewable energy facilities - ranging from residential solar installations to industrial wind farms - errors in SOH estimation can lead to incorrect generation planning and financial losses. Given that the modern Smart Grid paradigm implies decentralization, diagnostic algorithms are required to operate autonomously at each grid node, ensuring the reliability of computations of green energy supply and its analysis without imposing excessive computational resources.

Lithium-ion batteries have become the dominant technology in this field, finding wide application in electric vehicles (EVs), consumer electronics, and stationary battery energy storage systems (BESS) used for grid stabilization [2, 3]. However, despite their advantages, lithium-ion batteries are complex electrochemical systems prone to degradation processes that reduce their capacity and power over time and across operating cycles [4-6].

To ensure the safe, reliable, and efficient operation of these systems, the Battery Management System plays a key role [7-9]. One of the most critical functions of the BMS is the accurate estimation of the battery's internal states, among which the State of Health (SOH) is a fundamental indicator. SOH, typically defined as the ratio of the current maximum capacity to the initial capacity, serves as an indicator of the battery's "aging" level. Accurate SOH estimation is critical for predicting the Remaining Useful Life (RUL), optimizing charging and discharging strategies, and preventing hazardous failures associated with excessive degradation [10, 11].

The engineering challenge is that SOH estimation must be performed in real-time directly on board the device where the BMS operates. In recent years, many methods have been proposed for estimating SOH based on data, in particular, using complex deep learning architectures that demonstrate high accuracy in laboratory conditions. However, their high computational complexity and significant memory consumption make their practical implementation on resource-limited BMS platforms non-trivial, and often impossible.

Thus, there is a gap in research associated with the need for a systematic analysis of methods that would provide an optimal compromise between estimation accuracy and computational efficiency. The purpose of this work is to conduct a comparative analysis of two classic but powerful machine learning methods – the method of support vectors for regression (SVR) and random forest (Random Forest) – for the SOH estimation problem. Unlike studies focused solely on accuracy, the proposed analysis is conducted considering the key engineering constraints of an embedded system. The main contribution of this article is to provide a quantitative assessment of not only accuracy but also computational costs (forecasting time and model size), thereby enabling practical recommendations for BMS developers to select the most appropriate algorithm for implementation.

2. Materials and methods.

2.1. Description of the data set. The study is based on an open dataset [12]. This dataset contains long-term cycling data for eight pouch-type lithium-ion battery cells manufactured by Kokam with Nickel-Manganese-Cobalt (NMC) oxide-based cathodes. The experiment was conducted under controlled laboratory conditions at a temperature of 40 °C. Key characteristics of each battery cell are provided in Table 1. This data includes initial and final capacity, demonstrating the degree of degradation, as well as the total number of cycles performed.

Table 1. Summary of the battery cell characteristics in the dataset

Element	Initial Capacity (Ah)	Final capacity (Ah)	Final SOH (%)	Number of cycles
Cell1	724.121	530.596	73.3	8200
Cell2	718.741	505.717	70.4	7700
Cell3	718.763	535.989	74.6	8100
Cell4	721.116	555.575	77	5100
Cell5	720.406	430.906	59.8	5000
Cell6	716.658	560.977	78.3	5000
Cell7	713.381	553.081	77.5	8100
Cell8	711.957	528.389	74.2	8100

For this study, cell capacity data obtained during periodic characterization tests are used. Specifically, the capacity parameter during a 1C charge (denoted as C1ch in the original dataset) is analyzed, as it is a reliable indicator of degradation. Fig. 1 visualizes the raw capacity-degradation data for all eight cells.

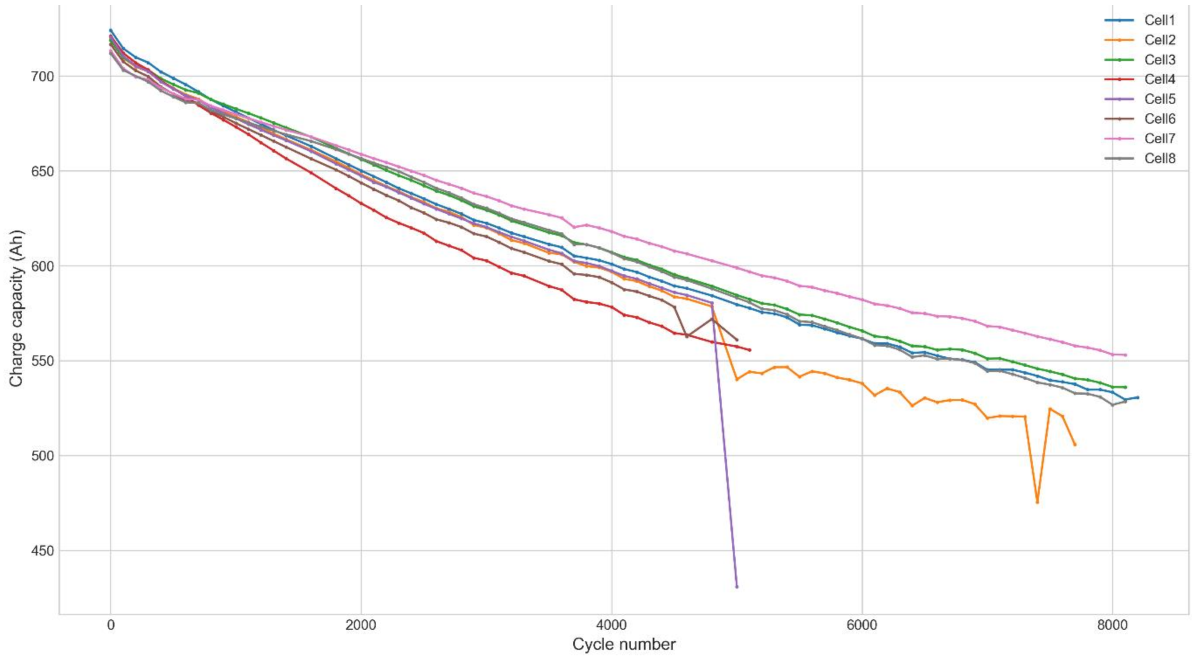

Fig. 1. Charge capacity degradation trajectories for all 8 cells from the Oxford dataset

As seen in Fig. 1, although all cells exhibit a similar general trend of capacity reduction, there is significant cell-to-cell variation in the degradation rate. This variability underscores the need to develop models capable of adapting to the individual behavior of each cell. The advantage of this dataset is the availability of complete degradation trajectories for several cells, which enables training and testing models on independent samples, thereby simulating real-world conditions in which a trained model is applied to a new, previously unknown battery cell.

2.2. SOH calculation and data preparation. The State of Health for each element was calculated as the ratio of the current maximum capacity to the initial capacity, expressed as a percentage, according to formula [13]:

$$SOH(n) = (Q_n / Q_{initial}) \cdot 100\%, \qquad (1)$$

where: $SOH(n)$ - the state of health at the n-th measurement cycle; Q_n - is the maximum charge capacity at the n-th measurement cycle; $Q_{initial}$ is the initial capacity, defined as the maximum charge capacity at the first available measurement cycle.

A data-based approach was chosen to train the models. The cycle number was used as the single input feature for the models, as it is a direct indicator of the battery's operating time. The calculated SOH was the target variable. This minimalist approach to feature selection is intentional, as it reduces the requirements for sensory equipment and BMS computational resources.

To ensure an objective assessment of the models' generalization ability, the data were split according to a "cross-cell validation" principle. Cells Cell1 through Cell6 were used to form the training set, while cells Cell7 and Cell8 were completely excluded from the training process and reserved for the final model testing.

2.3. Description of machine learning models.

Support Vector Regression (SVR). SVR is an extension of the Support Vector Method (SVM) for regression tasks [14]. The main idea of the method is to construct a hyperplane that best approximates the data, while ignoring points that fall within a certain "tube" around the hyperplane. This allows the model to be less sensitive to noise in the data. To model non-linear dependencies, such as SOH degradation, SVR uses the "kernel trick". In this work, the Radial Basis Function (RBF) kernel was used, which is versatile and effective for a wide range of tasks.

Random Forest is an ensemble machine learning method that averages predictions of a large number of independent decision trees for regression tasks [15]. Each tree in the "forest" is trained on a random subsample from a training dataset. Furthermore, when constructing each node of a tree, only a random subset of features is considered. This dual element of randomness makes the model robust against overfitting and capable of capturing complex nonlinear relationships in the data without requiring complex hyperparameter tuning.

2.4. Evaluation criteria. The performance of the proposed models was assessed in two main areas: accuracy and computational efficiency.

1. Estimation accuracy – to quantify the accuracy of SOH prediction, standard metrics for regression tasks were used [16]:

- Root Mean Squared Error (RMSE):

$$RMSE=\sqrt{\frac{1}{n}\cdot\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}\ . \tag{2}$$

- Mean Absolute Error (MAE):

$$MAE=\frac{1}{n}\cdot\sum_{i=1}^{n}\left|y_i-\hat{y}_i\right|, \tag{3}$$

where n is the number of points in the test sample, y_i is the real SOH value, and is $\hat{y}_i$ the predicted SOH value.

2. Computational efficiency – to assess the models' suitability for implementation in embedded systems, the following parameters were analyzed:

- Forecasting time measurements were taken on a standardized computing platform to ensure the comparability of results.
- Model size – the amount of memory (in kilobytes) required to store the trained model. This parameter directly correlates with the requirements for the BMS microcontroller's Flash memory.

3. Research results. This section presents the results of applying the trained SVR and Random Forest models to the independent test dataset (cells Cell7 and Cell8). The models' performance is evaluated based on the two key criteria defined in the previous section: prediction accuracy and computational efficiency.

3.1. Accuracy of SOH estimation. Quantitative indicators of forecasting accuracy for both models in the test sample are summarized in Table 2. The RMSE and MAE metrics were calculated by comparing the predicted SOH values with the actual values obtained from experimental data.

Table 2. Accuracy comparison of SVR and Random Forest models on the test sample

Model	Metric	Value (%)
SVR	RMSE	2.65
SVR	MAE	2.30
Random Forest	RMSE	3.08
Random Forest	MAE	2.68

The results turned out to be partially counter-intuitive. Despite Random Forest often being considered a more powerful algorithm, in this task, the simpler SVR model demonstrated higher prediction accuracy (RMSE 2.68% vs. 3.08%).

For a visual assessment of the prediction quality, Fig. 2 presents a graph of the actual SOH degradation for cell Cell7 (which was not used in training) and the predictions generated by both models.

Analysis of the forecast graph (Fig. 2) helps explain this phenomenon. The Random Forest model, trying to reproduce stochastic (random) fluctuations and anomalous capacity drops, generated a prediction with high variance. This resulted in significant local errors, which adversely affected the overall accuracy metric.

Instead, the SVR with the RBF core built a smooth, generalized degradation model. By ignoring sharp outliers, which are difficult to predict, SVR provided a more stable and robust forecast that, on average, was closer to the actual values.

To ensure an objective comparison and achieve maximum performance of each algorithm, a systematic hyperparameter tuning procedure was conducted. For this purpose, the *GridSearchCV* tool from the *scikit-learn* library was used, which implements an exhaustive search over a given grid of parameters using cross-validation. A 3-fold cross-validation strategy (cv=3) was applied to the training set (Cell1-Cell6) for a reliable assessment of each parameter combination's quality. Negative mean squared error (*neg_mean_squared_error*) was chosen as the optimization metric.

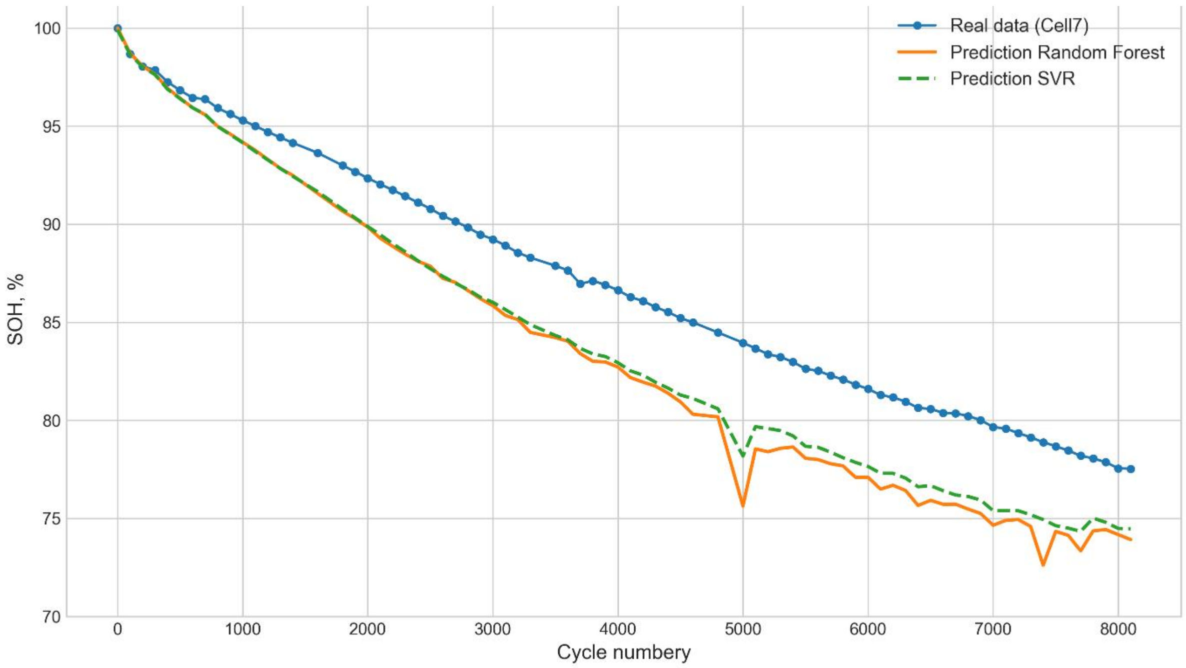

Fig. 2. Graphical comparison of SOH predictions from SVR and Random Forest models with actual data for test Cell7. (Blue line - actual data, orange - Random Forest prediction, green - SVR prediction)

Quantitative indicators of forecasting accuracy for optimized models on the test sample are summarized in Table 3. The RMSE and MAE metrics were calculated by comparing the predicted SOH values with the actual ones obtained from experimental data that was not used during the training.

Table 3. Accuracy comparison of optimized SVR and Random Forest models on the test sample

Model	Metric	Value (%)
SVR (optimal)	RMSE	2.67
SVR (optimal)	MAE	2.33
Random Forest (optimal)	RMSE	3.08
Random Forest (optimal)	MAE	2.68

The results obtained, even after systematic hyperparameter optimization, were partly counter-intuitive. Despite Random Forest often being considered a more powerful algorithm, in this task, the simpler SVR model demonstrated higher prediction accuracy (RMSE 2.67% vs. 3.08%). This indicates that SVR's advantage is not accidental but is due to the fundamental properties of the algorithm and the nature of the data.

For a visual assessment of the quality of forecasting, Fig. 3 presents a graph of the real degradation of SOH for the Cell7 element and the predictions generated by both optimized models.

This demonstrates a key trade-off between model flexibility and robustness. For systems where prediction stability and minimizing maximum error are important, a smoother model like SVR may be a better choice, even if it is not able to reproduce all the nuances of the process. For diagnostics tasks, where, conversely, it is important to capture an anomaly, the behavior of Random Forest might be more informative (but this is beyond the scope of simple SOH prediction).

3.2. Analysis of computational efficiency. To assess the suitability of the models for implementation in embedded BMS, an analysis of their computational requirements was conducted. The results, including the average time for one prediction and the size of the trained optimized model, are presented in Table 4.

Table 4. Comparison of the computational efficiency of the models

Model	Forecast Time (ms)	Model Size (kB)
SVR	**0.12**	**8.9**
Random Forest	23.568	968.5

The quantitative assessment of the models' computational efficiency, presented in Table 4, demonstrates the significant advantages of the SVR model in both parameters. Its size is 8.9 kB, which is more than 100 times smaller than that of the Random Forest model (968.5 kB). A similar difference is observed in performance: the inference time for SVR was 0.121 ms, while for Random Forest it was 23.5 ms, making SVR nearly 200 times faster.

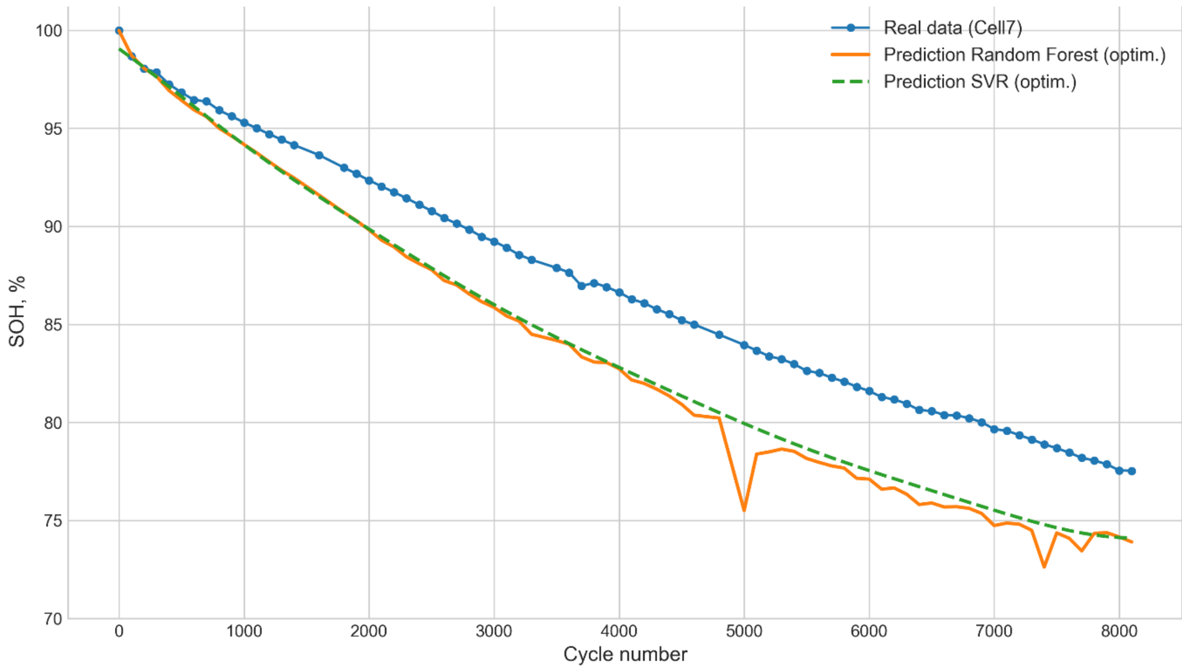

Fig. 3. Graphical comparison of SOH predictions from SVR and Random Forest models with actual data (optimized models) for test cell Cell7

4. Discussion of results. The results of the computational efficiency analysis (Table 4) are important for the practical implementation of the algorithm in embedded systems and definitively confirm the advantages of SVR. From an engineering perspective, the observed differences are critical. The SVR model size of just 8.9 kB allows it to be easily integrated into the memory of most low-cost microcontrollers used in BMS, which have limited Flash memory (often 64-256 kB). In contrast, the Random Forest model, with a size of almost 1 MB, requires a significantly more powerful and expensive hardware platform, which is unacceptable for many commercial applications.

Even more significant is the difference in prediction time. The SVR speed (0.121 ms) means that the SOH estimate places virtually zero load on the microcontroller's CPU. This allows the processor to perform other critical real-time tasks, such as voltage and current monitoring, cell balancing, and executing safety algorithms. The slower performance of Random Forest (23.568 ms) creates a significantly higher load, which can complicate the guaranteed execution of other BMS functions within strict time frames.

Thus, combining the accuracy analysis (Table 3) and the efficiency analysis (Table 4) yields an unambiguous conclusion. Despite SVR being a simpler model, it not only proved to be more accurate but also demonstrated orders of magnitude higher computational efficiency. This makes it not just a compromise, but the optimal choice for practical implementation in embedded battery management systems.

5. Conclusions. This paper conducted a comparative analysis of two machine learning methods, SVR and Random Forest, for the task of State of Health (SOH) estimation of lithium-ion batteries, with a focus on their suitability for implementation in embedded BMS.

Based on experimental data, it was established that the SVR model outperforms the Random Forest model across all criteria critical to engineering practice. It achieved higher prediction accuracy (RMSE 2.67% vs. 3.08%) and demonstrated computational efficiency orders of magnitude higher, being more than 100 times more compact and nearly 200 times faster.

The proposed approach is instrumental in the continued upscaling of renewable energy deployment. Energy storage systems coupled with solar or wind installations are frequently deployed in remote locations characterized by limited telemetry capabilities. The high computational efficiency of the SVR method facilitates the integration of high-precision diagnostics directly into the controllers of BESS units. This enhances the overall reliability of power systems with high RES penetration by enabling more accurate forecasting of available battery capacity for grid balancing and by extending the operational lifespan of cost-intensive storage assets.

Future research may focus on including additional parameters, such as temperature, in the SVR model's input feature vector to further enhance its accuracy under real-world operating conditions.

REFERENCES:

1. IEA (2025), Renewables 2025. Analysis and forecasts to 2030, IEA, Paris.
2. Tian, J., Fan, Y., Pan, T., Zhang, X., Yin, J., & Zhang, Q. (2024). A critical review on inconsistency mechanism, evaluation methods and improvement measures for lithium-ion battery energy storage systems. Renewable and Sustainable Energy Reviews, 189, 113978. https://doi.org/10.1016/j.rser.2023.113978
3. Lv, Y., Geng, X., Luo, W., Chu, T., Li, H., Liu, D., ... & Li, C. (2023). Review on influence factors and prevention control technologies of lithium-ion battery energy storage safety. Journal of Energy Storage, 72, 108389. https://doi.org/10.1016/j.est.2023.108389
4. Rahman, T., & Alharbi, T. (2024). Exploring lithium-Ion battery degradation: A concise review of critical factors, impacts, data-driven degradation estimation techniques, and sustainable directions for energy storage systems. Batteries, 10(7), 220. https://doi.org/10.3390/batteries10070220
5. Edge, J. S., O'Kane, S., Prosser, R., Kirkaldy, N. D., Patel, A. N., Hales, A., ... & Offer, G. J. (2021). Lithium ion battery degradation: what you need to know. Physical Chemistry Chemical Physics, 23(14), 8200-8221. https://doi.org/10.1039/D1CP00359C
6. Shchurov, N. I., Dedov, S. I., Malozyomov, B. V., Shtang, A. A., Martyushev, N. V., Klyuev, R. V., & Andriashin, S. N. (2021). Degradation of lithium-ion batteries in an electric transport complex. Energies, 14(23), 8072. https://doi.org/10.3390/en14238072
7. Habib, A. A., Hasan, M. K., Issa, G. F., Singh, D., Islam, S., & Ghazal, T. M. (2023). Lithium-ion battery management system for electric vehicles: constraints, challenges, and recommendations. Batteries, 9(3), 152. https://doi.org/10.3390/batteries9030152
8. S. Mishra, S. C. Swain and R. K. Samantaray, "A Review on Battery Management system and its Application in Electric vehicle," 2021 International Conference on Advances in Computing and Communications (ICACC), Kochi, Kakkanad, India, 2021, pp. 1-6, doi: 10.1109/ICACC-202152719.2021.9708114.
9. S. Thangavel, D. Mohanraj, T. Girijaprasanna, S. Raju, C. Dhanamjayulu and S. M. Muyeen, "A Comprehensive Review on Electric Vehicle: Battery Management System, Charging Station, Traction Motors," in IEEE Access, vol. 11, pp. 20994-21019, 2023, doi: 10.1109/ACCESS.2023.3250221
10. Cheng, M., Zhang, X., Ran, A., Wei, G., & Sun, H. (2023). Optimal dispatch approach for second-life batteries considering degradation with online SoH estimation. Renewable and Sustainable Energy Reviews, 173, 113053. https://doi.org/10.1016/j.rser.2022.113053
11. Pang, B., Chen, L., & Dong, Z. (2022). Data-driven degradation modeling and SOH prediction of Li-ion batteries. Energies, 15(15), 5580. https://doi.org/10.3390/en15155580
12. Christoph R. Birkl, "Diagnosis and Prognosis of Degradation in Lithium-Ion Batteries", PhD thesis, Department of Engineering Science, University of Oxford, 2017. https://doi.org/10.5287/bodleian:KO2kdmYGg
13. Chen, X., Hu, Y., Li, S., Wang, Y., Li, D., Luo, C., ... & Yang, Y. (2021). State of health (SoH) estimation and degradation modes analysis of pouch NMC532/graphite Li-ion battery. Journal of Power Sources, 498, 229884. https://doi.org/10.1016/j.jpowsour.2021.229884
14. Montesinos López, O. A., Montesinos López, A., & Crossa, J. (2022). Support vector machines and support vector regression. In Multivariate statistical machine learning methods for genomic prediction (pp. 337-378). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-89010-0_9
15. Salman, H. A., Kalakech, A., & Steiti, A. (2024). Random forest algorithm overview. Babylonian Journal of Machine Learning, 2024, 69-79. https://doi.org/10.58496/BJML/2024/007
16. Hodson, T. O. (2022). Root mean square error (RMSE) or mean absolute error (MAE): When to use them or not. Geoscientific Model Development Discussions, 2022, 1-10. https://doi.org/10.5194/gmd-15-5481-2022