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RESEARCH ARTICLE / ARAŞTIRMA MAKALESI

Capacity Estimation of Lithium-ion Battery by GA-KF Method

GA-KF Yöntemiyle Lityum-iyon Bataryanın Kapasite Tahmini

Göksu Taş

Department of Mechatronics Engineering, Manisa Celal Bayar Universiy, 45400, Manisa, TURKEY
Corresponding Author / Sorumlu Yazar : goksu.tas@cbu.edu.tr

Abstract

In this study, the capacity estimation of the lithium-ion battery was successfully proposed using the genetic algorithm-Kalman filter method. During the design phase of electrical devices, lithium-based batteries have begun to be preferred instead of wired electricity transmission due to flexibility, freedom of movement, and portability problems. In addition, from an environmental perspective, the use of electric vehicles has become more important than the use of internal combustion engine vehicles. In this study, the capacity estimation of the 18650 lithium-ion battery, which is the most preferred in electric vehicles, was made quickly and accurately. The performances of the Standard Kalman Filter and the Kalman Filter, whose parameters are determined by the Genetic Algorithm, were compared by estimating the battery capacity. By giving the results obtained by the Genetic Algorithm during the parameter search process, the most appropriate values and the important parameters of the Kalman Filter have been determined. The success of the proposed method is given by the experimental results. In the performance comparison, the success of the proposed method is given using RMSE, MSE, and R^2 metrics. When the average of all experiments was calculated using the R^2 metric, the Genetic Algorithm-Kalman Filter approach achieved the best results in estimating the capacity of the 18650 lithium-ion battery, with a value of 0.999874.

Keywords: *Lithium-ion Battery, Genetic Algoithm, Kalman Filter, Capacity Estimation, Electric Vehicle*

Öz

Bu çalışmada Lityum iyon bataryanın kapasite tahmini genetik algoritma-kalman filtre yöntemiyle başarılı bir şekilde yapılarak önerilmiştir. Elektrikli cihazların tasarım aşamasında esneklik, hareket özgürlüğü ve taşınabilirlik sorunlarından ötürü elektriği kablolu aktarım yerine lityum tabanlı bataryalar tercih edilmeye başlanmıştır. Ayrıca çevresel açıdan içten yanmalı motorlu araçların kullanımında ziyade elektrikli araçların kullanımı önem kazanmıştır. Bu çalışmada elektrikli araçlarda en çok tercih edilen18650 lityum iyon bataryanın kapasite tahmini hızlı, sağlıklı bir şekilde yapılmıştır. Standart Kalman Filtre ve parametrelerinin Genetik Algoritma tarafından belirlendiği Kalman Filtre ile batarya kapasite tahmini yaparak performansları karşılaştırılmıştır. Genetik algoritmanın parametre arama sürecinde elde ettiği sonuçlar verilerek en uygun değerler ile Kalman Filtrenin önemli parametrelerinin belirlenmiştir. Önerilen yöntemin başarısı deney sonuçlarıyla verilmiştir. Performans karşılaştırmasında RMSE, MSE, R^2 metrikleri kullanılarak önerilen yöntemin başarısı verilmiştir. Tüm deneylerin ortalaması R^2 metriği kullanılarak hesaplandığında, 18650 Lityum-iyon bataryanın kapasitesini tahmin etmede en iyi sonucu 0.999874 değeriyle Genetik Algoritma-Kalman Filtresi yaklaşımı elde etmiştir.

Anahtar Kelimeler: *Lityum-iyon Batarya, Genetik Algoritma, Kalman Filtre, Kapasite Tahmini, Elektrikli Araç*

1. Introduction

The long lifespan, high power density, and low maintenance costs of rechargeable lithium-ion batteries (LIBs) have brought them into the spotlight as a leading technology in the transportation, aerospace, and stationary energy storage industries. The shortage of super batteries has been felt due to transportation fuels and their environmental damage, which has recently caused a significant growth in the LIB market, thanks to great interest and high demand. Calculating the global market rate of LIBs [1], [2], [3], [4], [5] is difficult due to the nature of LIB values for two different markets, such as consumer electronics and electric vehicles. The combined market is expected to exceed 69 billion by 2022, growing at a compound annual growth rate of over 16%. Currently, the market is not yet fully developed and is still in its infancy. However, the high demand for electric vehicles provides more room for the LIB market to grow [6]. High LIB demand in the EV market will lead to 1 million LIB packages in 2030 and 1.9 million in 2040. The total number of EOL LIB packages created between 2015 and 2040 will reach 21 million. End-of-life options need to be considered now, although LIBs in these vehicles are expected to last at least ten to twelve years, to ensure that the infrastructure is ready when recycling needs reach larger volumes [7]. The application of LIB storage systems in EVs inherently limits their full usability. Research has shown that LIB storage systems are particularly prone to excessive cost, uniformity, safety and durability issues. LIBs need to operate in a healthy and safe environment to ensure functional success. However, external factors can affect this, especially those involving largely undesirable temperature and voltage windows. This is a major issue, leading to critical vulnerabilities in batteries and degradation in battery performance [8].

As the energy crisis and environmental problems increase, so does the increasing demand for energy. The development of the energy and power industry, such as lithium-ion batteries and

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supercapacitors, is actively promoted by various industries to reduce carbon emissions and fossil energy consumption. Lithium-ion batteries are the preferred battery type in electric vehicles, mobile phones, power grids and other applications due to their high energy density, high output voltage, low self-discharge rate, no memory effect and long service life. However, aging of Li-ion batteries is inevitable and is caused by a complex combination of internal reactions and external conditions. Battery capacity degradation is the most important process for external performance [9]. In actuality, batteries have shorter usage lifetimes due to performance deterioration, which includes capacity fading, an increase in internal resistance, and a drop in power capability. In addition, operating circumstances have a significant impact on battery aging [10]. In addition, accurate, fast and effective capacity estimation is critical for the efficient and high-performance use of the lithium-ion battery [11]. Because fast, accurate, reliable and healthy estimation of the capacity of electrical appliances and electric vehicles is of critical importance both in terms of environmental aspects and business profit.

For these reasons, a solution is presented in this study to improve energy management in electrical devices where these batteries are used, thanks to the accurate and reliable determination of the capacity of 18650-type lithium-ion batteries. In this study, it was aimed to use the energy correctly by successfully estimating the capacity of four different batteries. In addition, the problem of determining the parameters of the Kalman filter, which is used to estimate the capacity and health status of the lithium-ion battery, has been solved using the Genetic Algorithm. With these results, it has been shown that 18650 lithium-ion batteries can be used in battery management systems by successfully estimating the capacity of 18650 lithium-ion batteries using the Genetic Algorithm-Kalman Filter method.

2. Related Work

Estimation of situations such as SOH, SOE, SOC, SOP, and Capacity is critical for reasons such as using the energy of the lithium battery efficiently and being able to predict the use of vehicles and devices. There are many methods for estimating these parameters such as Machine Learning, Coulomb Counting, Deep Learning [12], OCV, and Kalman filter. In one study, SOH and SOC estimation of a lithium-ion battery with a capacity of 1.3ah was performed. With the findings obtained from the experiments, the LSTM method achieved the lowest average error value of 0.58% in SOH estimation. In addition, the MNN method was proposed with the lowest average error value of 0.973% [13]. In another study, the SOH of a lithium-ion battery with a capacity of 3000mah was estimated through experiments at different temperatures. Back Propagation Algorithm was used in the incremental capacity curve-based SOC prediction model. The proposed method achieved an average error of 1.16% [14]. In another study, SOH was estimated using the NASA data set. In the study, the prediction made by using double bi-directional long short-term memory (DBiLSTM) was recommended by achieving success with an error of RMSE 0.0084 [15]. In another study, SOH and RUL were estimated using the NASA and CALCE datasets. GBLS Booster, GBLS, BiLSTM, and CNN methods were used as estimation methods. According to the results obtained, the GBLS Booster method was recommended, achieving success with minimum error in SOH estimation of 0.3348% according to the Mean Absolute Percentage Error (MAPE) metric and Relative Error (RE) of 0.01% according to the RUL estimation [16]. In another study, SOH was estimated using the NASA dataset. For model training, the XGboost model is selected as the SOH prediction model and the B0005 features extracted by the specified method are used as input. The trained model then predicts the SOHs of B0006 and B0007. Experimental results are given by recommending the use of the LAOS-XGboost model to estimate the SOH. According to these results, according to prediction experiments, Xgboost models have achieved success levels higher than 97% according to the R^2 metric [17].

3. Materials and Methods

In this study, capacity estimation was made using the MATLAB programming language. Additionally, it was studied on a personal computer and a publicly accessible dataset.

3.1. Experimental Data

In this study, capacity estimation was made using a publicly available dataset known as the NASA dataset [18]. The relevant dataset has been edited separately for B0005, B0006, B0007 and B0018 batteries. Voltage, Current, Temperature, and Capacity columns have been arranged for each battery. Studies have been carried out on the method to estimate capacity by normalizing the data obtained and reducing the mathematical calculation burden. Since capacity estimation will be made on the NASA dataset using the MATLAB programming language, the dataset has been brought to the appropriate form. The battery was charged at 1.5A in the CC mode until the voltage hit 4,2V. For batteries 5, 6, and 7, the discharge was done at a CC level of 2A until the battery voltage dropped to 2.7V, 2.5V, and 2.2V, respectively. When the batteries hit a 30% decline in rated capacity, the trials were terminated [19]. The battery characteristics in this dataset are given in Table 1 [20].

Table 1. Characteristic features of the data set.

Battery	B005	B0006	B007	B0018
Discharge Current (A)	2	2	2	2
Rated Capacity (mAh)	2000	2000	2000	2000
Cut-of Voltage	4.2/2.7	4.2/2.5	4.2/2.3	4.2/2.5
Cycles	168	168	168	132

3.2. Genetic Algorithm

Natural selection serves as the inspiration for the Genetic Algorithm (GA), an optimization technique. This search algorithm is population-based and makes use of the idea of survival of the fittest. By using genetic operators on members of the population iteratively, new populations are created. The main components of GA are chromosomal representation, selection, crossover, mutation, and fitness function calculation. The GA process works like this. Random initialization is performed on a population (Y) with n chromosomes. Every chromosome in Y has its fitness calculated. A pair of chromosomes, designated as C_1 and C_2, are chosen from population Y based on their fitness value. To create an offspring, let's say O, a single-point crossover operator with crossover probability (C_p) is applied to C_1 and C_2. The created offspring (O) with mutation probability (M_p) is then subjected to a uniform mutation operator, producing O′. The new progeny O′ is assigned to a new population. Until the new population is complete, the current population will undergo selection, crossover, and mutation processes again. GA reaches the optimum solution by constantly changing the search process with mutation and crossover probabilities. Encoded genes can be modified by GA. GA can evaluate a large number of individuals and offer the best solutions. As a result, GA has international calling capability. Offspring created by crossing parental

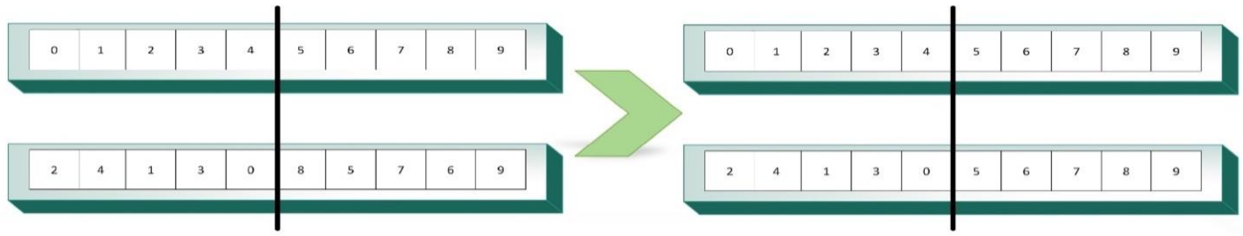

Figure 1. Genetic Algorithm crossover process.

chromosomes are likely to eliminate parental chromosomes containing fascinating genetic schemes. The crossover formula is given in Equation 1 [21].

$$R = (G + 2\sqrt{g})/3G \tag{1}$$

where G is the total number of evolutionary generations determined by population and g is the number of generations. By transferring genes between the parents, a crossover operator can produce new children and enhance the genetic makeup of individuals. The crossover is executed using a variety of methods [22]. Genetic data after the swap are given i. Both parents swapped tail sequence bits to breed their new offspring .

3.3. Kalman Filter

The Kalman Filter (KF), sometimes called Linear Quadratic Prediction, predicts the future state of a system based on its past and current states. Although KF is expressed as an equation, it is divided into two stages: update and prediction. In the forecasting phase, a forecast for the current state is obtained using a series of state forecasts from previous periods. This expected forecast is considered preliminary since it is based on previous forecasts and is not an observation for the current state of the system. In the update phase, previous predictions are combined with existing data to provide a prediction of the current and future states of the system.

KF is a useful tool for system parameter estimation; under certain circumstances, it aims to decrease error covariance by minimizing noise in the estimate process. It may be applied to the estimate of state changes in a variety of time-varying systems. It laid the groundwork for the advancement of modern control theory and real-time signal processing. KF has evolved beyond optimum state estimation to many other technical fields, including robotics, monitoring of targets, location, connection, data processing, computational imaging, voice signal processing, and earthquake forecasting. As a result, it has become one of the most widely used instruments in process optimization, control, and data [23].

$$\begin{aligned} x_k &= F_{k-1}x_{k-1} + W_{k-1} \\ z_k &= H_k x_k + V_k \end{aligned} \tag{2}$$

When studying time series, KF is an optimum estimator that offers a recursive answer. These unidentified states use a collection of z_i process measurements to compute a set of x_i. where W and V are specified as white noise with covariance QK and RK, respectively, and F is the state transition and the H is observation model. KF guesses the x_k state based on a noisy measurement of z_k, using the Equations (2). The estimation of the prior state may be found in the equation $x_k\ z_k = H_k\ x_k + v_k$. When all measurements are available until k − 1, the prior estimation (also known as prediction in KF) in time k, xk is state estimation. The prior state and error covariance are given in Equation 3.

$$\begin{aligned} x_k^- &= F_{k-1}x_{k-1} \\ P_k^- &= F_{k-1}P_{k-1}^+F_{k-1}^T + Q_k \end{aligned} \tag{3}$$

Next state and error covariance are given in Equation 4.

$$\begin{aligned} \hat{x}_k &= x_k^- + K_k(y_k - H_k x_k^-) \\ \hat{P}_k &= (I - K_k H_k) + P_k^- \end{aligned} \tag{4}$$

Equation 5 calculates the Kalman optimum result after forecasting the state and covariance using the results of earlier predictions.

$$K_k = P_k^- H_K^T (H_k\ P_k^- H_K^T + R_k)^{-1} \tag{5}$$

The Kalman optimum result is subsequently given in Equation 6 to utilized for updating the state estimate.

$$\hat{x}_k = \hat{x}_k + k_k(z_k - H_k \hat{x}_k) \tag{6}$$

Lastly, the covariance matrix is updated as shown in Equation 7, and I is the identity matrix.

$$P_k = (I - K_k H_k)P_k \tag{7}$$

Figure 2 shows the evaluation stages of the signal processing process of the Kalman filter.

4. Results and Dicussion

In this study, the dataset was edited and rearranged according to columns. The resulting edited data set consists of four columns. Additionally, a separate dataset file was created for all battery types. There are approximately 40.000 lines of data for each. In Table 2, the search range and values of covariance matrices, which have a significant place in the Kalman Filter of the Genetic Algorithm in this study, are given. Additionally, Kalman filter values obtained through trial and error are given.

Table 2. Parameter values of both KF and GA-KF methods.

Method	Q		R	
Standard KF	0.1		150	
Genetic Algorithm	Search	Find	Search	Find
	0-1	1	50-200	50

The values obtained from the Kalman Filter using the Genetic Algorithm and the parameters obtained through normal trial and error were applied to the Kalman filter and their prediction performances were evaluated separately. The experimental results obtained are given in Table 3. While the value of 0.1 was

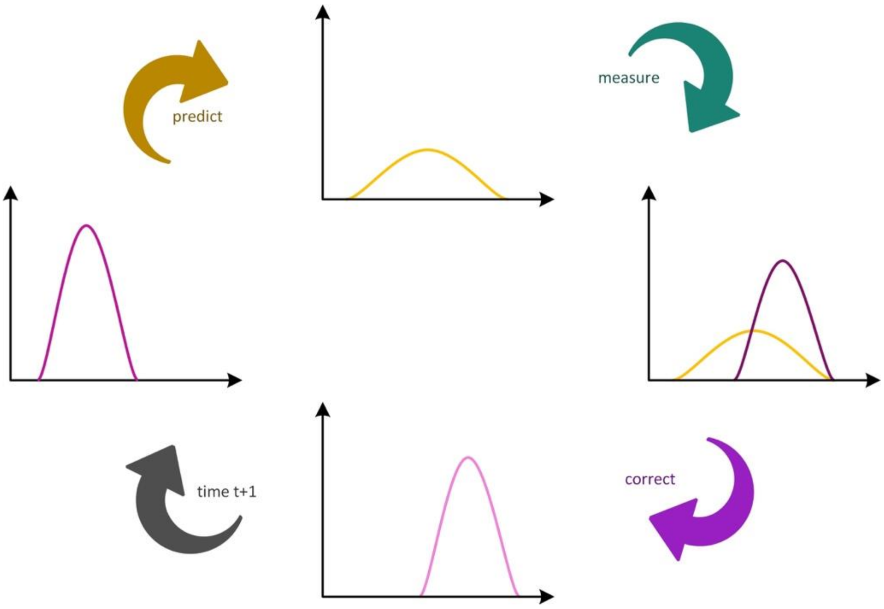

Figure 2. Kalman filter signal processing operations.

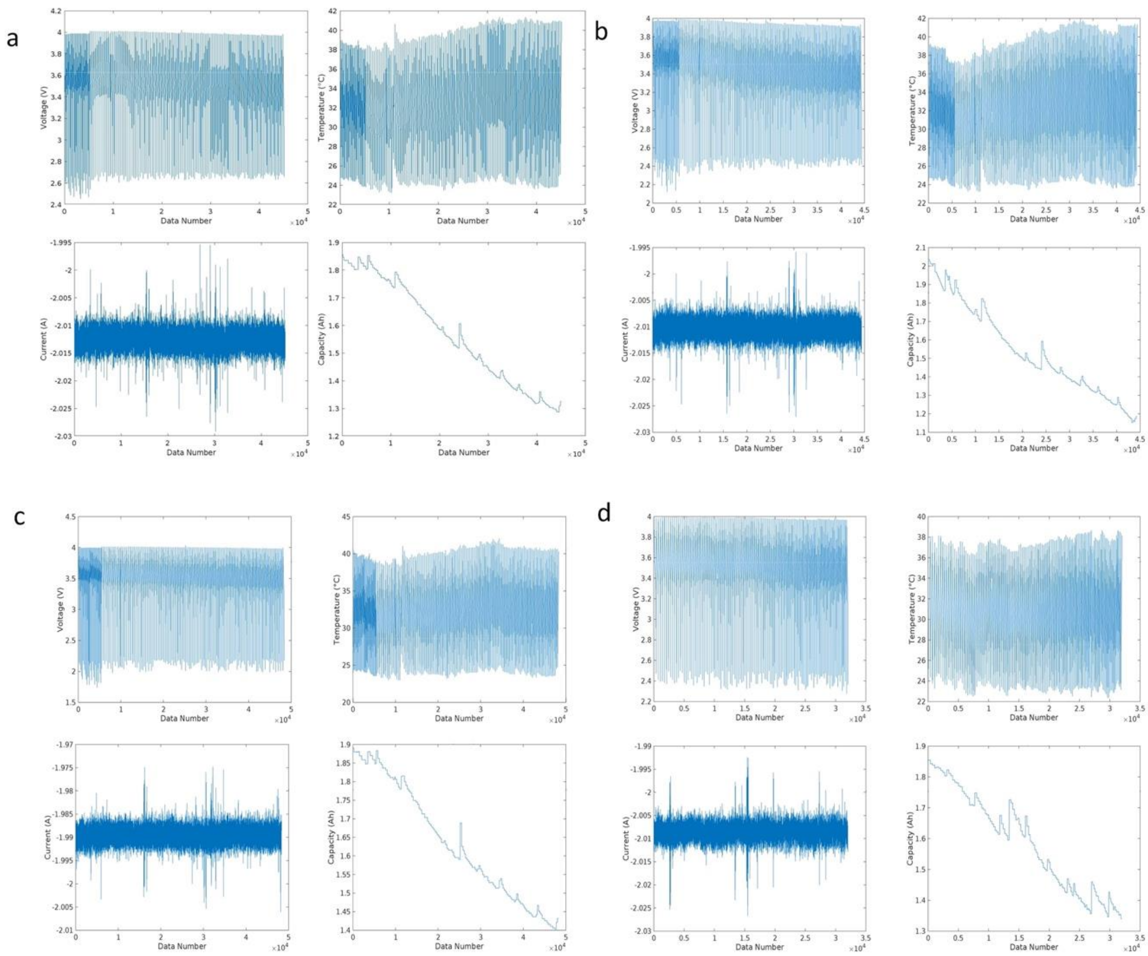

Figure 3. Specifications of batteries a-B005, b-B0006, c-B0007, B0018.

determined by trial and error for the covariance matrix Q with the KF method, the prediction result obtained by applying this value to the Kalman filter is given in Table 3. When the KF method was applied to the B0005 battery data, a prediction error of 3.807×10^{-5} was obtained according to the mean squared error (MSE) metric. In the B0006 battery, the error in estimation reached a value of 5.088×10^{-5} according to the MSE metric. When the B0007 battery was evaluated using the KF method, the estimated result was MSE 4.177×10^{-5} according to the MSE metric. When the B0018 battery was used, the error value in MSE estimation was 1.4931×10^{-4}. The GA-KF method was obtained by finding the values of the Q and R matrices by the GA and applying these values to the Kalman Filter. Successful results were obtained by successfully applying the GA-KF method to the edited B005, B0006, B0007, and B0018 battery data.

Table 3. Estimation results of both KF and GA-KF methods

Method	Battery	Metric		
		MSE	RMSE	R^2
GA-KF	B0005	0.00000618	0.00248530	**0.99993963**
	B0006	0.00000825	0.00287315	**0.99988473**
	B0007	0.00000678	0.00260343	**0.99993002**
	B0018	0.00002426	0.00492530	**0.99973969**
KF	B0005	0.00003807	0.00617037	0.99962790
	B0006	0.00005088	0.00713289	0.99928957
	B0007	0.00004177	0.00646268	0.99956879
	B0018	0.00014931	0.01221937	0.99839777

When the capacity estimation was made by applying the GA-KF method to the B0005 battery, an estimation error value of 6.18×10^{-6} was reached according to the MSE metric. This value gave a more successful result than the value when the KF method was applied to the B0005 battery. When B0006 battery data was applied to the GA-KF method, it was more successful than the standard KF method, reaching a prediction error value of 8.25×10^{-6} according to the MSE metric. When capacity estimation was made with the GA-KF method using B0007 battery data, it made a 6.78×10^{-6} error in estimation according to the MSE metric and achieved a more successful result than the KF method. When estimating the capacity of the lithium-ion battery using B0018 battery data, the GA-KF method made a 2.426×10^{-5} prediction error based on the MSE metric, while the KF method made a 1.4931×10^{-4} prediction error. It was observed that the GA-KF method made 1.2505×10^{-4} less estimation error than the KF method in estimating the capacity using the B0018 battery data according to the MSE metric.

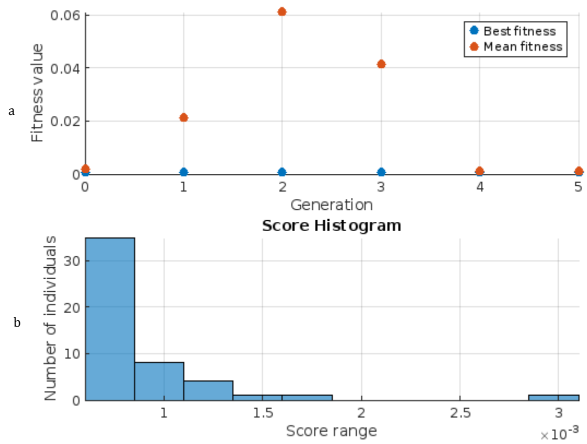

Figure 4. Result of Genetic Algorithm search.

Figure 4 shows the search result when the Genetic Algorithm determines the appropriate parameters for the Kalman Filter. According to the results obtained, image b is the histogram image, while image a is the image of the fitness value. In Figure 4, graph b gives the number of individuals in each generation in the Genetic Algorithm, each expressing the appropriate solution, while graph a represents a situation that shows how close the individual is to the solution of the problem. While the x-axis of image A represents the completion of a cycle, this process is the process of the formation of new individuals and processes such as mutation. The mean fitness value expresses the average of the values offered by all individuals to the solution of the problem.

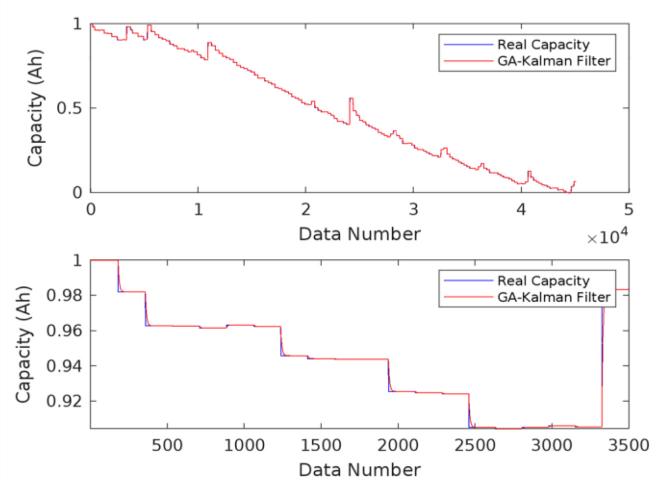

Figure 5. Estimation of capacity of B0005 battery by GA-KF.

Figure 5 shows the capacity estimation result of the B0005 battery using the GA-KF method. The first graph shows the actual capacity value and the estimated value made by the GA-KF method, while the second graph shows the prediction graph of a specific zoomed-in region. As can be seen from the graph, the GA-KF method achieved a prediction success rate of 99.993963% according to the R^2 metric in the B0005 battery data.

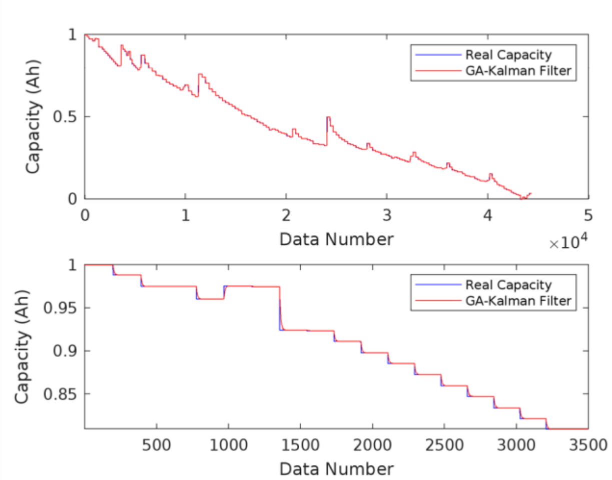

Figure 6. Estimation of capacity of B0006 battery by GA-KF.

In Figure 6, capacity estimation was made with the GA-KF method using B0006 battery data. The prediction result obtained and the prediction result of the GA-KF method are given. GA-KF method achieved a prediction success rate of 99.988473% according to the R^2 metric compared to real values. In addition, according to the RMSE metric, the GA-KF method achieved success by making a prediction error of 0.00287315. Due to the large amount of data, the second graph gives the zoomed prediction result of a certain region.

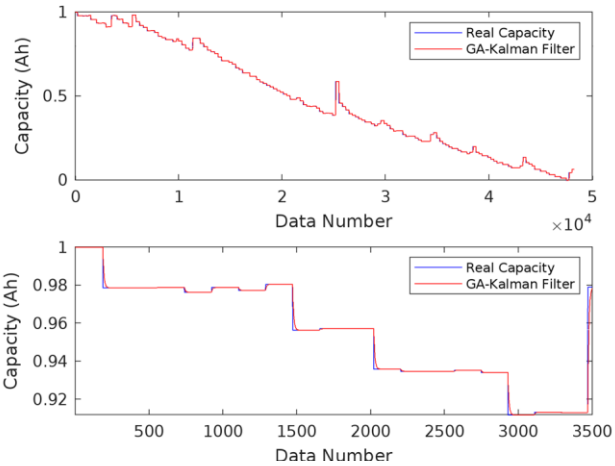

Figure 7. Estimation of capacity of B0007 battery by GA-KF.

Figure 7 shows the prediction result obtained by using B0007 battery data as prediction data for the GA-KF method. In addition, an attempt was made to make the difference more understandable by presenting a zoomed regional graph in the second line of the graph. According to the RMSE metric, the GA-KF method made a prediction error of 0.00260343 compared to the actual capacity data. In addition, according to the R^2 metric, the GA-KF method achieved a prediction success rate of 99.993002% in capacity estimation in B0007 battery data.

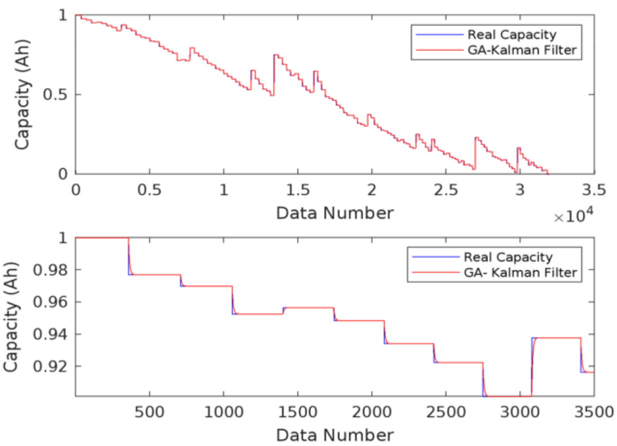

Figure 8. Estimation of capacity of B0018 battery by GA-KF.

In Figure 8, capacity estimation is given by the GA-KF method using B0018 battery data. An attempt has been made to understand the difference between the prediction results of the GA-KF method and the actual capacity values. Additionally, a zoomed-in graph is given in the second line to better understand this difference. According to the RMSE metric, a prediction error of 0.00492530 was reached between the actual measured capacity values and the predicted values made by the GA-KF method. In addition, according to the R^2 metric, a prediction success rate of 99.973969% was achieved between the actual value and the predicted value.

Figure 9 shows the prediction result graph of the actual capacity value of the B0005 battery using the KF method. According to the results obtained, the prediction error reached 0.00617037 according to the RMSE metric.

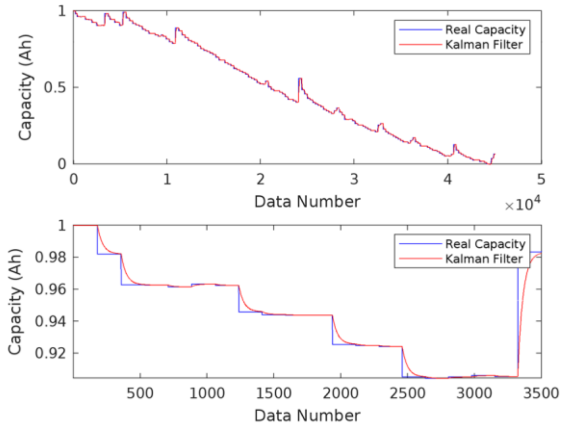

Figure 9. Estimation of capacity of B0005 battery by -KF.

In Figure 10, the capacity estimate made by the KF method using the B0006 battery data is given. A zoomed-in graphic is given in the bottom line to better understand the difference between the estimate and the real value. According to the RMSE metric, the KF method reached a prediction error of 0.00713289. In addition, according to the R^2 metric, the KF method was successful in predicting the B0006 battery capacity with a value of 99.928957%.

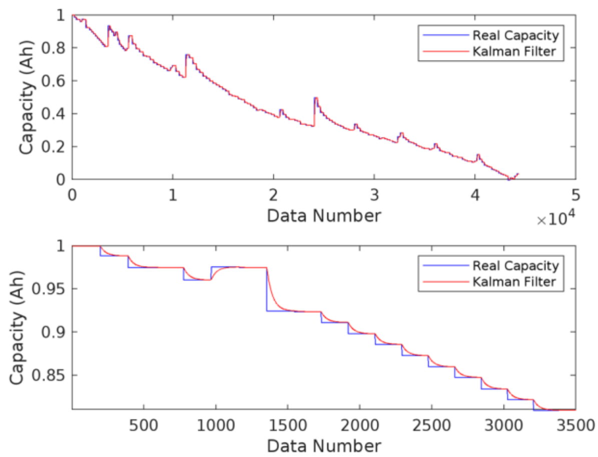

Figure 10. Estimation of capacity of B0006 battery by -KF.

Figure 11 shows the prediction result of the KF method using B0007 battery data. An attempt was made to better notice the difference by presenting a zoomed-in graph of the actual value and the prediction result. According to the RMSE metric, the KF method reached a prediction error of 0.00646268 when estimating the B0007 battery capacity value. Moreover, according to the R2 metric, it reached a prediction success value of 0.99956879.

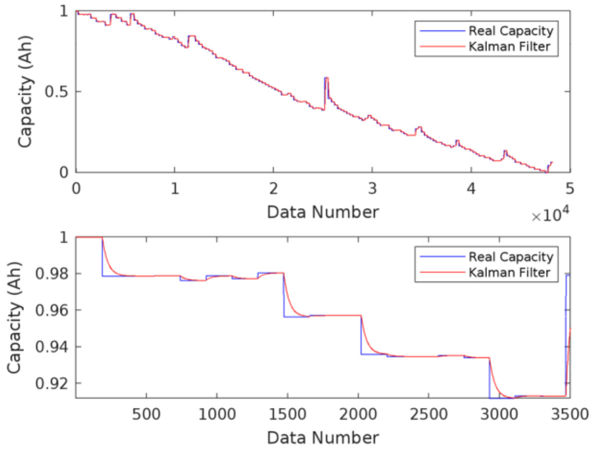

Figure 11. Estimation of capacity of B0007 battery by -KF.

Figure 12 shows the result of capacity estimation using the KF method using B0018 battery data. According to the results obtained, the difference between the predicted value and the actual value is presented in the graph in the second line. According to the RMSE metric, there was a prediction error of 0.01221937 between the actual value and the predicted value. In addition, according to the R^2 metric, the B0018 battery was successful between the actual value and the prediction result with a value of 0.99839777.

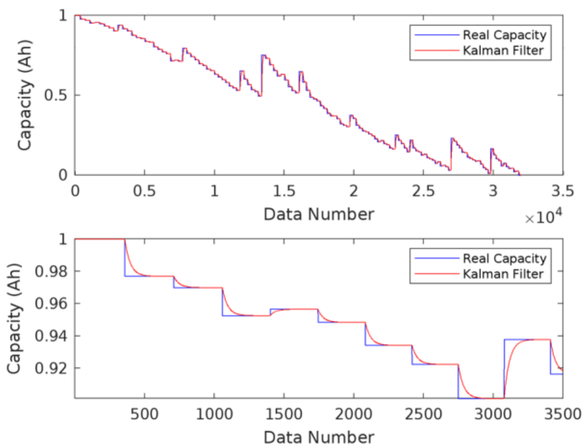

Figure 12. Estimation of capacity of B0018 battery by -KF.

While the GA-KF method's estimated result and real data are plotted in Figure 5, Figure 6, Figure 7, Figure 8, the KF method's estimated result and real values are plotted in Figure 9, Figure 10, Figure 11, and Figure 12. When the same battery data is compared, Figure 5 and Figure 9 should be compared. The same situation should be compared between Figure 6-Figure 10 and Figure 7-Figure 11 and Figure 8-Figure 12. For this reason, it is seen that the GA-KF method's estimate for the B0005 battery data in Figure 5 is more successful than the KF method's estimate in Figure 9 and has a graph closer to the real data. The graphs in the second row of the graphs give the zoomed-in version of a certain region of the graph in column 1. When the B0006 battery data is used, it is seen that the estimation result of the GA-KF method in Figure 6 is more successful than the estimation result of the KF method given in Figure 10. When the B0007 battery data is used, the estimation result of the GA-KF method is given in Figure 7. According to this result, a more successful result is achieved than the estimation made by the KF method in Figure 11. When the capacity estimation is made using the B0018 battery data, it is seen from the graph that the estimation result of the GA-KF method in Figure 8 is closer to the real value than the estimation result of the KF method in Figure 12.

5. Conclusions

The importance of lithium-ion batteries has increased with the decrease in the use of wired electricity in electric vehicles and electrical devices. Lithium-ion batteries are of critical importance in battery management systems when used in such devices and vehicles. Accurate capacity estimation is critical due to the features of this battery type such as protection from overcharge and discharge, efficient energy use, and healthy charging. In this study, Genetic Algorithm was used to determine the parameters of the Kalman Filter, which is frequently used in determining parameters such as SOH and SOE in lithium-ion batteries, in a convenient and fast way. The performances of the Kalman Filter parameters determined by trial and error and the Kalman Filter parameter values determined by the Genetic Algorithm were compared separately. Using four different battery data separately, their performances were compared according to MSE, RMSE, and R^2 metrics. According to the average of all Kalman filter experiments, the GA-KF method achieved a prediction success of 0.999874 according to the R^2 metric. When the average of all experiments was taken according to the R^2 metric, there was a success difference of 0.065251% between the GA-KF method and the KF method. In another study using the CALCE battery dataset, A123 battery data was used for SOC estimation. The study estimated SOC using a temporal convolutional network (TCN) with a gated recurrent unit (GRU) that incorporated a multi-head self-attention mechanism (MHA) method based on the Robust Adaptive Kalman Filter (RAKF). According to the RMSE metric, the proposed method made less than 1% estimation error [24]. In this study, when the average of all experiments was taken for capacity estimation, an error value of 0.003221 was obtained with the GA-KF method according to the RMSE metric. The success of the proposed method is presented with different battery types and different metrics. In future studies, the author plans to work on estimating battery power status using the deep learning method.

Ethics committee approval and conflict of interest statement

This article does not require ethics committee approval. This article has no conflicts of interest with any individual or institution.

References

[1] Yurek, Y.T., Ozyoruk, B., Ozcan, E., 2024. Multi-objective optimization of energy system with battery storage—A case study of Turkey. J. Energy Storage, Vol. 93, p. 112101.

[2] Zheng, K., Meng, J., Yang, Z., Zhou, F., Yang, K., Song, Z., 2024. Refined lithium-ion battery state of health estimation with charging segment adjustment. Appl. Energy, Vol. 375, p. 124077.

[3] Hou, J., Xu, J., Lin, C., Jiang, D., Mei, X., 2024. State of charge estimation for lithium-ion batteries based on battery model and data-driven fusion method. Energy, Vol. 290, p. 130056.

[4] Karaburun, N.N., Hatipoglu, S.A., Konar, M., 2024. SOC Estimation of Li-Po Battery Using Machine Learning and Deep Learning Methods. Journal of Aviation, Vol. 8(1), pp. 26–31.

[5] Wang, Y., et al., 2024. Progress and challenges in ultrasonic technology for state estimation and defect detection of lithium-ion batteries. Energy Storage Mater., Vol. 69, p. 103430.

[6] Zeng, X., et al., 2019. Commercialization of lithium battery technologies for electric vehicles. Adv. Energy Mater., Vol. 9(27), p. 1900161.

[7] Chen, M., et al., 2019. Recycling end-of-life electric vehicle lithium-ion batteries. Joule, Vol. 3(11), pp. 2622–2646.

[8] Ralls, A.M., et al., 2023. The role of lithium-ion batteries in the growing trend of electric vehicles. Materials, Vol. 16(17), p. 6063.

[9] Sun, H., Sun, J., Zhao, K., Wang, L., Wang, K., 2022. Data-driven ICA-Bi-LSTM-combined lithium battery SOH estimation. Math. Probl. Eng., Vol. 2022, p. 9645892.

[10] Luo, G., Zhang, Y., Tang, A., 2023. Capacity degradation and aging mechanisms evolution of lithium-ion batteries under different operation conditions. Energies, Vol. 16(10), p. 4232.

[11] Cetinkaya, U., Bayindir, R., Avci, E., Ayik, S., 2022. Battery energy storage system sizing, lifetime and techno-economic evaluation for primary frequency control: A data-driven case study for Turkey. Gazi Univ. J. Sci. Part C: Design and Technology, Vol. 10(2), pp. 177–194.

[12] Tas, G., Bal, C., Uysal, A., 2023. Performance comparison of lithium polymer battery SOC estimation using GWO-BiLSTM and cutting-edge deep learning methods. Electr. Eng., Vol. 105(5), pp. 3383–3397.

[13] Lee, J.H., Lee, I.S., 2021. Lithium battery SOH monitoring and an SOC estimation algorithm based on the SOH result. Energies, Vol. 14(15), p. 4506.

[14] Wen, J., Chen, X., Li, X., Li, Y., 2022. SOH prediction of lithium battery based on IC curve feature and BP neural network. Energy, Vol. 261, p. 125234.

[15] Guo, Y., Yu, P., Zhu, C., Zhao, K., Wang, L., Wang, K., 2022. A state-of-health estimation method considering capacity recovery of lithium batteries. Int. J. Energy Res., Vol. 46(15), pp. 23730–23745.

[16] Yang, P., et al., 2024. Joint evaluation and prediction of SOH and RUL for lithium batteries based on a GBLS booster multi-task model. J. Energy Storage, Vol. 75, p. 109741.

[17] Zhang, M., Chen, W., Yin, J., Feng, T., 2022. Lithium battery health factor extraction based on improved Douglas–Peucker algorithm and SOH prediction based on XGBoost. Energies, Vol. 15(16), p. 5981.

[18] Saha, B., Kai, G., 2024. Battery data set. NASA AMES Prognostics Data Repository. https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/#battery (Accessed: July 21, 2024).

[19] Alvarez-Monteserin, I., Sanz-Bobi, M.A., 2022. An online fade capacity estimation of lithium-ion battery using a new health indicator based only on a short period of the charging voltage profile. IEEE Access, Vol. 10, pp. 11138–11146.

[20] Darwish, A., 2024. An attention-based deep learning approach for lithium-ion battery lifespan prediction: analysis and experimental validation. Inf. Sci. Appl., Vol. 2, pp. 58–76.

[21] Katoch, S., Chauhan, S.S., Kumar, V., 2021. A review on genetic algorithm: past, present, and future. Multimed. Tools Appl., Vol. 80(5), pp. 8091–8126.

[22] Alhijawi, B., Awajan, A., 2024. Genetic algorithms: theory, genetic operators, solutions, and applications. Evol. Intell., Vol. 17(3), pp. 1245–1256.

[23] Khodarahmi, M., Maihami, V., 2023. A review on Kalman filter models. Arch. Comput. Methods Eng., Vol. 30(1), pp. 727–747.

[24] Qi, W., Qin, W., Yun, Z., 2024. Closed-loop state of charge estimation of Li-ion batteries based on deep learning and robust adaptive Kalman filter. Energy, Vol. 307, p. 132805.