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Estimation of Discharge Energy of Lithium-ion Battery for Different Temperatures by FOX-Bidirectional Recurrent Neural Network Method

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Anahtar Kelimeler

Elektrikli Araçlar
Lityum-iyon Batarya
FOX Optimizasyonu
Bi-RNN
Enerji Tahmini

Graphical/Tabular Abstract (Grafik Özet)

The discharge energy of lithium-ion battery under DST drive cycle and different temperature conditions is estimated by FOX-BiRNN method. The performance of different deep sampling methods is compared. /Lityum-iyon bataryanın DST sürüç çevrimi ve farklı sıcaklık koşullarında deşarj enerjisi FOX-BiRNN yöntemiyle tahmin edilmiştir. Farklı derin örğenme yöntemlerinin performansı karşılaştırılmıştır.

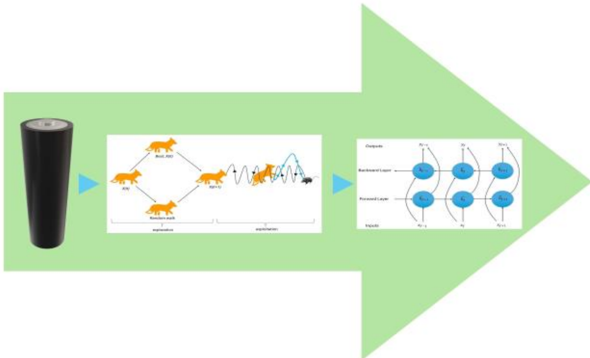

Figure A*: Flow chart of discharge energy estimation of lithium-ion battery under different temperature conditions./* ***Şekil A:****Lityum-iyon bataryanın farklı sıcaklık koşullarında deşarj enerjisi tahminin akış diagramı*

Highlights (Önemli noktalar)

- *Estimation of lithium-ion battery discharge energy under DST driving cycle and different temperature conditions/Lityum-iyon bataryanın deşarj enerjisinin DST sürüş çevrimi vefarklı sıcaklık koşullarında tahmini,*
- *The estimation performance of BiGRU, BiLSTM, BiRNN and FOX-BiRNN methods for discharge energy estimation is compared /Deşarj enerjisi tahmini için BiGRU, BiLSTM, BiRNN ve FOX-BiRNN yöntemlerinin tahmin performansı karşılaştırılmıştır*
- *Hyperparameter values of the BiRNN method were determined with FOX optimization./FOX optimizasyonuyla BiRNN yönteminin hiperparametre değerleri belirlenmiştir.*

Aim (Amaç): *The aim of this study is to estimate the discharge energy of lithium-ion battery under DST driving cycle and different temperature conditions with FOX-BiRNN method and different deep learning methods./ Bu çalışmanın amacı, lityum-iyon bataryanın deşarj enerjisini DST sürüş çevrimi ve farklı sıcaklık koşulalrı altında FOX-BiRNN yöntemi ve faklı derin öğrenme yöntemelriyle tahmin etmek.*

Originality (Özgünlük): *The most successful discharge energy estimation was obtained by applying the hyperparameter values determined by the FOX optimization to the BiRNN method./ FOX optimizasyonuyla belirlenen hiperparametre değerlerinin BiRNN yöntemine uygulanmasıyla en başarılı deşarj enerjisi tahmini elde edilmiştir.*

Results (Bulgular): *The FOX-BiRNN method achieved 99.4186% prediction success at 0 ^{0}C according to the R^2 metric, 99.6080% at 25 ^{0}C according to the R^2 metric, and 99.4148% at 45 ^{0}C according to the R^2 metric./ FOX-BiRNN yöntemi, R^2 metriğine göre 0 ^{0}C 'de %99.4186, R2 metriğine göre 25 ^{0}C' de %99.6080 ve R^2 metriğine göre 45 ^{0}C' de %99.4148 tahmin başarısı elde etmiştir.*

Conclusion (Sonuç): *While estimating the discharge energy of the lithium-ion battery, the hyperparameter value of the BiRNN method was determined quickly by FOX optimization and the most successful results were obtained./Lityum-iyon bataryanın deşarj enerjisi tahmini yapılırken FOX optimziasyonu tarafından BiRNN yönteminin hiperparametre değeri hızlı bir şekilde belirlenerek en başarılı sonuçalar elde edilmiştir.*

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Abstract

In this study, the discharge energy of the lithium-ion battery was estimated by using the FOX-Bidirectional Recurrent Neural Network (Bi-RNN) method for the Dynamic Stress Test (DST) driving cycle method and different temperatures. For lithium-based batteries, discharge energy estimation is critical for long-term use, while problems such as overheating are major problems. For this reason, in this study, the discharge energy of lithium-ion batteries under different temperature conditions was estimated using bidirectional-based deep learning methods. In addition, the hyperparameter values of the BiRNN method were determined with FOX optimization, and the FOX-BiRNN method was proposed. The discharge energy estimations of FOX-BiRNN, BiRNN, Bidirectional Gated Recurrent Unit (Bi-GRU), and Bidirectional Long-short term (Bi-LSTM) methods were compared. The obtained estimation results were compared using the most commonly used battery parameter estimation metrics in the literature for performance comparison. The estimation success of the proposed method was presented using many comparison metrics and graphics. The FOX-BiRNN method was the most successful method for discharge energy estimation by obtaining values of %99.4186 at 0 ^{0}C according to the R^2 metric, %99.6080 at 25 ^{0}C according to the R^2 metric, and %99.4148 at 45 ^{0}C according to the R^2 metric.

Farklı Sıcaklıklar için Lityum-iyon Bataryanın Deşarj Enerjisinin FOX-Çift Yönlü Tekrarlayan Sinir Ağı Yöntemi ile Tahmini

Makale Bilgisi

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Öz

Bu çalışmada, lityum-iyon pilin deşarj enerjisi, Dinamik Stres Testi (DST) sürüş çevrimi yöntemi ve farklı sıcaklıklar için FOX- Çift Yönlü Tekrarlayan Sinir Ağı (Bi-RNN) yöntemi kullanılarak tahmin edilmiştir. Lityum bazlı bataryalar için, deşarj enerjisi tahmini uzun süreli kullanım için kritik öneme sahipken, aşırı ısınma gibi sorunlar büyük problemlerdir. Bu nedenle, bu çalışmada, lityum-iyon pillerin farklı sıcaklık koşullarındaki deşarj enerjisi, çift yönlü tabanlı derin öğrenme yöntemleri kullanılarak tahmin edilmiştir. Ayrıca, BiRNN yönteminin hiperparametre değerleri FOX optimizasyonu ile belirlenmiş ve FOX-BiRNN yöntemi önerilmiştir. FOX-BiRNN, BiRNN, Çift Yönlü Kapılı Tekrarlayan Birim (Bi-GRU) ve Çift Yönlü Uzun-Kısa Dönem (Bi-LSTM) yöntemlerinin deşarj enerjisi tahminleri karşılaştırılmıştır. Elde edilen tahmin sonuçları, performans karşılaştırması amacıyla literatürde en sık kullanılan batarya parametre tahmin metrikleri kullanılarak karşılaştırılmıştır. Önerilen yöntemin tahmin başarısı birçok karşılaştırma metrikleri ve grafikler kullanılarak sunulmuştur. FOX-BiRNN yöntemi, R^2 metriğine göre 0 ^{0}C'de %99.4186, R^2 metriğine göre 25 ^{0}C'de %99.6080 ve R^2 metriğine göre 45 ^{0}C'de %99.4148 değerleri elde ederek deşarj enerjisi tahmini için en başarılı yöntemdi.

1. INTRODUCTION (GİRİŞ)

Nearly 28% of all carbon dioxide (CO_2) emissions are attributed to the transport sector, with road transport accounting for more than 70% of these emissions, according to a research by the European Union. In order to reduce the concentration of air pollutants like CO_2 and other greenhouse gases, the governments of the majority of industrialized nations are promoting the usage of electric vehicles (EVs) [1]. Energy storage is one of the key technical developments for the development of new energy electric vehicles and smart networks. Of all the existing chemical and physical solutions, the lithium-ion battery is the type of energy storage [2] technology that is evolving at the fastest rate due to

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the rapid development of new energy electric cars. Because there have been so many electric car fires lately, people's opinions about them have shifted. Additionally, this has created obstacles and elevated expectations for battery management solutions [3], [4]. For this reason, the discharge energy state estimation of lithium-based batteries is of critical importance. In terms of energy management and safety, accurate estimation of lithium-based battery parameters is very important [5]. For this reason, there are many studies in the literature to determine battery parameters. Because State of Health (SOH) [6], [7], [8], [9] measures a battery's residual capacity relative to its initial value, it has gained popularity as an additional indication of battery deterioration in recent years [10]. The latest techniques for estimating lithium battery parameters include both hybrid and data-driven algorithms [11]. Therefore, data-driven techniques have been receiving more and more attention as battery operating data becomes more widely available. Gaussian process regression (GPR) is a commonly used technique for estimating SOH among them [12]. In a study, it was shown that GPR has the best performance in SOH estimation among four typical data-driven methods (linear regression, support vector machine, relevance vector machine and GPR) [13]. In order to estimate SOH, deep learning techniques like deep convolutional neural networks, long short-term memory neural networks, and prior knowledge-based neural networks were also used [14]. However, when estimating parameters such as SOH, State of Energy (SOE), and capacity of lithium-based batteries using machine learning, determining the appropriate hyperparameter values is a very important problem. Along with SOH estimation on a long time scale and State of Charge (SOC) estimation on a short time scale, model-based dual-time SOH and SOC combined estimation approaches were also presented [15]. In a study, a new method was proposed for energy state estimation in experiments conducted at different temperatures for lithium-ion batteries. Energy state estimation was successfully performed with the Particle Filter-Extended Kalman filter method [16]. In another study, Adaptive FOX optimization and RNN method were used to predict Crude Oil Prices [17]. In another study, the use of Bi-RNN method in confidence estimation provided significant improvement [18]. In deep learning methods, determining hyperparameters appropriately is critical for making appropriate predictions due to reasons such as time, speed, and success. Since determining these hyperparameter values is based on long-term trial-and-error methods, determining them quickly with metaheuristic optimization methods is a very important development. This study was carried out to solve the hyperparameter search problem by estimating the discharge energy of lithium-ion battery under different temperatures and DST driving cycle data with FOX optimization-BiRNN method. In addition, estimating the battery discharge energy in a healthy and reliable way is of critical importance due to energy management in the use of electric vehicles. In this study, discharge energy was estimated for each of the different temperatures. With this study, it was presented that FOX optimization can be used in deep learning-based lithium battery parameter estimation. In addition, it was concluded that FOX optimization, a new metaheuristic optimization method in the literature, found very effective results in the hyperparameter search process.

2. MATERIALS AND METHODS (MATERYAL VE METOD)

In this study, deep learning training was performed on a personal computer with an i7 processor and an Ubuntu operating system. In addition, the hyperparameter search process of the Bi-RNN method was performed using the code written in the Python programming language using the FOX optimization with a population number of 20. Deep learning training was performed by converting the data to .csv format for the use of the dataset.

2.1. Experimental Data (Deneysel Veri)

The data used in this study is a publicly available dataset. A publicly available dataset consisting of experimental data at 0 ^{0}C, 25 ^{0}C, and 45^{0}C and the DST driving cycle was used [19]. Batteries were tested at low temperature (0 ^{0}C), room temperature (25 ^{0}C) and high temperature (40 ^{0}C). In general, testing batteries at these temperatures is to examine temperature changes that affect their performance and life. Additionally, when this battery dataset was examined, it was seen that the Arbin BT2000 Battery Test System was used to test the battery. In the battery dataset used in this study, the test samples were subjected to dynamic stress testing to determine the model parameters. DST applies a dynamic discharge regime to a lithium battery. The battery behavior is tested according to the current profile of DST. Although DST takes into account regenerative charging and uses a series of current steps with varying amplitudes and durations, it is a simplification of the real battery charging conditions [20]. The characteristics of the INR 18650-20R lithium-ion battery used in charge-discharge experiments and test drive profiles during the preparation of the public data set used in this study are given in Table 1 [21].

The properties of the dataset used in this study are given in Figure 1. Graphs are presented for different temperature values. The dataset was created using batteries for 80% battery level and 50% battery level for testing. In addition, the effect of temperature change on performance was examined under three different temperature conditions and the data was recorded. In the dataset where many different driving methods were used, only the data used for the DST driving method was used for this study. In addition, data with separate data files for all temperature values and a battery level of 50% were used. Figure 1-a shows the data obtained at 0°C temperature conditions, Figure 1-b shows the results obtained at 25°C temperature conditions, and Figure 1-c shows the results obtained during the operation of the lithium battery at 45°C temperature conditions. Figure 1 shows the graphical representation of the input data and output data values of deep learning models for three different temperature values. The dV/dT value of these data features indicates the change in the voltage value over time and is very important for battery

Table 1. Lithium-ion battery features (Lityum-iyon batarya özellikleri)

Parameters	**Specifications**
Capacity Rating	2000mAh
Cell Chemistry	LNMC/Graphite
Max current (A)	22
Cut-off voltage	2.4/4.2
Max. Voltage	4.2V ± 0.05V

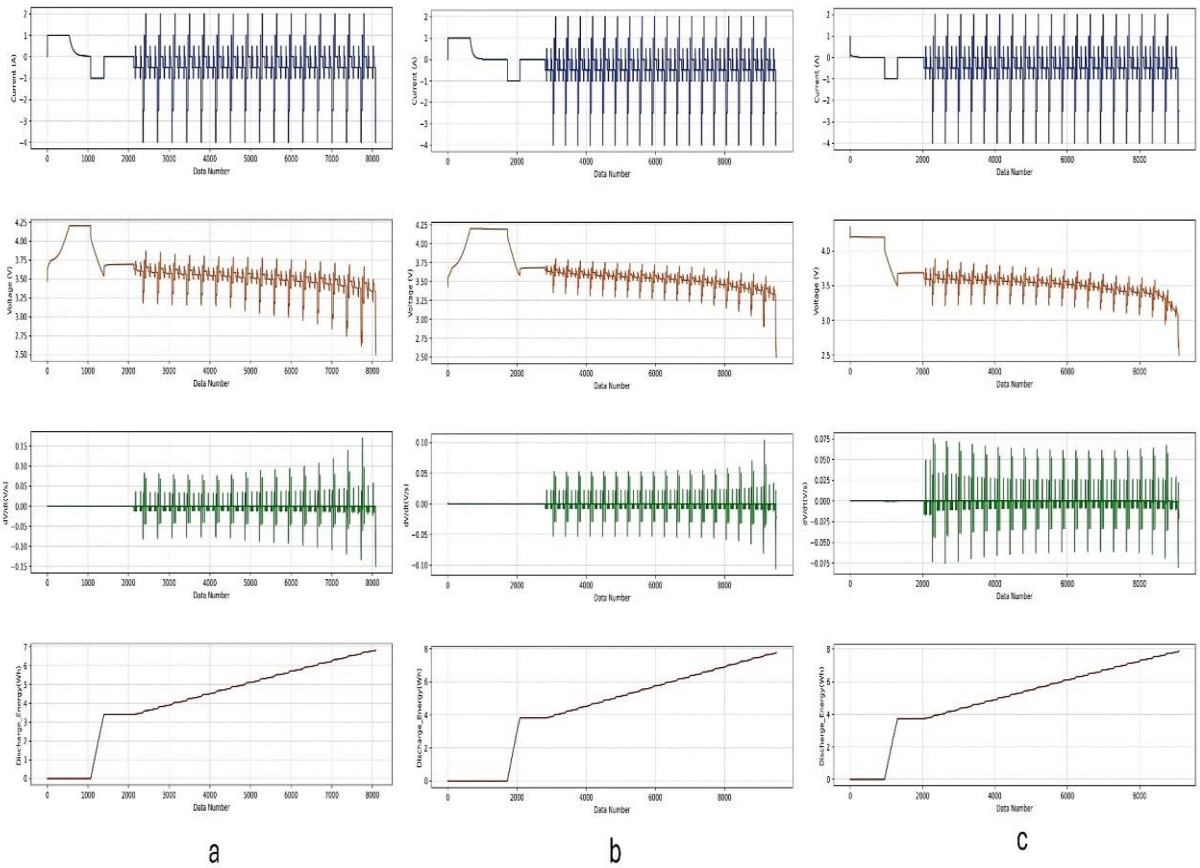

Figure 1. Dataset properties, a-0 ^{0}C, b-25 ^{0}C, and c-45^{0}C (Veriseti özellikleri, a-0 ^{0}C, b-25 ^{0}C, and c-45^{0}C)

performance and health. While the Voltage value indicates the voltage value in the battery, the Current value indicates the change in the current in the DST driving mode applied to the battery. The Discharge Energy value indicates the change in the internal energy while the battery is being discharged. While the Voltage, Current, and dV/dT values are the input data, the Discharge Energy value is the value that should be estimated by deep learning. The data was prepared as a result of measuring the Voltage, Current, and dV/dT values of the battery at different temperature values under the DST driving mode of the battery. The Discharge Energy value of the lithium battery at different temperatures was estimated using the data in the graph in this study.

2.2. FOX Optimization (FOX Optimizasyonu)

A fox may survive in an environment with low productivity and few species. Although foxes come in various colors, white and red are the most prevalent hues. The red fox and the arctic fox are the two most prevalent species of fox. The most common animal is the red fox, which has expanded to cities across the USA, Europe, Canada, Japan, Australia, and Europe. The FOX algorithm mimics the hunting behavior of a red fox when it dives into the snow to hunt its prey [22]. The arctic fox is highly skilled at hunting its prey from both above and below. To find prey, the red fox initially roams the search area at random. It uses the prey's ultrasonic sound to locate its prey. The red fox may hear the sound of its prey while it seeks. The red fox is at the exploitation stage after detecting the noise. The sound of the prey takes some time to reach the red fox because it is capable of hearing ultrasonic sounds. In an attempt to decide whether to jump against the prey, the red fox advances the target. As a result, the red fox attempts to leap in response to how long it takes for prey to become visible. The red fox's hunting habits are shown in Figure 2. In addition, the coefficients c_1 and c_2 specified in Table 2 represent the jumping coefficients of the red fox. In addition, the number of epochs in deep learning models and the number of epochs - iterations in the optimization method are determined as 10. FOX first initializes the population, often known as the *X* matrix. The location of red foxes is an *X*. Next, each search agent's fitness is determined for each iteration using conventional benchmark functions. The fitness value of each search agent (each row in an *X* matrix) is compared to the fitness of other agents (other rows) in order to determine the optimal location (*BestX*) and best fit (*BestFitness*). In order to compare the fitness of the current row

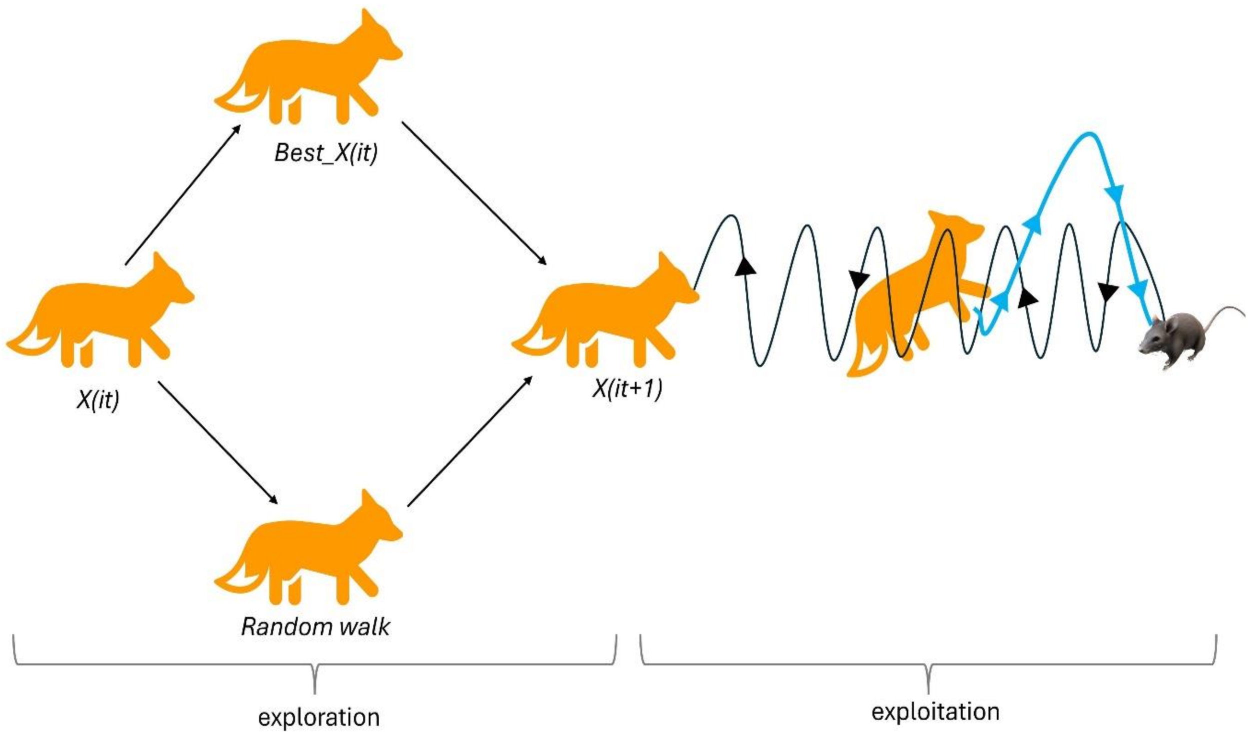

Figure 2. FOX population search for prey (FOX popülasyonunun av arayışı)

(*fitness*$_{i+1}$) to the fitness of the preceding row (*fitness*$_i$) throughout the course of iterations, *BestFitness* and *BestX* are performed using a condition. There is a condition on the possibility of killing the prey during the exploitation phase.

The random variable p has a value between 0 and 1. Consequently, it is necessary to determine the red fox's new location if the random number p is larger than 0.18. In order to determine a new location, one must compute the distance sound travels $Dist\_S\_T_{it}$, the red fox's distance from the prey $Dist\_Fox\_Prey_{it}$, and the leaping value $Jump_{it}$. Consequently, the sound travel time $Time\_S\_T_{it}$ is assigned a random integer between 0 and 1. By multiplying the speed of sound in the air (Sp_S) by the time sound travels (T_{it}), one may get the distance of the sound from the red fox. Equation (1) is used to find the distance traveled by the sound, which means distance

$$Dist\_S\_T_{it} = Sp\_S * Time\_s\_T_{it} \quad (1)$$

The ideal resolution the discovery process is significantly impacted by $BestX_{it}$ that has been discovered. Equation (2) illustrates the fox's exploration strategy for locating a new location in the search space $X_{(it+1)}$ [23].

$$X_{(it+1)} = BestX_{it} * rand(1, dimension) * MinT * a \quad (2)$$

2.3. Bidirectional Recurrent Neural Networks
(Çift Yönlü Yinelenen Sinir Ağı)

Bidirectional RNNs were initially introduced in 1997. The concept involves connecting two recurrent networks that have been trained in opposing directions, meaning they are trained by reading the input sequence once from the left and once from the right, and then feeding into the same output layer. Unlike unidirectional RNN, the network with this design collects more information since it knows everything about the neighboring points before and after each data point [24]. The working diagram of a Bi-RNN architecture is given in Figure 3.

Mathematics is used to specify the network in Equations 3-5. Iterating the forward layer from *f*=1 to *F* yields the forward hidden sequence, $\vec{h}_f^l$. Iterating the backward layer from *f=1* to *F* yields the backward hidden sequence, $\overleftarrow{h}_f^l$. The weight matrices that are input are $W^l_{x\vec{h}}$, $W^l_{x\overleftarrow{h}}$, the hidden weight matrices are $W^l_{\vec{h}\vec{h}}$, $W^l_{\overleftarrow{h}\overleftarrow{h}}$, and the bias terms for the forward and backward hidden layers are $b^l_{\vec{h}}$, $b^l_{\overleftarrow{h}}$, respectively. A deep bidirectional RNN may be created by stacking many bidirectional RNN layers. The input for each hidden layer comes from the forward and backward layers that came before it, or from $\vec{h}^l_{f-1}$ and $\overleftarrow{h}^l_{f-1}$. Equation-5 states that the hidden activations $\vec{h}_f^{L-1}$ and $\overleftarrow{h}_f^{L-1}$ f of the final

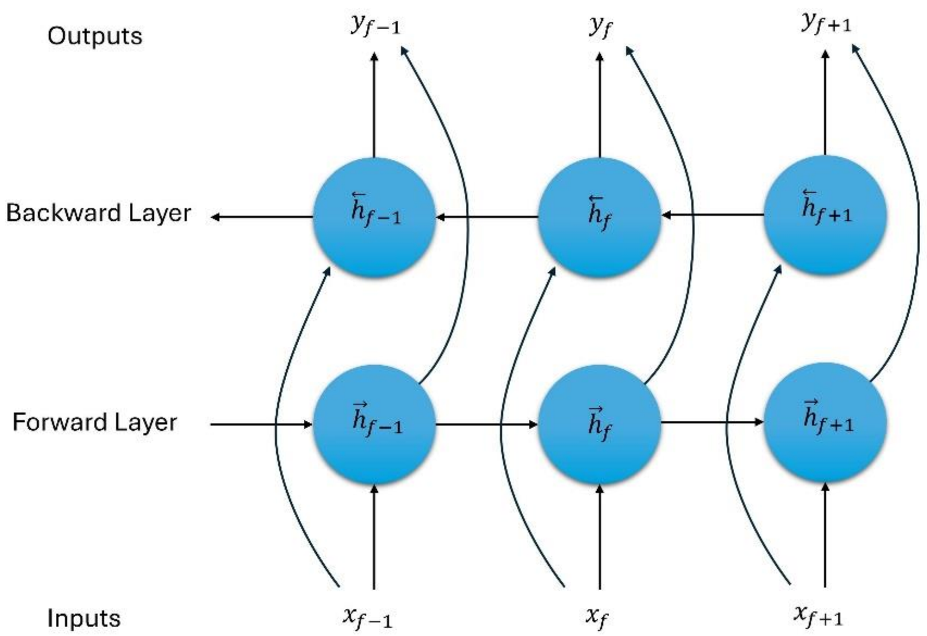

Figure 3. Bi-RNN architecture (Bi-RNN mimarisi)

hidden layer $L-1$ are used to update the output layer y_f. The output weight matrices are denoted by $W_{\vec{h}y}$ and $W_{\overleftarrow{h}y}$, and by the output bias term [25].

$$\vec{h}_f^l = g(W^l_{x\vec{h}} x^l_f + W^l_{\vec{h}\vec{h}} \vec{h}^l_{f-1} + b^l_{\vec{h}}) \quad (3)$$

$$\overleftarrow{h}_f^l = g(W^l_{x\overleftarrow{h}} x^l_f + W^l_{\overleftarrow{h}\overleftarrow{h}} \overleftarrow{h}^l_{f-1} + b^l_{\overleftarrow{h}}) \quad (4)$$

$$y_f = m(W_{\vec{h}y} \vec{h}_f^{L-1} + W_{\overleftarrow{h}y} \overleftarrow{h}_f^{L-1} + b_y) \quad (5)$$

Figure 4 shows the process of determining the hyperparameter values of the deep learning method of the FOX optimization method. In this study, deep learning models were first created. Among the models with the same parameter numbers, the hyperparameter values of the BiRNN method were found with the FOX optimization method and candidate solutions. As can be seen in the figure, the deep learning model was created and the learning rate and Beta_1 hyperparameter value were tried to be found with the FOX optimization. The hyperparameter values were updated according to prediction performance of the new deep learning models was tested. Finally, the BiRNN model was obtained according to the appropriate hyperparameter values.

3. RESULTS (BULGULAR)

In this study, the discharge energy estimation of lithium-ion batteries was performed for different temperature conditions with deep learning methods. Hyperparameter values of the Bi-RNN method were determined by searching in a wide range with the FOX optimization method. Figure 5 shows the hyperparameter search sought in the deep learning method. While estimating the discharge energy of the lithium-ion battery using the BiRNN method, the determination of hyperparameter values was made using FOX optimization. The most important hyperparameters in the BiRNN method include the learning rate and Beta_1 hyperparameters. The Beta_1 hyperparameter value indicates the rate at which past gradient values will be taken into account, while the learning rate is the term related to the updating of the model weights. Figure 4 represents the application of candidate values and

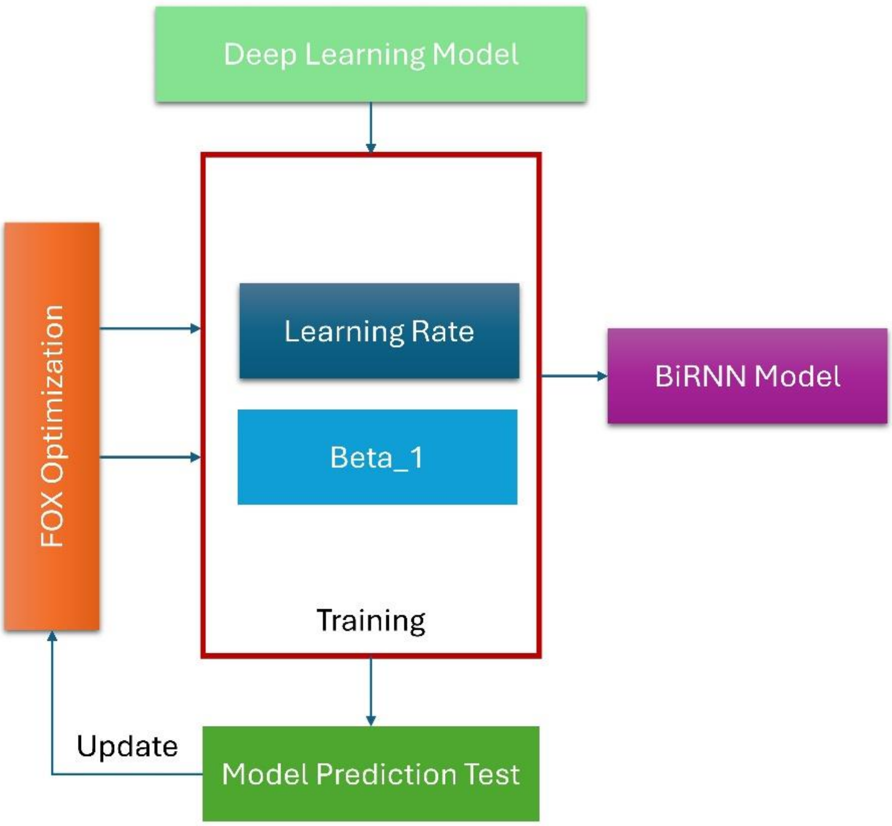

Figure 4. Determining hyperparameters of deep learning method by FOX optimization method (FOX optimizasyon yöntemi ile derin öğrenme yönteminin hiperparametrelerinin belirlenmesi)

the fitness value up to the epoch value and the the updating of these values according to the result while determining the appropriate hyperparameter value with FOX optimization. The features of the FOX optimization method are given in Table 1. While the population size of the FOX optimization method was determined as 20, the c values for the jumps coefficient values of the population members were determined as 0.5 and successful results were obtained. FOX optimization parameter values are

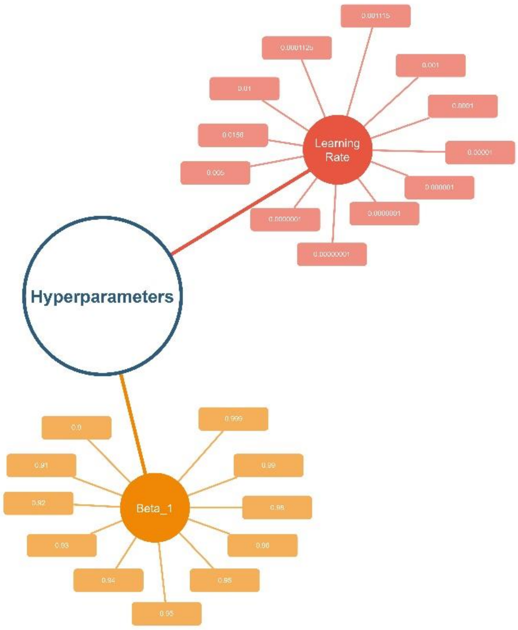

Figure 5. Hyperparameters different search
(Hiperarametrelerin farklı aranması)

Table 2. FOX optimization method's parameters (FOX optimizasyon yönteminin parametreleri)

Parameter	**Detail**
pop_size	20
c_1	0.5
c_2	0.5

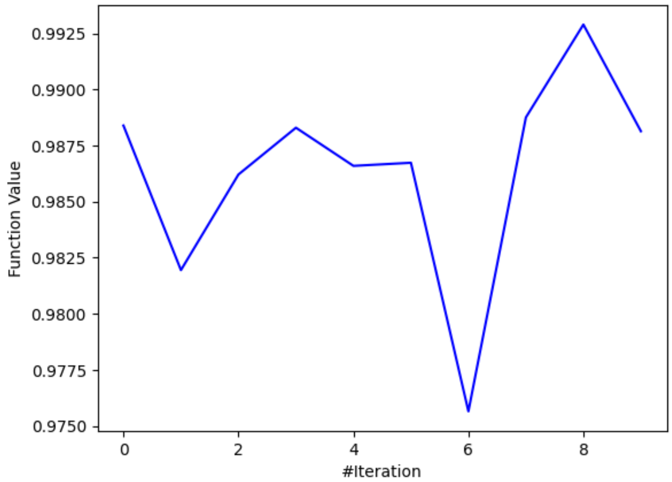

Figure 6. Fitness value obtained while searching for suitable parameters with the optimization method. (Optimizasyon yöntemi ile uygun parametreler aranırken elde edilen uygunluk değeri)

given in Table 2. The change of fitness value over time in the deep learning hyperparameter determination process using FOX optimization is given in Figure 6. In deep learning methods, the hyperparameter, which is considered the first parameter to be adjusted in overfitting and underfitting problems, is the learning rate hyperparameter. For this reason, in this study, a wide range was used while determining the learning rate and beta_1 hyperparameter value with the FOX optimization method. Table 3 shows the hyperparameter values searched with the FOX optimization method in the Bi-RNN method in this study. The fitness value of the appropriate values found by searching these two hyperparameter values together in the FOX optimization is 0.995412.

Table 4. FOX optimization method's search areas (FOX optimziasyon yönteminin arama alanları)

Hyperparameter	Search Area	Found
learning rate	0.0000001- 0.01	0.004011210229063557
beta_1	0.9- 0.999	0.9876397443378757

Table 3. Deep learning experimental results (Derin öğrenme deneysel sonuçları)

Temperature	Model	MSE	RMSE	MAE	R^2
0 ^{0}C	**Bidirectional LSTM**	0.076318	0.276257	0.166312	0.981507
	Bidirectional RNN	0.059190	0.243290	0.111000	0.985657
	Bidirectional GRU	0.030730	0.175299	0.086079	0.992554
	FOX-BiRNN	0.023992	0.154893	0.061595	**0.994186**
25 ^{0}C	**Bidirectional LSTM**	0.098343	0.313597	0.184775	0.984295
	Bidirectional RNN	0.026196	0.161851	0.059866	0.995817
	Bidirectional GRU	0.034208	0.184955	0.094992	0.994537
	FOX-BiRNN	0.024546	0.156670	0.059706	**0.996080**
45 ^{0}C	**Bidirectional LSTM**	0.103336	0.321460	0.214098	0.978626
	Bidirectional RNN	0.041659	0.204104	0.114284	0.991383
	Bidirectional GRU	0.048836	0.220988	0.148079	0.989899
	FOX-BiRNN	0.028295	0.168210	0.094473	**0.994148**
Average	**Bidirectional LSTM**	0.092666	0.303771	0.188395	0.981476
	Bidirectional RNN	0.042348	0.203082	0.095050	0.990952
	Bidirectional GRU	0.037924	0.193747	0.109716	0.992330
	FOX-BiRNN	0.025611	0.159924	0.071925	**0.994805**

After determining the hyperparameter values of the Bi-RNN method using FOX optimization, the FOX-BiRNN method was obtained by applying these values to the Bi-RNN method. The discharge energy estimation results of the lithium-ion battery of the FOX-BiRNN, Bi-RNN, Bi-LSTM, and Bi-GRU methods were given, and experiments were carried out for different temperature values. The deep learning experiment results are given in Table 4. According to the results given in Table 3, the worst estimation performance as a result of the training carried out using 0 ^{0}C data was obtained by the Bi-LSTM method with the value of 0.076318 according to the MSE metric. The Bi-RNN method reached the second most unsuccessful estimation result at this temperature value and this value was 0.059190 according to the MSE metric. The most successful method was the FOX-BiRNN method, which made an error in estimation with the value of 0.023992 with the MSE metric. As a result of deep learning trainings performed using 25 ^{0}C data at a different temperature value, the least successful method was the Bi-LSTM method with a value of 0.098343 according to the MSE metric and made the most error in prediction. FOX-BiRNN method became the most successful method by reaching the value of 0.024546 according to the MSE metric and

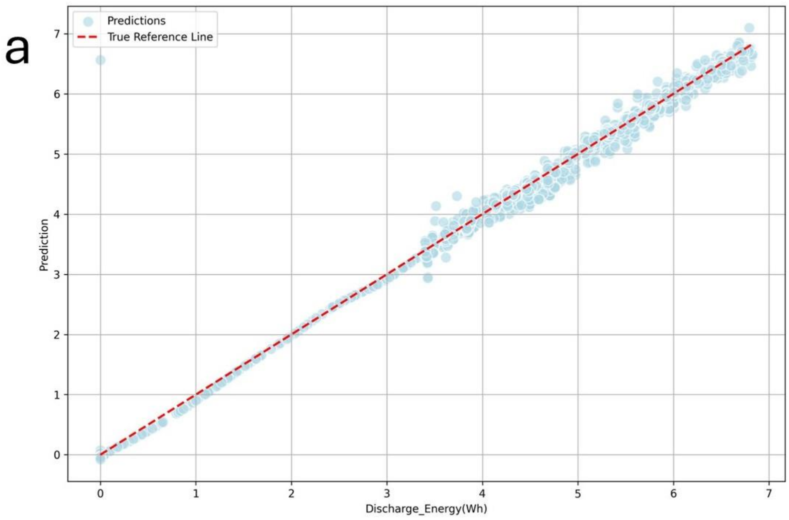

Figure 7.a. FOX-BiRNN estimation results for 0 ^{0}C (FOX-BiRNN 0 ^{0}C için tahmin sonuçları)

making the least error in prediction. In the training performed using 45 ^{0}C data at a different temperature value, the Bi-LSTM method became the least successful method by making the error in prediction with the value of 0.103336 according to the MSE metric. In the training performed at the same temperature value, the FOX-BiRNN method achieved success by making the least error in prediction with the value of 0.028295 according to the MSE metric.

4. CONCLUSIONS (SONUÇLAR)

As the importance of comfort and healthy use in electric vehicles has increased, the healthy, long-term, and safe use of lithium-based batteries that provide the energy needs of electric vehicles has become very important. The healthy use of lithium-based batteries depends on accurate, fast, and reliable estimation of battery parameters. In addition, it is critical to know the behavior of lithium batteries under different temperature conditions and different drive cycles. In this study, discharge energy estimation of lithium-ion batteries was successfully performed with four deep learning methods using a publicly available dataset with the data obtained at 0 ^{0}C, 25 ^{0}C, and 45 ^{0}C in the DST driving method. Since one of the most important problems in the process of determining the parameters of lithium batteries based on artificial intelligence is the determination of hyperparameters, the hyperparameter values of the Bi-RNN method were determined by using FOX

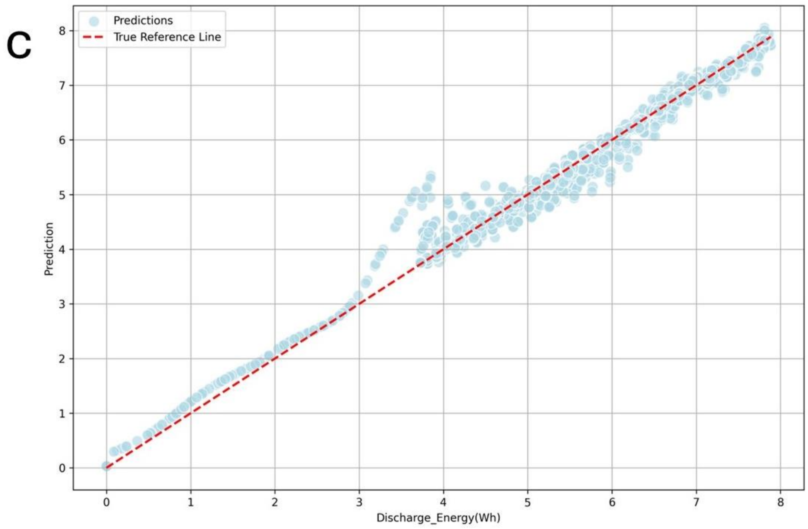

Figure 7.c. FOX-BiRNN estimation results for 45 ^{0}C (FOX-BiRNN 45 ^{0}C için tahmin sonuçları)

optimization in this study. In addition, the prediction performance of four deep learning methods, Bi-LSTM, Bi-RNN, Bi-GRU, and FOX-BiRNN methods are compared. The discharge energy prediction results of the lithium-ion battery were evaluated by using the most commonly used prediction metrics in the literature. According to the results obtained, the FOX-BiRNN method was proposed by making the most successful prediction with a value of 99.4805% according to the R^2 metric when averaged over all experiments. The prediction of the discharge energy of the lithium battery by the proposed method is presented as a result of graphics and tables with different prediction metrics. The obtained results will provide intuition for solving other problems in real life. The author intends to estimate the parameters of lithium-based batteries by comparing the success of different optimization methods in further studies.

DECLARATION OF ETHICAL STANDARDS
(ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

Göksu TAŞ: He conducted the experiments, analyzed the results and performed the writing process.

Deneyleri yapmış, sonuçlarını analiz etmiş ve maklenin yazım işlemini gerçekleştirmiştir.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

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