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Research Article

Predicting battery capacity with artificial neural networks

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Abstract: Li-ion batteries are a commonly used type of battery in various electronic devices and electric vehicles. The capacity of these batteries can decrease over time and affect the lifespan of the device. Therefore, predicting the capacity status of Li-ion batteries is important, there are several ways to estimate the SOC of a battery. When the literature was reviewed and relevant articles were examined, it was observed that artificial neural networks could be an effective tool for predicting the capacity status of Li-ion batteries. In this study, a study was conducted to predict the capacity status of Li-ion batteries using artificial neural networks. For this purpose, data collection, data preprocessing, and the use of artificial neural networks were carried out in stages for the prediction of the capacity status of Li-ion batteries. When the results obtained were examined, it was seen that artificial neural networks were able to correctly predict the capacity status of Li-ion batteries. The comparative analysis among various ANN models, including RNN, LTSM, and GRU highlights the superiority of GRU in performance, with RNN exhibiting comparable performance and LSTM lagging. These predictions can be used to extend the lifespan of Li-ion batteries and optimize the performance of the device. In addition, efforts such as expanding the data set and optimizing the network structure can be made to increase the accuracy of these predictions. This research presents an exemplary study of predicting Li-ion battery capacity using ANNs and has been successfully conducted using NASA datasets.

Keywords: Artificial Neural Network, Li-ion Battery, Battery Capacity Prediction, RNN, LSTM, GRU State of Capacity, SOC

Yapay sinir ağları ile batarya kapasite durumu tahmini yapılması

Özet: Li-ion bataryalar, günümüzde çeşitli elektronik cihazlarda ve elektrikli araçlarda sıklıkla kullanılan batarya türlerindendir. Bu bataryaların kapasitesi zaman içinde azalabilmekte ve cihazların ömrünü etkileyebilmektedir. Bu nedenle, Li-ion bataryaların kapasite durumunun tahmin edilmesi önemlidir ve bunu yapmanın birkaç yolu vardır. Literatürde ilgili makaleler incelendiğinde, yapay sinir ağlarının Li-ion bataryaların kapasite durumunu tahmin etmede etkili bir araç olabileceği görülmüştür. Bu araştırmada, yapay sinir ağları kullanarak Li-ion bataryaların kapasite durumunun tahmin edilmesi için bir çalışma yapılmıştır. Bu amaçla, veri toplama, veri ön işleme ve yapay sinir ağları kullanımı gibi adımlar izlenmiştir. Elde edilen sonuçlar incelendiğinde, yapay sinir ağlarının Li-ion bataryaların kapasite durumunu doğru bir şekilde tahmin edebildiği görülmüştür. RNN, LTSM ve GRU gibi çeşitli ANN modelleri arasındaki karşılaştırmalı analiz, GRU'nun performans açısından üstünlüğünü ortaya koymaktadır; RNN benzer bir performans sergilerken LSTM geride kalmaktadır. Bu tahminler, Li-ion bataryaların ömrünü uzatmak ve cihazın performansını optimize etmek için kullanılabilir. Ayrıca, bu tahminlerin doğruluğunu artırmak için veri setinin genişletilmesi ve ağ yapısının optimize edilmesi gibi çalışmalar da yapılabilir. Bu araştırma, Li-ion batarya kapasitesinin ANN'lerle tahmin edilmesine örnek bir çalışma sunmakta olup ve NASA veri setlerini kullanılarak başarılı bir şekilde gerçekleştirilmiştir.

Anahtar Kelimeler: Yapay Sinir Ağları, Li-ion Batarya, Batarya Kapasite Tahmini, RNN, LSTM, GRU, SOC

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1. Introduction

Li-ion batteries are a subset of batteries that make use of the ability of lithium ions to store energy. Because of their small size, high energy density, and extended lifespan, these batteries are frequently chosen in electronic products and electric vehicles (Kim et al, 2019). Li-ion batteries also have the advantage of being rechargeable and not requiring high voltage when being charged. Making estimates about battery capacity allows for the optimization of device performance because the battery life of these batteries may shorten with time (Manoharan et al, 2022).

The importance of this battery type has expanded with the widespread usage of Li-ion batteries in electric vehicles and other electronic gadgets (Li et al, 2019). Predicting battery capacity is a significant field of research to increase battery life and improve device performance (Chau and Chan, 2007). By calculating the rate at which the battery capacity is decreasing, these projections can be used to evaluate battery performance while the device is in use (Ren et al, 2015). For instance, a cell phone battery's capacity degrades with time, and the rate of this degradation varies depending on the device. For cell phone users to evaluate battery performance, it is crucial to make forecasts about battery capacity (Schneider et al, 2017).

State of charge (SOC) is used to determine the battery's remaining capacity, and remaining battery capacity prediction is at the core of battery management systems (Dubarry et al, 2017). The capacity of the battery can be fully utilized, which enhances battery performance and reduces the risk of safety issues brought on by overcharging or over discharging the battery (Ng et al, 2020). For battery energy management and control, research on estimating remaining battery capacity is crucial. The link between the observable battery signals (voltage, current, temperature, etc.) and SOC is highly erratic and depends on temperature and charging/discharging current (How et al, 2019). SOC is not an observable number. The method of ampere-hour integration, which is frequently used to estimate SOC, has two fundamental problems that cause SOC prediction mistakes to grow with time: current measurement errors and SOC beginning value inaccuracies. Calibration tests are used to identify the relationship between OCV and SOC (Baccouche et al, 2017). The OCV approach is difficult to employ in real applications and has trouble guaranteeing measurement conditions during SOC prediction. It can only be used to SOC prediction as an auxiliary method (Cuma and Koroglu, 2015).

Modern machine learning technology is developing more quickly than ever before because of the constant improvement in computer speed and the expanding access to billions of data. Utilizing Artificial Neural Networks (ANN) for predicting the State of Charge (SOC) of lithium-ion batteries offers a potent solution owing to their capability to learn intricate patterns from large datasets.

To estimate the state of charge (SOC) of lithium-ion batteries, pure data-driven deep learning algorithms can be integrated with the huge quantity of operational data generated by lithium-ion batteries, such as voltage, current, and temperature (Hannan et al, 2017). Deep neural networks that process time-related sequences well include the Gated Recurrent Unit Neural Network (GRU), Long Short-Term Memory Network (LSTM), and Recurrent Neural Network (RNN). SOC fluctuates continually over time, making lithium-ion battery SOC estimate a prediction problem related to time series (Cui et al, 2022; Li et al, 2021)

For these factors, a broad explanation of the idea of artificial neural networks will be given, along with explanations of its sub-branches, such as GRU (Gated Recurrent Unit Neural Network), LSTM (Long Short-Term Memory Network), and RNN (Recurrent Neural Network).

This study, it is delved into the realm of battery capacity forecasting, focusing particularly on the utilization of artificial neural networks (ANNs) and their effectiveness in handling time-related information. Investigation encompasses a review of existing literature about battery capacity and ANNs, with a keen emphasis on methodologies optimized for temporal data processing. Furthermore, to assess the predictive capabilities of deep neural networks in forecasting the state of charge (SOC) of lithium-ion batteries, a practical ANN was developed.

Due to the general assumption in the reviewed articles, the pre-processing phase involved the random allocation of a dataset into 70% for training and 30% for testing.

For modeling endeavors, recurrent neural network (RNN), long short-term memory (LSTM), and gated recurrent unit (GRU) architectures were used within the ANN framework. Each model was structured with 5 layers and in each layer, 50 neurons were employed, with the activation function tanh utilized uniformly across all layers to facilitate performance comparison. Moreover, to optimize the models' performance, the Adam (Adaptive Moment Estimation) optimization algorithm is used, aimed at minimizing the loss function during training. Our novel approach in this study serves as a benchmark for other researchers utilizing the NASA dataset, enabling them to compare and evaluate the accuracy and efficacy of our methodology. The developed models underwent rigorous internal comparison, wherein their respective strengths and weaknesses are elucidated in the results section. By referencing the model, researchers embarking on similar endeavors can explore new avenues and foster the expansion of research within this domain.

2. Literature Review

A literature review has been conducted on the studies carried out in the field of battery capacity estimation using artificial neural networks.

Xueyan Yang et al. (2022) developed a TCN model using artificial neural networks based on 1-year real data. Using Arrhenius formula, they trained and tested the data set by considering variables such as temperature, charge/discharge rate and cycle time on battery capacity estimation. When trained and tested with other models (RNN, LSTM, GRU) and compared the test results, the method proposed by the authors was found to be successful.

However, they suggested that the model is data dependent, and that the success rate may be low in other vehicle data, and they suggested to work on learning transfer.

Tianyun Hao et al. (2022) developed a hybrid model using an artificial neural network model and a Kalman filter. Using an open-source dataset, the authors used a CCM-based Kalman filter with a time-varying CCM-based Kalman filter together with the trained dataset. According to 3 different driving models, they found that using FNN + Kalman filter performed better than the results obtained before using the model.

Alessandro Aliberti et al. (2022) trained and tested various artificial neural network models on NASA battery data set and compared their results. LSTM, GRU, CNN and hybrid models were used on the dataset, especially battery capacity, V, I and temperature values were considered. The best hyperparameters were determined on the Google Colab platform after sharing 90%-10% as training and test data. Using Adam as the optimization function, relu and tanh as activation functions, the authors determined 1D-CNN as the most successful model according to the test results. While LSTM was the model with the highest variance, the GRU model was very dependent on the training data, while the CNN-LSTM model predicted the battery health status without learning the training data.

Bowen Jiang, Yujing Liu and Junfei Tang (2022) propose a battery state of health (SOH) prediction structure by combining recurrent neural network and convolutional neural network. Using the NASA dataset as 70%-30% training and test data, the authors compare LSTM, RFNN, RCNN models. The proposed structure uses not only the cycle measurement but also the measurements and predictions from the previous two cycles for the health state prediction of the studied cycle. The results show that RCNN reduces the validation set loss by 31.5% and 18.8% compared to LSTM and RFNN, respectively.

Di Zhu et al. (2021) reviewed the studies conducted to create a research paper on batteries and identified the advantages and disadvantages of each neural network for battery health-capacity prediction and parameter identification. In the in-depth research, the error rates of RNN, MLP, MLP+BSA, MLP+ADAM, DBN+SWM algorithms and combinations were compared for SOC. For SOH, RNN, MLP, MLP+Autoencoder, MLP+MarkovChain, PNN algorithms and combinations were analyzed in the same way. As parameters, it was observed that voltage, current and temperature values generally played the main role. It was emphasized that algorithms that learn by repetition are more successful. They observed that the importance of historical data in online studies and data cleaning, reducing the size of the data and examining their correlations with each other and giving them as input to the algorithm accordingly in studies with ready-made data sets that are not online increase the success in general.

Jacob c. Hamar et al. (2021), in a joint study conducted by the BMW Research Center and the University of Munich, estimated the battery health status using 2 artificial neural network methods with data obtained from 700 vehicles. They encountered 3.4% error in the semi-empirical model and 3% error in the artificial neural network model. They commented that the error rate will decrease as the number of data increases.

Yuanjun Guo et al. (2020) proposed the use of the JAYA optimization scheme for better tuning of neural network parameters when predicting battery capacity status in an energy system consisting of many batteries. Instead of using all features, the ones with the highest correlation with each other were selected and the RBF neural network model was trained and tested. Error rates were observed to be lower in the model optimized with Jaya.

In a 2020 study, Mengllong XU and colleagues develop a BPNN artificial neural network model with data from charging stations of smart bicycles. They train and test two different models with 20 and 100 neurons. While the BPNN model with 100 neurons has a 1% error rate with test data after a long training time, the model with 20 neurons stands out with a shorter training time. However, the test data with an error rate of 16% showed that the model failed. In addition, the authors made two different trials of the SWM algorithm and concluded that it is not suitable for this system with its high error rate.

Chao Lyu et al. (2020) used GRU, LSTM, RNN models for battery capacity prediction on a public dataset and compared their results. While the training time is considerably longer in GRU and LSTM compared to the RNN model, it is observed that RNN has the worst error rate. Although GRU and LSTM have similar error rates, GRU is one step ahead in time.

In their study, Carlos Vidal et al. (2019), since designing a traditional Kalman filter and then applying it to the battery is a serious task for each battery, they transferred the artificial neural network model and studied how it would work in another battery. Using the LSTM + RNN model, the researchers used data from 4 different batteries. In the training data set, while there were mixed data from driving cycles for each battery, 4 different neural network models were trained and tested in 4 different ways. First, the error rate on the test data was compared without model transfer, while in the second comparison, the other 3 models were trained again on the first models according to the battery and the test results were compared. In the third stage, the transferred models were trained and tested again on their own training data and the results were observed. In the last stage, all the data was mixed, and the transfer model was trained and tested on the test sets, and as a result, they reported that significant reductions in the error rate were observed. Overall, the study shows the advantages of transfer learning to reduce training time, improve SOC prediction accuracy and reduce the amount of training data required.

After reviewing the neural network articles in the field of battery capacity and health prediction, the purpose of the study, the methodology used, the contribution to the literature, the results obtained, and the recommendations of the study are presented in Table 1, Table 1.1, and Table 1.2. In our study on battery capacity prediction, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Recurrent Neural Network (RNN) architectures were chosen due to their inherent advantages in sequence modelling tasks. In contrast to the examined studies, our experiment was distinguished by thoroughly assessing the performance of Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Recurrent Neural Network (RNN) architectures in the same conditions, individually. LSTM, with its ability to retain long-term dependencies and mitigate the vanishing gradient problem, was deemed effective for capturing temporal dynamics in battery data. Similarly, GRU, offering a simplified architecture compared to LSTM while maintaining competitive performance, was found to be efficient for processing sequential data. RNN, although less complex, remained relevant for its simplicity and applicability in certain scenarios. The training and test data were separated with a split of 70%-30% to ensure adequate generalization while evaluating model performance.

A meticulous comparison was conducted across these recurrent neural network models, aiming to elucidate their respective strengths and weaknesses, particularly focusing on factors such as training time and prediction accuracy. This approach enabled a focused and insightful analysis of LSTM, GRU, and RNN performance in battery capacity and health prediction tasks, contributing valuable insights to the field. Through this approach, contributions were aimed towards the development of more robust and transferable models for battery capacity and health prediction in diverse operational environments.

3. Material and Method

3.1. Method

3.1.1. Artificial Neural Networks

Artificial neural networks (ANNs) are a machine learning method and are based on mathematical models that mimic natural nervous systems. ANNs consist of an input layer, several hidden layers, and an output layer (Malkoç, 2017).

The input layer provides data input to the network and the hidden layers process and send this data to the output layer. The output layer outputs the result of the data processed by the network. ANNs are shaped according to the data by changing the weights of the connections between the layers of the network during learning, and thus can make predictions in accordance with the data (Chitnis et al, 2018). ANNs can be used to solve a variety of problems, but they are most used in prediction problems such as classification and regression.

Today, artificial neural networks (ANNs) are used in many different fields. For example, they are used to process audio, image, and text data, they are used to solve prediction problems, and they are used to solve classification problems (Das and Behera, 2017). Artificial neural networks can be found in every field where neural network, i.e., the human brain, can be found. It can work in most areas that humans can do, and there will be more areas to work in the future (Jain et al, 1996). In the coming years, the areas of use of artificial neural networks will expand even further and the impact of this technology will increase even more. Although it is said that this will increase unemployment, it is emphasized that some professions will disappear, but new professions will come.

3.1.2. Artificial Neural Networks Study Areas

Artificial neural networks (ANNs) are used in many different fields. For example, they are used to process audio and video data. The ANNs used in these areas are usually of the Convolutional Neural Networks (CNN) type. In this way, spoken words can be predicted in voice recognition systems and objects in images can be identified in image recognition systems.

ANNs can also solve prediction problems. ANNs used in these areas are usually Fully Connected Neural Networks (FCNN). For example, a store can predict future sales by processing sales data, and a healthcare institution can predict disease by processing symptoms and data of patients.

Table 1. Summary information about the studies reviewed

Author(s) Name(s) Year	Article Title	Aim of the Study	Method Used	Contribution to the Literature	Obtained Result
Yang, X., Hu, J., Hu, G., & Guo, X. (2022)	Battery state of charge estimation using temporal convolutional network based on electric vehicles operating data	Battery capacity was estimated using the Arrhenius formula.	TCN RNN LSTM GRU	They enabled a new perspective on battery capacity estimation by taking chemical reactions into account.	The proposed method was found to be more successful than the existing methods.
Hao, T., Ding, J., & Tu, T. (2022).	A hybrid Kalman filter for SOC estimation of lithium-ion batteries	They developed a hybrid model consisting of a Kalman filter and an artificial neural network.	FNN Kalman Filter	It has been a reference model for the use of Kalman filters and artificial neural networks.	The hybrid model was found to be more successful than the simple pedestrian neural network model.
Aliberti, A., et al. (2022)	Comparative Analysis of Neural Networks Techniques for Lithium-ion Battery SOH Estimation	Models were trained and compared using the Nasa dataset.	LSTM GRU CNN	It has been a reference research for authors who will use the same data set.	The 1D-CNN model was the most successful.
Jiang, B., Liu, Y., & Tang, J. (2022)	Lithium-ion Battery State of Health Estimation with Recurrent Convolution Neural Networks	Recurrent neural network and convolutional neural network are combined to predict battery health.	RFNN LSTM RCNN	The proposed structure has been the reference research in the sense that it uses not only the loop measurement but also the measurements and predictions from the previous two cycles.	RCNN model made the most successful predictions.

Table 1.1 Summary information about the studies reviewed

Author(s) Name(s) Year	Article Title	Aim of the Study	Method Used	Contribution to the Literature	Obtained Result
Zhu, D., Cho, G., & Campbell, J. J. (2021)	Neural Networks Battery Applications: A Review	They identified the advantages and disadvantages of each neural network for battery health-capacity prediction and parameter identification.	RNN, MLP, MLP+BSA, MLP+ADAM, DBN+SWM, MLP+Autoencoder, MLP+Markov Chain, PNN	The study with various variations of repeated learner models has been a reference research.	The observed voltage, current and temperature values played the main role as parameters. It was emphasized that algorithms that learn by repetition are more successful.
Hamar, J. C., et al. (2021)	State-of-health estimation using a neural network trained on vehicle data	They tested real-life habitual data with semi-empirical and artificial neural networks.	Authors without model information used semi-supervised and artificial neural network models.	It has been a real-time study with data of reasonable value.	The neural network model predicted battery health better than the semi-empirical model.
Guo, Y., Yang, Z., Liu, K., Zhang, Y., & Feng, W. (2021)	A compact and optimized neural network approach for battery state of charge estimation of energy storage system	They aimed to improve the accuracy of the neural network using the Jaya optimization tool.	JAYA RBF	It has been a reference work for researchers working with optimization tools.	Error rates were lower in the model optimized with Jaya.

Table 1.2 Summary information about the studies reviewed

Author(s) Name(s) Year	**Article Title**	**Aim of the Study**	**Method Used**	**Contribution to the Literature**	**Obtained Result**
Xu, M., Wu, W., Zhou, W., Ma, Y., Shi, X., & Li, J. (2020)	State of Charge Estimation of Low-speed Electric Vehicle Abttery using Back Propagation Neural Network	They studied the effect of the number of neurons when designing an artificial neural network model on the data of electric bicycles.	BPNN SWM	It has been a reference study for researchers working on the battery health status of smart bicycles.	In the designed model, the success rate of 20 neurons was not satisfactory, while the learning time was a problem in the system with 100 neurons.
Lyu, C., Han, Y., Guo, Q., Wang, L., & Song, Y. (2020)	State-of-Charge Estimation of Lithium-ion Batteries Based on Deep Neural Network	Models were trained and compared using an open-source dataset.	GRU LSTM RNN	It has been a reference for researchers who will use open source artificial neural network models.	The training time is considerably longer for GRU and LSTM compared to the RNN model, while RNN has the worst error rate.
Vidal, C., Kollmeyer, P., Chemali, E., & Emadi, A. (2019)	Li-Ion Battery State Of Charge Estimation Usıng Long Short-Term Memory Recurrent Neural Network With Transfer Learning	After the training was completed, 4 different batteries were analyzed by transferring the model.	LSTM + RNN	Unlike the work on uniform batteries, there has been serious work on the transportation of learning.	All the data was mixed, the transfer model was trained and tested on test sets, and as a result, they reported significant reductions in the error rate.

ANNs can also solve classification problems. ANNs used in these areas are usually of the FCNN type. For example, when classifying products on an e-commerce site, the category to which the products belong can be predicted, and a bank can predict the credit risks of customers by processing customer data.

These are just a few examples of applications, and the uses of neural networks are much broader. In the coming years, the uses of artificial neural networks will expand even further, and the impact of this technology will increase even more.

3.2. Material

3.2.1. Lithium-Ion Batteries

Lithium-ion batteries (Li-ion) are high energy density batteries that work by transporting lithium ions with their electronic charge. This means that a Li-ion battery of the same weight and volume can store more energy and run longer.

Li-ion batteries generally last longer than other battery types and can be recharged. For this reason, Li-ion batteries are often preferred for applications such as electronic devices and electric vehicles. To prolong the life of Li-ion batteries, it is important to use correct charging and discharging techniques.

In addition, since the operating temperature range of Li-ion batteries is narrow, temperature conditions can also have an impact on battery life (Blomgren, 2016).

3.2.2. Usage Areas of Lithium-Ion Batteries

Lithium-ion batteries are used in many different fields due to their diverse design and high energy density. Most commonly, these batteries are used for electronic devices, electric vehicles, and hybrid electric vehicles. They are also used for lightweight vehicles such as electric bicycles, scooters, and electric cars (Lu et al, 2013).

Lithium-ion batteries are also used for solar panel systems, home automation systems and other energy storage systems. For example, solar panel systems use lithium-ion batteries to store energy generated during the day and make it available at night or in cloudy weather. Home automation systems use lithium-ion batteries to save energy in the home and automatically adjust the home's temperature and lighting.

Lithium-ion batteries are also used for power generation systems in remote areas. For example, wind turbines and solar panel systems use lithium-ion batteries to store the energy generated and make it available for later use. In this way, people in remote areas can also benefit from the use of electrical energy (Kim et al, 2019).

As a result, lithium-ion batteries are very versatile and have a wide range of uses. They are used in many different fields such as electronic devices, electric vehicles, energy storage systems, militaristic applications, and aerospace sectors. Lithium-ion batteries have advantages over other battery types due to their high energy density, light weight, long life, and wide operating temperature range (Wu et al, 2022).

4. Application

Five steps were followed in the implementation process. First, an open-source NASA data set was created, second, the necessary data pre-processing operations were performed, third, models were created using artificial neural network algorithms, fourth, model results were compared, and finally, the models were tested with test data from outside the training data set. The schematic of training and test data sets and capacity estimation with LSTM, GRU and RNN models is shown in Figure 1.

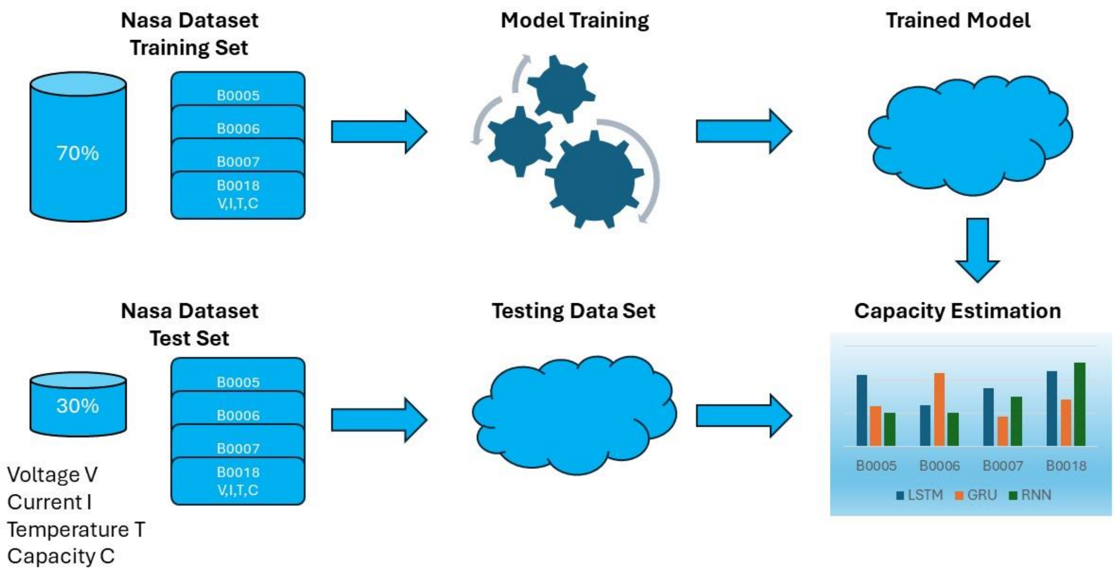

Figure 1. Implementation process of LSTM, GRU and RNN models

4.1. Data Set

Open-source data set was used for the data set. For this, the dataset available on the NASA website was used (Saha and Goebel, 2007). There are 28 different battery types in this data set. Batteries numbered 5-6-7 and 18 were selected. There are 50285 lines of data for the first 3 batteries and 34866 lines of data for battery number B0018. The features are listed as number of cycles, ambient temperature, date, capacity, voltage, current, battery temperature, current load, voltage load and duration. The capacity and cycle information of the data sets are visualized below in the Figure 2.

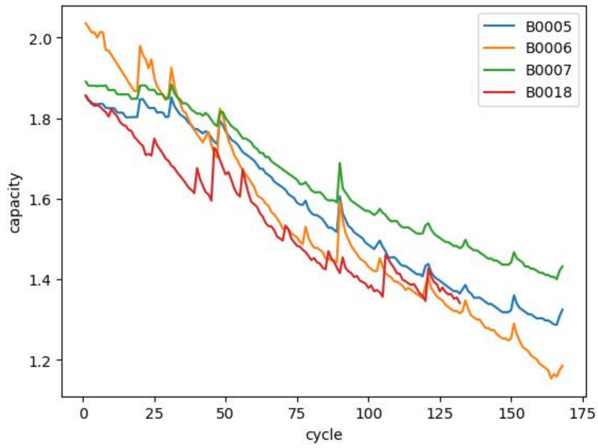

Figure 2. Capacity/Cyle for Each Battery

4.2. Data Pre-Processing

When the unique rows in the data set are checked, there are 50285 rows. Duplicate rows are removed from the data set to prevent the algorithms from memorizing. Since the open-source data is presented as .mat file, firstly, the conversion to .csv format was done using Python language for faster processing.

4.3. Modelling

The pre-processed data set was randomly allocated to be used as 70% training data and 30% test data. RNN, LSTM and GRU structure from artificial neural network algorithms were used in the modelling process.

Each model consists of 5 layers and tanh was used as the activation function of each model for performance comparison. Each layer contains 50 neurons and dropout method is used to help the model learn better by reducing the tendency of overfitting the weight coefficients. Adam (Adaptive Moment Estimation) optimization algorithm was used to minimize the loss function of the models.

4.4. Comparison of Results

When we look at the performance data we obtained from the validation data in the training data, we see that the battery belonging to the B0007 dataset has the most successful results in all models, followed by another successful battery B0005 in the Figure 3. Although the other two batteries have relatively lower performance, the mean squared error values of each model are very low. When we examine the training times of the models, we observe that the LSTM model is by far the lowest performing model in all data sets. Although the GRU and RNN models seem to perform very close to each other, the RNN model completed the training period in a shorter time by a very small margin. When we look at the performance of the trained models on the test data, battery B0018 was the most successful in contrast to the training data, followed by battery B0005 in the Figure 4. When we look at the training and test data in general, it is seen that battery B0006 gives the most unsuccessful results of the models.

4.5. Applicability of Models

According to the results, it is foreseen that it will be difficult to make a clear comment on the applicability of the models. Because it has been observed that depending on the characteristics of the data and the purposes of use, which model will perform better may change. However, in general, these results show that the LSTM model may perform less than the other models in some cases, but the RNN model has a faster training time.

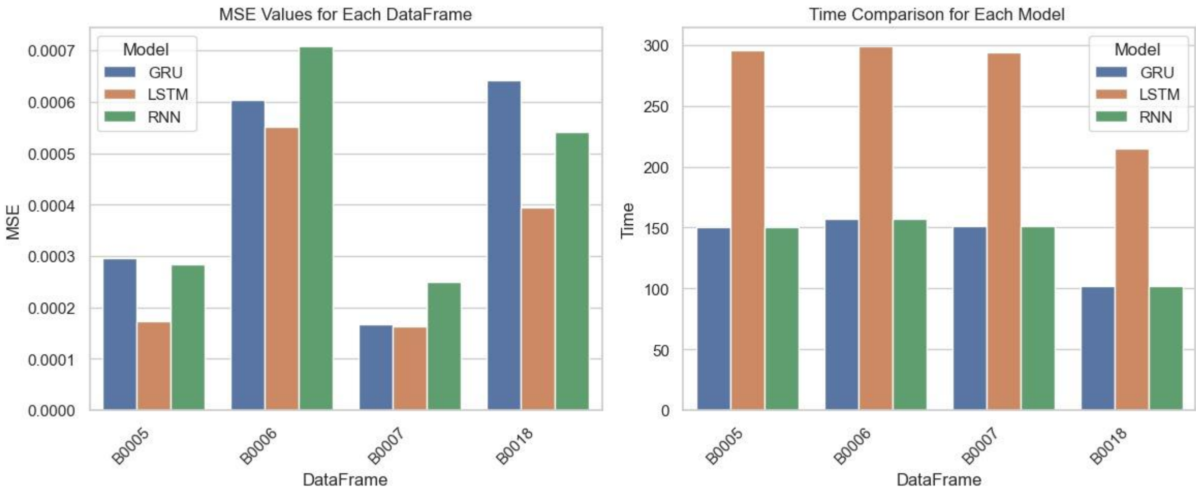

Figure 3. MSE Values for Each Data Frame && Time Comparison for Each Model

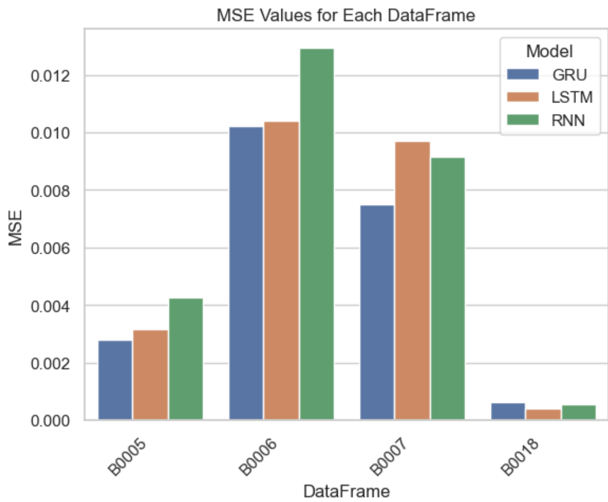

Figure 4. Trained Model MSE Values for Each Data Frame

5. Conclusion

In this study, the concept of artificial neural networks in battery capacity estimation and the literature review of the studies conducted in this field are reviewed. With the increasing interest in electric and autonomous vehicles in recent years, the concept of artificial neural networks has an important place in research and development studies in this field. To develop accurate and effective models in the studies to be carried out, a database infrastructure should be created according to the battery models.

When we examine the studies, it is seen that effective models are RNN, LTSM, GRU, FNN and CNN artificial neural networks. For this reason, RNN, GRU and LSTM models were selected within the scope of the study and the tests performed on the relevant data set were compared. While GRU was the most successful model in terms of performance, the RNN model was ahead of the GRU model with a very small difference in training time. The LSTM model was observed as the least successful model in both scales.

When the model was checked with the test data not included in the dataset after the model run was completed, while the results of the validation data were parallel to the results of the validation data in batteries B0005 and B0006, better results were obtained in battery B0018, and worse results were obtained in battery B0007 compared to the validation data. As a result, it is predicted that artificial neural networks will remain popular today and will increase soon with the increasing use of artificial neural networks in predicting battery capacity status and the number of stored data positively affecting the performance of artificial neural networks.

In comparing the experiment results with the literature review on battery capacity estimation using artificial neural networks, several similarities and differences are observed. Firstly, recurrent neural network architectures, specifically RNN, LSTM, and GRU, were utilized, aligning with existing research known for their efficacy in sequence modelling tasks. This choice reflects a common trend observed in the literature, where these architectures have been demonstrated to successfully capture temporal dynamics in battery data.

Similarly, the evaluation methodology, including the split of training and test data, mirrors practices adopted in several reviewed studies, ensuring adequate generalization and robust model assessment. Moreover, findings resonate with prior research, showcasing GRU as the most successful model in terms of performance, consistent with the observed competitive performance of GRU in battery capacity prediction tasks. However, nuances not extensively explored in the literature are highlighted, such as variations in model performance across different battery datasets. While results show comparable performance to the literature in certain datasets, discrepancies are noted, particularly in battery B0007, indicating potential challenges in generalizing model performance across diverse battery types.

Overall, valuable insights are contributed by the experiment by reaffirming the efficacy of recurrent neural network architectures in battery capacity estimation while also shedding light on the need for further investigation into the generalizability of these models across varying battery characteristics. For future investigation, it is recommended to explore Transfer learning methodologies in ANN, which could potentially enhance model generalization across various battery datasets.

Researchers' Contribution Rate Statement

Prof. Dr. Musa Aydin: Research design, creation of theoretical framework.

Assoc. Prof. Dr. Hasan Sahin: Critical review.

Ms. Student Ismail Kılıç: Data collection, data analysis, literature review, text writing, and visualization of results.

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