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Estimating the Impact of Temperature on the Thermal Resistance of a Lithium-ion Battery Using a Combination of the Finite Difference Method and Neural Networks

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ESTIMATING THE IMPACT OF TEMPERATURE ON THE THERMAL RESISTANCE OF A LITHIUM-ION BATTERY USING A COMBINATION OF THE FINITE DIFFERENCE METHOD AND NEURAL NETWORKS

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Abstract

This article focuses on the sustainable development of electric vehicle equipment to ensure the safety of people and property. It contributes to improving the thermal management of lithium-ion batteries in order to slow down wear and tear, increase battery life, range, and performance. The objective of this work is to evaluate the impact of temperature increase on the thermal resistance of lithium-ion battery cells during charging. To this end, an experimental study was conducted to determine the thermal power generated during battery charging using a methodology based on Joule's law. The combination of the finite difference method and neural networks was used to estimate the temperature increase and thermal resistance. The correlation coefficient, with a value of approximately 0.72 and the mean square error, with a value of approximately 0.41 across all test data, are performance indicators that demonstrate the high accuracy of the combined finite difference-neural network model. The thermal power generated and the initial temperature were used as input data for the model. The results showed that an increase in initial temperature has an influence on the thermal resistance of lithium-ion battery cells.

Keywords: Temperature; thermal resistance; batteries; lithium-ion; neural network; finite difference

Introduction

With technological advances in several industrial sectors, a number of countries are contributing increasingly to the growth in global energy capacity. This is particularly true of China and the United States, which invested approximately $103 billion and $44.1 billion respectively in their energy capacity in 2015 (UNEP, 2015). Within

this investment, optimizing the performance and autonomy of new sources of electrical energy that emit less carbon dioxide (CO2) is becoming increasingly important in several industrial sectors, particularly in the automotive sector today. Among these energy sources are lithium-ion batteries, which have become major players in the energy transition due to their high energy density and long life, representing approximately 200 to 300 charge and discharge cycles (EFFIS, 2025). However, these batteries are very sensitive to heat and raise real concerns about fire safety, particularly due to their high combustion potential. In 2024, Europe recorded a 34% increase in fires involving electric vehicles (EFFIS, 2025). In Cameroon, some vehicle fire risks are linked to battery installations that have deteriorated due to heat and humidity (Ahmidou, 2025; CarCameroun, 2024). During charging, batteries are subjected to several stresses. Among these, thermal stress is the most recognized cause of progressive deterioration of internal resistance (Riadh, 2018). It is therefore important to know the lifespan of a lithium-ion battery when it is subjected to thermal stress. The loss of the insulating properties of the plates in a battery can result in a sudden increase in temperature, which can lead to thermal runaway and fire. Several studies have been conducted in the literature to find solutions to the deterioration of electrical equipment. This is the case of Zhao et al. (2009), who worked on the development of an artificial neural network (ANN) for the monitoring and diagnosis of capacitive equipment. The network was able to predict the dielectric loss angle based on input parameters such as voltage, current, capacitance, temperature, and humidity, but the results obtained were not accurate enough. Shpreker et al. (2019) proposed a recurrent neural network (RNN) to predict the insulation resistance of electrical equipment, enabling early detection of damage by taking into account external factors such as humidity and air temperature. However, the results obtained by the model still contained errors. Gulrukh et al. (2020) conducted research on the role of neural networks in estimating the impact of thermal stress on the progressive deterioration of insulation. Analysis of the results showed a time saving of 1,680 hours when the thermal lifetime of the insulating material is predicted using ANNs. Wallscheid et al. (2021) worked on monitoring the temperature of electric motors during operation using supervised machine learning, and the results obtained were quite significant. Zhang et al. (2025) conducted research on the influence of thermal aging on the service life of electrical machine insulation systems using physics-of-failure (POF) models. The results obtained provided an in-depth understanding of the degradation mechanisms in order to predict service life. However, this model does not take all parameters into account. In this article, the previous models were replaced by the combined finite difference method-artificial neural network (FDM-ANN) model. The latter is an artificial intelligence model that can model temperature diffusion in space and the evolution of thermal resistance over time, taking into account the terms of diffusion, accumulation, and the source term.

The objective of this work is to evaluate the impact of temperature increase on the thermal resistance of lithium-ion battery cells during charging.

The results of this work contribute to improving the thermal management of lithium-ion batteries in order to slow down wear and tear, increase their lifespan, range, and performance. The results also help prevent the risks of electrolyte evaporation and thermal runaway.

Materials and methods

Experimental

The experimental study was conducted daily between January 2022 and December 2025 at the Energy, Electrical and Electronic Systems Laboratory of the University of Yaoundé I, using a MASTERVOLT lithium-ion battery (Fig. 1), which is widely used in Cameroon due to its very high energy density. This lithium-ion battery is characterized by thermal conductivity λ =84.7W.m^{-1}.K^{-1}; a density ρ = 20 kg.m^{-3} and a specific heat C = 3582J.kg^{-1}.K^{-1}. Each cell consists of: a collector; active materials; electrodes; an electrolyser; lithium ions; and a separator. This lithium-ion battery has a lifespan of approximately 3 years when used regularly on a daily basis within an optimal range of 288 to 308 K.

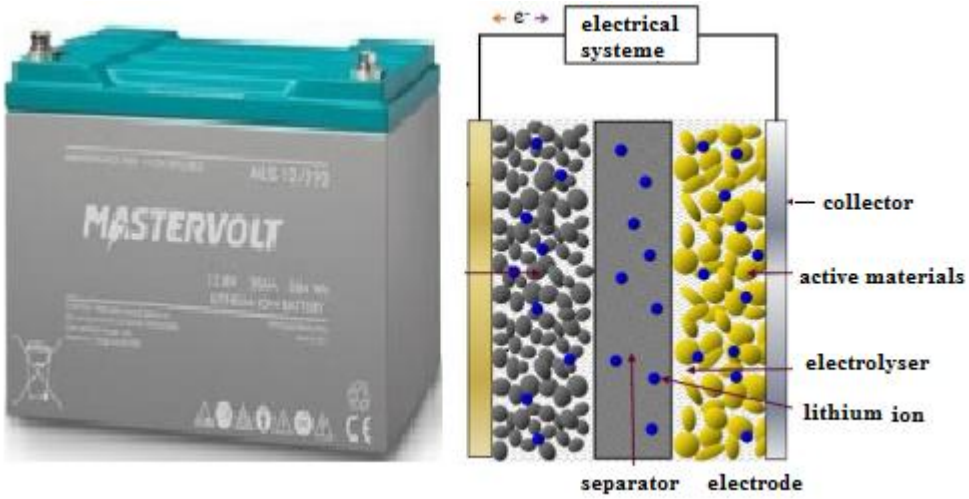


Fig.1 Lithium-ion battery

To conduct this experiment, a device consisting of: a 12.3 V lithium-ion battery with a capacity of 30 Ah, whose positive cable is connected to the starter motor; a voltage regulator connected between the alternator and the battery; an alternator with a maximum voltage of 14.6 V and a current of 100 A, which generates the electricity needed to recharge the lithium-ion battery; a digital multimeter to measure the voltage at the battery terminals; a temperature sensor placed on the surface of the battery to measure its internal temperature; and a motor to rotate the alternator. During this experimental study, two tests were carried out. First, a multimeter was used to test the lithium-ion battery at rest, and the voltage at its terminals was 12.3V, indicating that the lithium-ion battery was in good condition. Then a second test was performed by turning on the motor. Figure 2 shows the curve of the voltage at the terminals of the lithium-ion battery as a function of time. This figure shows that during the charging of the lithium-ion battery when t=0s, the voltage goes from a value of U=12.3V and increases rapidly to reach approximately U=13.8V after t=2400s. This voltage then increases slowly until it reaches approximately U=14.4V at t=3600s. This rapid increase in voltage at the start of charging is due to an increase in the motor speed, which can cause the lithium battery cells to overheat.

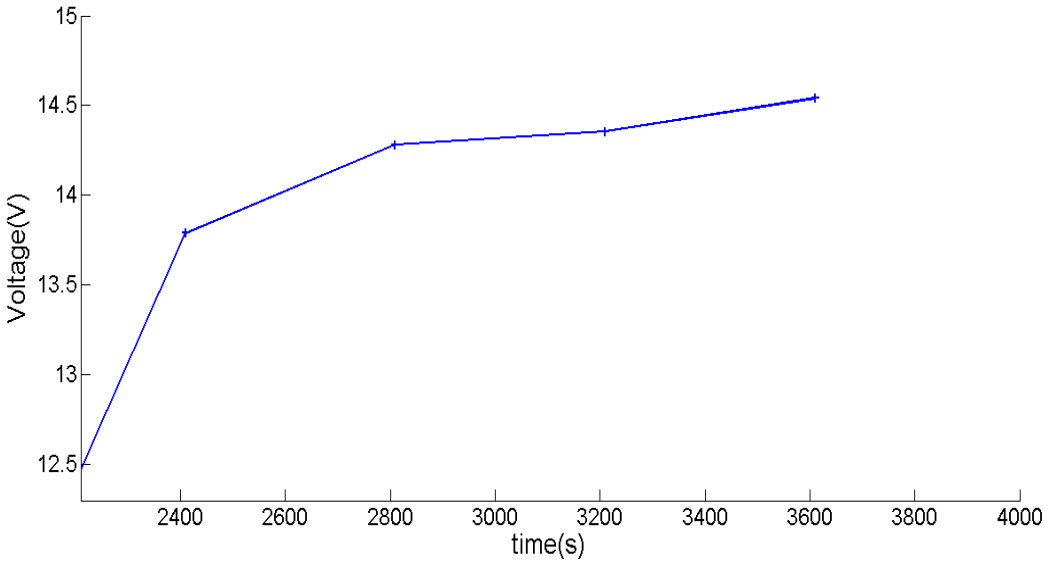


Fig.2 Voltage evolution over time

During the experiment, the temperature sensor placed on the lithium-ion battery detected a gradual increase in temperature from 298 K to 318 K, due to the medium's ability to resist electrical charge transfer. The thermal power generated was determined using Joule's law :

$$P_{th} = U \times I \quad (1)$$

P_{th} : Thermal power generated (W)

U : Charge voltage (V)

I : Current supplied (A)

This generated thermal power is distributed throughout the lithium-ion battery, hence the relationship:

$$R_{th} = \frac{\Delta T}{P_{th}} \quad (2)$$

R_{th} : Thermal resistance (m^2. K. W^{-1})

ΔT : Temperature increase (K)

Using Fourier's law, it was possible to write the equation for transient heat diffusion (3).

$$\frac{\partial T}{\partial t} - \alpha \frac{\partial^2 T}{\partial x^2} - \alpha \frac{\partial^2 T}{\partial y^2} = P_{th} \quad (3)$$

$$\alpha = \frac{\lambda}{\rho \times C} \quad (4)$$

$\frac{\partial T}{\partial t}$ represents the accumulation terms; $\alpha \frac{\partial^2 T}{\partial x^2}$ et $\alpha \frac{\partial^2 T}{\partial y^2}$ represents the diffusive terms; P_{th} represents the thermal power generated (W) ; α represents the thermal diffusivity of the lithium-ion battery; λ represents the thermal conductivity ($W.m^{-1}.K^{-1}$) ; ρ represents the density ($kg.m^{-3}$) ; C represents the specific heat capacity ($J.kg^{-1}.K^{-1}$).

Presentation of Combination of the FDM-ANN

The finite difference method (FDM) is an approximation method that consists of replacing the derivatives of differential equations with their limited Taylor series expansion approximation to obtain a discretized equation (Kewalee et al. 2018; Konglook et al. 2016; Goncalvès 2011). The finite difference method allows the terms of the heat diffusion equation to be approximated using a time-progressive and spatially-centered discretization scheme (Thongmoon et al. 2008). The discretized heat diffusion equation (5) est :

$$\frac{T_{i,j}^{n+1} - T_{i,j}^{n}}{\Delta t} - \alpha \frac{T_{i+1,j}^{n} - 2T_{i,j}^{n} + T_{i-1,j}^{n}}{\Delta x^2} - \alpha \frac{T_{i,j+1}^{n} - 2T_{i,j}^{n} + T_{i,j-1}^{n}}{\Delta y^2} = P_{th} \quad (5)$$

In this article, the surface of one of the cells of the square lithium-ion battery (250 mm × 250 mm) representing the study area is subdivided into elementary areas connected by nodes on which the unknown temperatures are

sought $T^n_{i-1,j}$, $T^n_{i,j-1}$, $T^n_{i,j}$, $T^n_{i+1,j}$ et $T^n_{i,j+1}$ in space based on the initial conditions (Fig. 3). The discretized heat diffusion equation solved is used as an input variable for ANNs.

The artificial neural network (ANN) is a black box consisting of an input layer, several hidden layers, and an output layer (Fig.3). Each hidden layer consists of several neurons that use sigmoid functions to transform the discretised input data into numerical output variables (Gulrukh et al. 2020; Pelliccionia et al.2006). In this study, one input layer, two hidden layers and one output layer were used to design the ANN architecture. Each neuron in the hidden layer consists of a sigmoid activation function, and the output neuron consists of a linear function. The sample size {20,20} was used to create two subsets, including the stop set, which allows data learning to be interrupted in the event of overfitting of a ANN. Après discrétisation des termes de diffusifs, puis détermination de la puissance thermique générée et de la diffusivité thermique ; une normalisation des variables d'entrée est par suite effectuée avant d'être introduit dans le modèle pour calculer la température de la batterie de lithium-ion $T^{n+1}_{i,j}$. After calculating the temperature, when the difference between the estimated value and the experimentally measured value is large, the learning process adjusts the input parameters so that the error at the neuron's output is as small as possible. The correct selection of input variables and parameters influencing temperature estimation is crucial for better data learning. The ANN is used to optimise the estimation of the value of the temperature $T^{n+1}_{i,j}$ (Fig.3). To estimate this temperature, The discretized heat diffusion equation is solved, then fed into neural networks to be transcribed and programmed, in order to have at the output layer the predicted temperature.

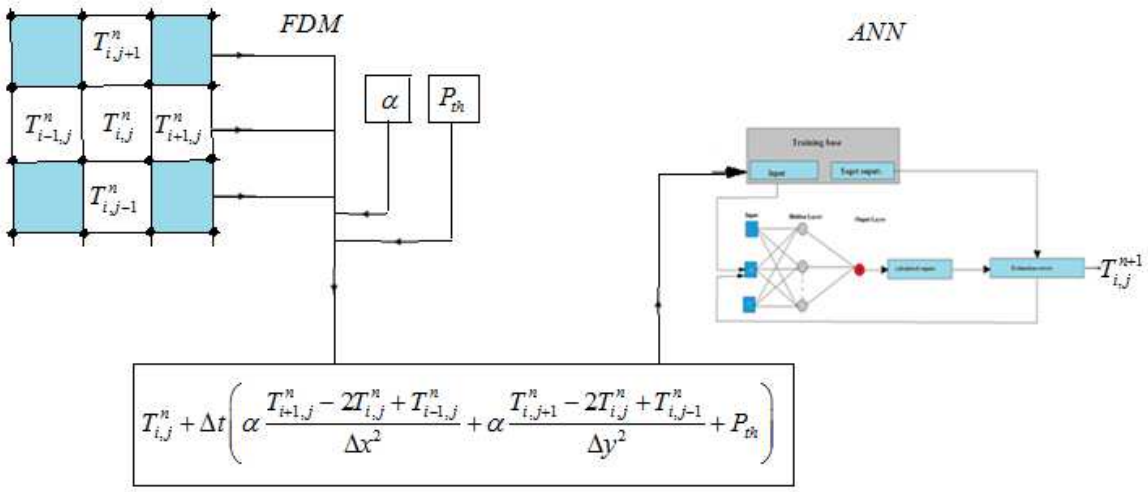


Fig.3 Combination of the FDM-ANN

Results and discussion

Performance of the FDM-ANN

In this study during data learning, the quality of the ANN is evaluated on the test dataset using performance indicators such as squared correlation coefficient (R^2) and root mean square error (RMSE). Figure 4 shows that most of the temperature values are closely aligned with the Y=T fit line, with R^2 values of around 0.72 for the test case and around 0.99 for the learned case. Figure 4 shows the evolution of the mean square error (MSE) as a function of the number of iterations. It can be seen from this figure that the MSE decreases with an increasing number of iterations, and the best MSE value on the test data set is around 0.41. These performance indicators collectively demonstrate the excellent performance of ANN on test data, in line with the findings of (Ferhat et al.2006) and (Rongxiao et al. 2018) in their work. Therefore, ANN demonstrates high accuracy in water content estimation.

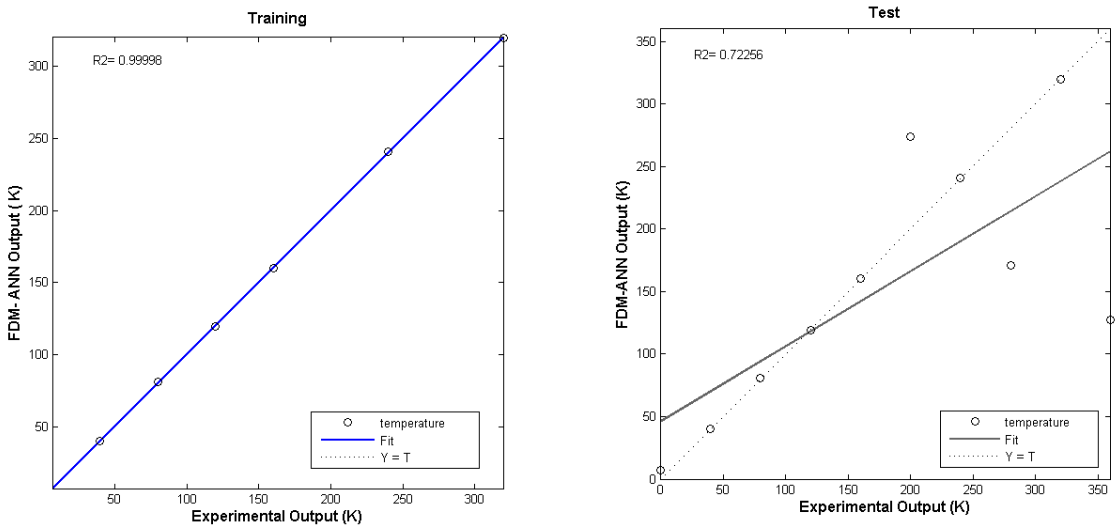


Fig. 4 FDM-ANN prediction results on learning and testing

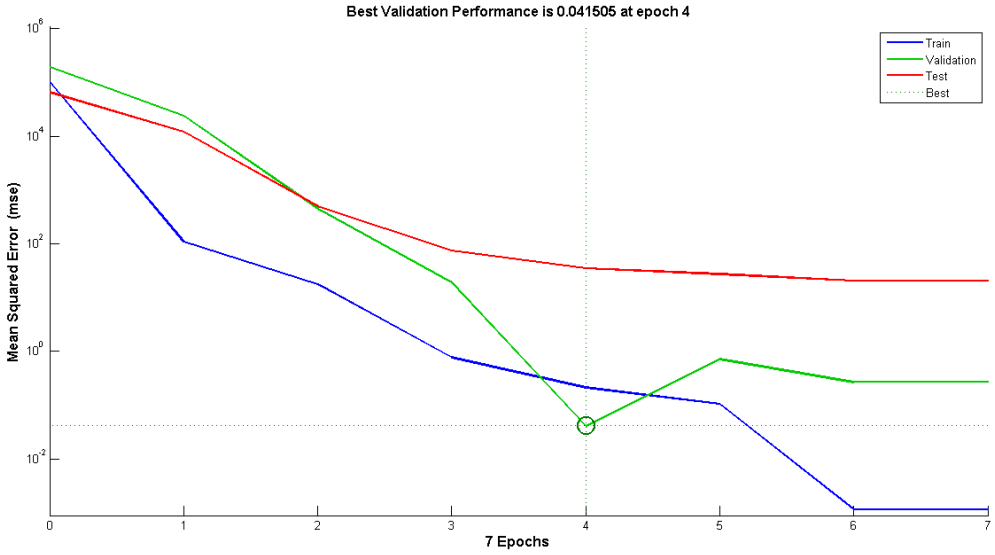


Fig.5 The MSE of the FDM-ANN

Figures 6 and 7 show the 2D and 3D temperature distribution on a lithium-ion battery cell (250 mm × 250 mm). The figure shows colors ranging from red to blue, passing through yellow and green. The red color indicates a high temperature of approximately 318K at the center of the battery cell, while the yellow and green colors indicate a low temperature spreading toward the cold surface of the cell. This increase in temperature at the center of the cell is due to the increase in power generated in the lithium-ion battery. This can lead to a loss of thermal resistance in the lithium-ion battery cells.

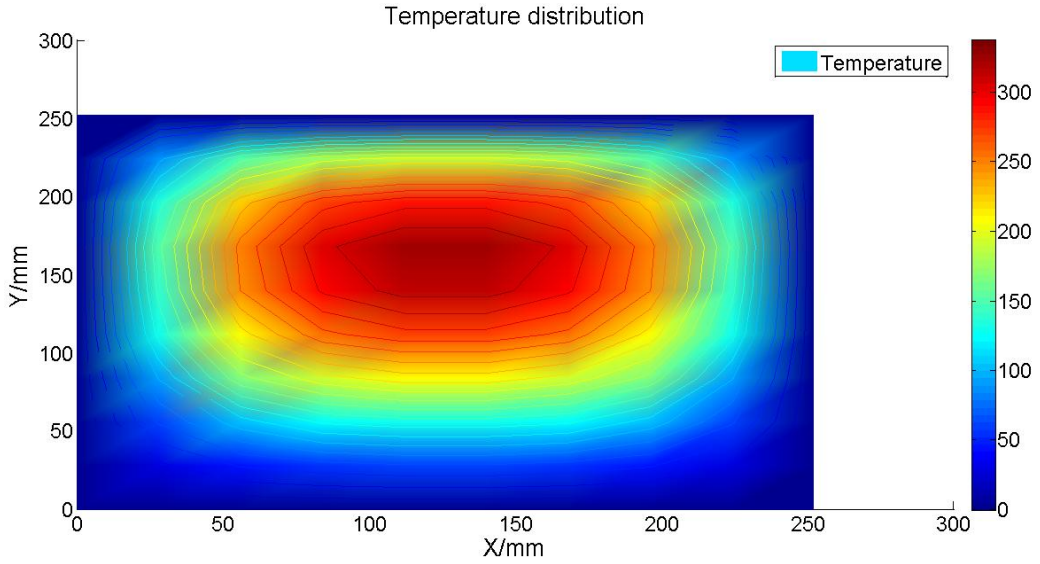


Fig.6 2D temperature distribution in a lithium-ion battery cell based on a combination of FDM and ANNs

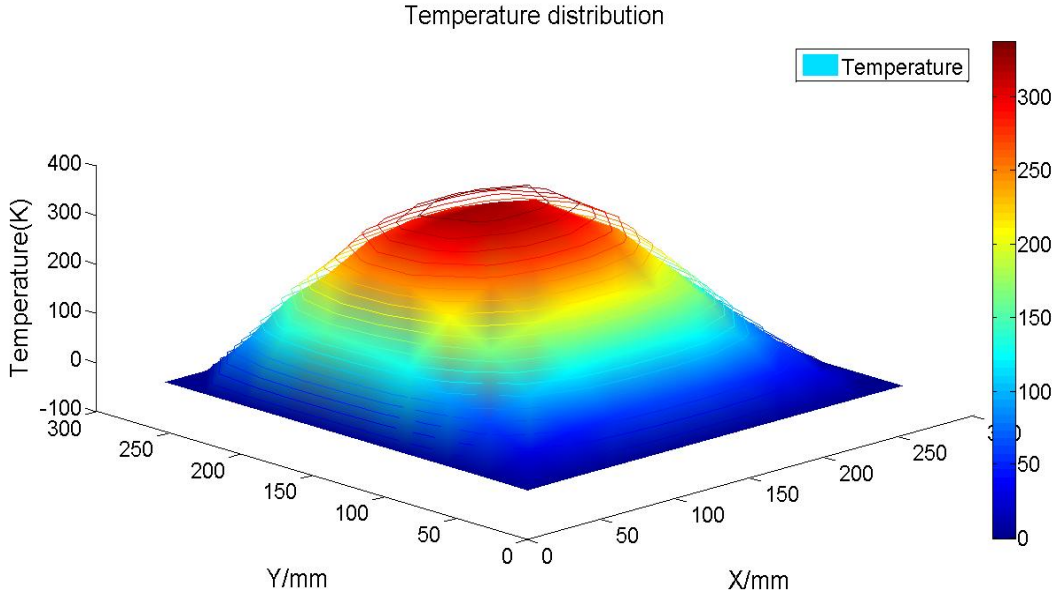


Fig.7 3D temperature distribution in a lithium-ion battery cell based on a combination of FDM and ANNs

Figure 8 shows a comparison of the evolution of thermal resistance over time for the CFD model, the FDM-ANNs model, and the experimental model. The figure shows that the CFD and FDM-ANNs models underestimate certain thermal resistance values beyond approximately 180 days. However, compared to the

thermal resistance values obtained experimentally, the FDM-ANNs model is more accurate than the CFD model.

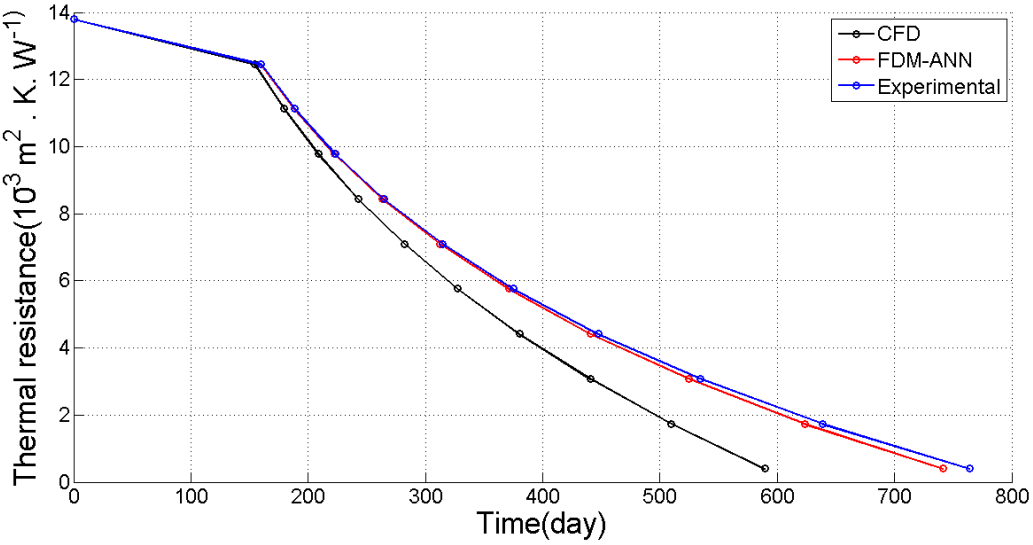


Fig.8 Comparison between the FDM-ANNs and CFD models

The curve (Fig. 9) shows the evolution of thermal resistance as a function of time and temperature. We observe that for different temperature values. When the temperature T= 318K, the thermal resistance ranges from a maximum value of approximately Rth= 13.8×10-3 m2.K.W-1 and gradually decreases to a value of approximately Rth= 0.2×10-3 m2.K.W-1 after a time t=399 days. When the temperature T= 316K, the thermal resistance ranges from a maximum value of approximately Rth= 13.8×10-3 m2.K.W-1, gradually decreasing to a value of approximately Rth= 0.2×10-3 m2.K.W-1 after a time t=599 days. When the temperature T= 305K, the thermal resistance ranges from a maximum value of approximately Rth= 13.8×10-3 m2.K.W-1 and gradually decreases to a value of approximately Rth= 0.2×10-3 m2.K.W-1 after a time t=780 days. We can see that temperature has an influence on the reduction in thermal resistance of the lithium-ion battery because, when the temperature is high, the thermal resistance decreases rapidly over time, and when the temperature is low, the thermal resistance decreases slowly over time. This sharp increase in temperature may be due to rapid charging of the lithium-ion battery afterwards. This decrease in the thermal resistance of the cells can lead to degradation of the plates, decomposition of the envelope separator, accelerated self-discharge, and reduced lithium-ion battery life.

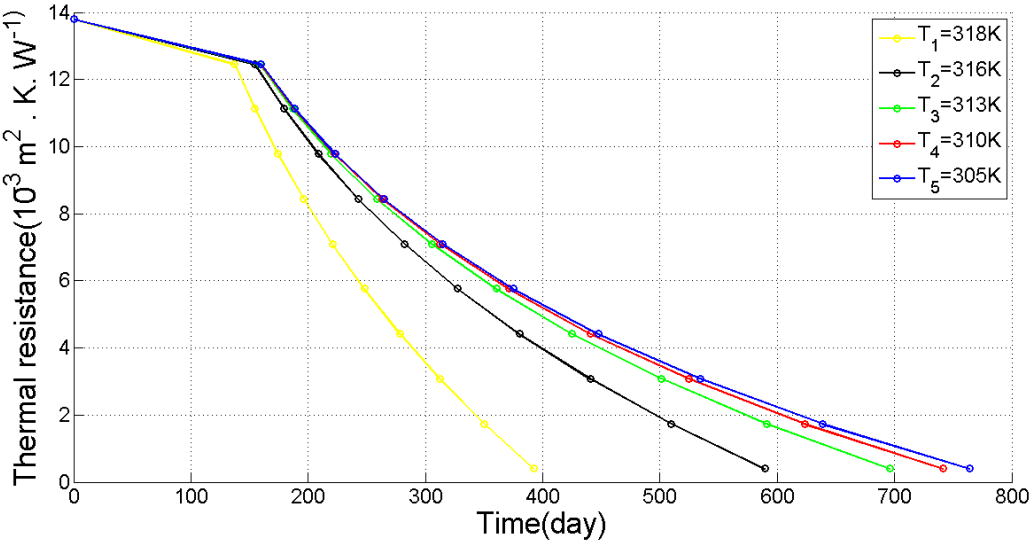


Fig.9 Evolution of thermal resistance as a function of time and temperature based on FDM-ANNs combination

Conclusion

This article estimates the effect of temperature increase on the thermal resistance of lithium-ion battery cells using the combined FDM-ANNs model. To do this, a scientific approach was taken, based on three methods. First, an experimental study was carried out at the energy, electrical and electronic systems laboratory to determine the thermal power generated using Joule's law. The performance of the model was then evaluated taking into account performance indicators such as the coefficient of determination and the mean square error. Finally, the combined FDM-ANNs model was used to model the evolution of temperature and thermal resistance inside the lithium-ion battery as a function of time and space. The results showed that the values obtained for the correlation coefficient square of approximately 0.41 and the mean square error of approximately 0.72 across all test data indicate a high degree of accuracy for the combined FDM-ANNs model. Modeling the evolution of temperature and thermal resistance as a function of time and space in the lithium-ion battery showed the influence of temperature on the reduction of the thermal resistance of lithium-ion battery cells and, consequently, on their lifespan. While the vehicle's engine is running, it is recommended to avoid ultra-fast recharging, to install a temperature sensor that signals in case of abnormal temperature rise, and to use a ventilation system on the lithium-ion battery to dissipate heat, which could help maintain the optimal range of 288 to 308 K.. These results represent a potential opportunity, as they could enable the automotive sector to make accurate and rapid decisions to improve the lifespan of lithium-ion batteries and prevent thermal runaway, which can lead to fire. However, this model has limitations because it underestimates certain thermal resistance values. It will be important to look to other models such as Random Forests.

Acronyms and Abbreviations

FDM: finite difference method

ANNs: neural networks

MSE: mean square error

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Declarations

Ethics approval All authors have read, understood and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors

Ethics approval Not applicable

Consent to participate Not applicable

Consent to publish Not applicable

Author’s Contributions:

Goune Achille Clovice was involved in the conceptualisation, data collection, methodology, interpretation of the data and writing of the article. **Essombo Essombo Bathelemy** was responsible for revising, editing and writing the article. **Seutche Jean Calvin** was responsible for revising, editing and writing the article. **Bangoup Ntegmi Ghislain Junior** participated in the revision of the article. **Nsouandele Jean Luc** was responsible for supervising, examining, organising and interpreting the data. **Ben-Bolie Germain Hubert** was responsible for supervising, examining, organising and interpreting the data.

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Conflict of interest

The authors declare no competing interests.

Consent to publication

All authors agree with the content of the submission and have given their consent to the submission.

Competing interests

The authors declare that they have no known competing interests whatsoever or personal relationships that could have appeared to influence the work reported in this paper.

PROVIDE THE DATA AVAILABILITY STATEMENT

The data used to support the conclusions of this study are available on the zonodo accredited website from the link below

A. C. Goune, J. C. Seutche*, & J. L. Nsouandele. (2023), (2024), (2025). Database of (2019-2020-2021-2022-2023) (Microsoft office Excel) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.6948521

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