Work in Progress. Outcomes of the Project: ”Developing an AI application for EVs’ thermal management of the battery system” on an ”Engineering for Sustainable Development” technical elective course.

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Abstract.

In this work-in-progress paper, the authors present the outcomes of the project, "Developing an AI application for electric vehicles (EVs) thermal management of the battery system," in an Engineering for Sustainable Development technical elective course. The authors realized that the world is becoming unsustainable primarily due to the misuse of technology. In this context, the project's objective will be defined upon completion of the Engineering for Sustainable Development course, which is offered to upper-level engineering students across all majors. The engineering technical elective course was established in the curricula of a major university in the southwest following rigorous, multi-year pedagogical research published by the authors in previous years. The mathematical model for the thermal management system is derived within the scope of circular designs for circular economies, as outlined in the course Engineering for Sustainable Development. The energy and momentum equations, along with the conservation of mass, are then used. In this approach, each equation is simplified to the specific problem at hand. A thorough instructor-led literature review led to the provision of specific, up-to-date thermal management system models to students, thereby facilitating the development of the control system algorithm. Incorporating artificial intelligence training into EV battery operation, using data from literature as a baseline and then from Simulink, yielded an incipient yet robust model that exposes engineering students to the complexity of artificial intelligence applied to sustainable engineering designs. Notably, following completion of the course and project, a survey of participating students revealed positive feedback, indicating enthusiasm for the project and underscoring the success of applying an innovative combination of pedagogical techniques in the Engineering for Sustainable Development technical elective course.

Introduction.

This paper examines the outcomes of applying problem-based learning techniques to integrate fundamental machine learning concepts into the complex, multidisciplinary sustainable design problem of thermal management systems for electric vehicle batteries.

As defined by the National Academy of Engineering (NAE), Engineering creates and advances technology to address human needs by applying principles from the sciences, mathematics, computing, and operations research. [1]. However, it is fair to state that "The world is becoming unsustainable mainly because of the misuse of technology." This makes it imperative to train engineering students with a sustainable development mindset to develop new technologies that balance societal needs, the circular economy, and environmental protection.

Given the need to develop sustainability skills in engineering programs, engineering educators often encounter dense, established technical curricula and struggle to integrate new concepts in sustainability and engineering for sustainable development. Additionally, the advent of AI tools has prompted a renewed review of teaching and learning to support their adoption [2].

As a viable alternative to the complexity of the project's multidisciplinary approach and to the implementation of these new concepts, the authors endorse active, integrated, and practice-based methodologies [3], [4], [5], which complemented with Problem-based learning, would potentially promote interdisciplinary thinking, teamwork, and, importantly, the application of contextualized knowledge by the participating students [6].

At a large university in the southwest, the course Engineering for Sustainable Development has been adopted as a general elective in the undergraduate engineering curriculum [7]. The course syllabus includes a project design assignment that consolidates content on AI-based engineering design, sustainability, and the circular economy through a tangible application. The selected project title is "AI-based thermal management systems for electric vehicles (EV) batteries."

To solve this complex problem, the energy and momentum equations, along with the conservation of mass, are used to develop a mathematical model. In this approach, each equation is simplified to the problem's specifics. A thorough instructor-led literature review provided details on the control system algorithm, including artificial intelligence training based on operating data from EV batteries [8]. [9], [10]. Students were informed that the AI-based thermal management system will be an integral component of the EV battery system's digital twin [11].

Project description.

Electric vehicle batteries operate under dynamic thermal conditions with temperatures from -20°C to 45°C during normal operation. The thermal variations combined with aging effects create complex patterns that influence both normal performance and long-term degradation. The challenge lies in developing predictive thermal management systems that can anticipate the temperature changes across multiple time scales while at the same time accounting for cell-to-cell variations and degradation states [12]

The design methodology combines a mathematical battery model with a Long Short-Term Memory (LSTM) neural network, enabling Artificial Intelligence to predict potential runaway thermal events. This hybrid system integrates an electrothermal coupling model that accounts for internal temperature, state of charge (SOC), and the mathematical-equivalent circuit parameter. The LSTM network is trained on real-time voltage, current, and surface temperature data, obtained from the literature for our application. Further development will require a physical test bank or data collected from an electric vehicle (EV) in operation, as this methodology relies on temperature trends. A diagnostic module would analyze these predictions to issue early warnings. This early-stage project stops at the stage where the data are evaluated for accuracy in predicting potential-temperature runaways. This hybrid prediction model is unique in its ability to provide improved accuracy and early anomaly detection using only readily available sensor data, making it particularly suitable for real-time applications in commercial EV battery management systems [13].

Mathematical model.

We will assume that the battery pack's structure is optimized and that a reciprocating airflow system is employed for efficient cooling, thereby reducing energy consumption. The intelligent cooling method based on fuzzy model predictive control (FMPC) dynamically adjusts the cooling intensity. The Takagi-Sugeno Fuzzy Model is used to linearize the battery model by piecewise linear interpolation [12].

For the coupled Electric Circuit Model (ECM) and the Thermal Model, based on the initial condition (State of Charge, SOC) and temperature, the ECM parameters will be generated by the designed Mamdani Fuzzy Model. Then, the ECM outputs the SOC and the parameters required by the thermal model. Finally, the thermal model calculates the battery temperature through energy balance [13].

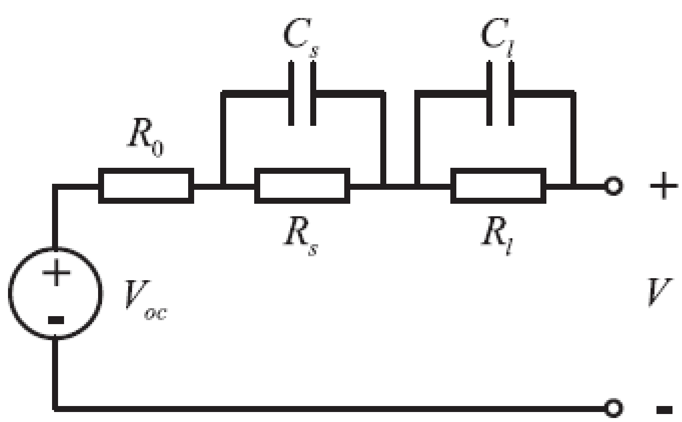

Figure 1. The 2nd-order RC equivalent circuit model. [12].

The ECM shown in Fig. 1 is governed by the following equations [15]:

$$SOC = I/Q_0 \tag{1}$$

$$U_s = -\frac{1}{R_S C_S} U_s + \frac{I}{C_S} \tag{2}$$

$$U_l = -\frac{1}{R_l C_l} U_l + \frac{I}{C_l} \tag{3}$$

In Eq. (1), Eq. (2), and Eq. (3), $U_s$and U_l, R_s and R_l, Cs and Cl represent the voltages, equivalent resistance, and equivalent capacitances of two RC loops in the second-order RC equivalent circuit model, respectively. According to Kirchhoff's law of voltage, solving for have [16]:

$$Voc = V + IR_0 + U_s + U_s \tag{4}$$

Additionally, the thermal model of the battery is described by an energy balance between heat generation and dissipation:

$$M_{bat}C_{bat}\,T = I(V_{oc} - V) + \ IT\,\frac{DV}{DT} - hs(T - T_{in}) \quad (5)$$

In Eq. (5), $\frac{DV}{DT}$ is the temperature coefficient. The first item on the right side of Eq. (5) represents the irreversible heat generation rate of equivalent ohmic resistance and two RC loop circuits. To validate the battery numerical model, the thermal response of a single cell is measured using an experimental system, yielding results consistent with those from a similar cooling configuration.

For the cooling system, energy consumption is positively related to the air velocity required to keep the battery temperature near the reference temperature, thereby reducing energy consumption.

Design method.

The battery model was calibrated in Simulink to account for temperature and State of Charge (SOC) variations using an RC pair.

An equivalent-circuit battery model was implemented in Simulink, and the block modeling was completed. During battery discharge, a positive voltage (+V) decreases current; consequently, the State of Charge (SOC) should decrease, and vice versa.

By maintaining a current of 0 A while varying the temperature, the battery voltage changes according to the specified parameters.

As part of the practical circuit, we utilized a 3-phase power supply and rectified the voltage using a 3-phase uncontrolled rectifier.

The output voltage from this setup was DC (264V) with minimal ripple

The buck converter was connected to the rectifier output and to a control voltage source at the buck converter load. Current from the load is supplied to the battery, and the battery's output voltage is then applied to the control voltage source.

To monitor temperature changes, students applied a step input at 1-second intervals to account for variations in the battery's RC parameters. The battery voltage is used as a reference, and a closed-loop control system is implemented for the buck converter.

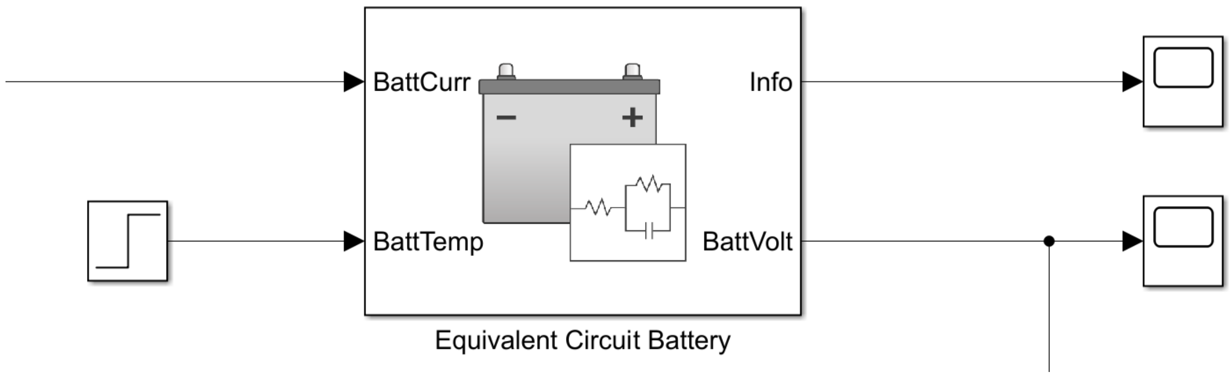

Figure 2. Equivalent circuit battery components.

Core Battery parameters

The equivalent circuit battery (mask) (link) implements a resistor-capacitor circuit for the battery, parametrized using an Equivalent Circuit Model (ECM). To simulate the State of Charge (SOC) and the terminal voltage in Simulink, the block uses a load current and an internal core temperature, calculates the combined network battery voltage using lookup tables that are functions of the SOC and battery temperature, use the estimated circuit battery block to help create the lookup tables.

Block options:

Initial battery capacitance. Parameter

Output battery voltage: Unfiltered

Core battery parameters: R and C table data. Cell limits

Number of series RC pairs: 2

Open circuit voltage data, Em [V]	360; 359 358; 357	360; 359 358; 357	360; 359 358; 357	360; 359 358; 357	360; 359 358; 357
Series Resistance Data Ro [Ohm]	0.0975;0.0929 0.0532;0.0337	0.0913;0.0681 0.0454;0.0304	0.0825;0.0526 0.0364;0.0277	0.0744;0.0568 0.0374;0.0276	0.1113;0.0705 0.0505;0.311
State of charge breakpoints SOC_BP[]	0.1	0.2	0.5	0.8	0.9
Temperature breakpoints Temperature_BP[K]	273.15	283.15	298.15	318.15	

Battery Capacity BattCap [Ah]	28	28	28	28	
Initial Battery Capaciy BattCapInit [Ah]	28				
Initial Capacitor Voltage, InitCapVoltage [V]	0	0			

Table 1. Core battery parameters: R and C table data. Cell limits. Number of series RC pairs: 2

2nd Order RC parameters used:

Equivalent circuit battery (mask) (link)

Implements a resistor-capacitor (RC) circuit that can be parameterized using an equivalent circuit model (ECM). To simulate the state of charge (SOC) and terminal voltage. The block uses load current and internal core temperature to calculate the combined network battery voltage, looking up tables that are functions of SOC and battery temperature. Use the Estimations on the Equivalent Circuit Battery block to help create the lookup tables.

Block options:

Initial battery capacity: Parameter

Output battery voltage: Unfiltered

Network Resistances Data R1 [Ohms]	0.0825	0.0238	0.0270	0.0019	0.0734	0.0189	0.0019	0.0006	0.0100	0.0090
	0.0010	0.0680	0.00810	0.0017	0.0005	0.0004	0.0250	0.0074	0.0005	0.000024
Network Capacitances Data [F]	13.33	54.62	25.93	421.05	12.96	42.33	421.05	1333.33	89.11	1000.00
	8000.00	1176.47	111.11	588.24	1800.00	2250.00	47.43	121.62	1800.00	37037.04
Network Resistances Data R2 [Ohms]	0.0092	0.0067	0.0019	0.0009	0.0018	0.0013	0.0011	0.0008	0.0014	0.0002
	0.0008	0.0006	0.0016	0.0015	0.0009	0.0008	0.0026	0.0088	0.0015	0.0010
Network Capacitances Data C2 [F]	1097.83	1567.16	6578.95	14000.00	6777.78	9153.85	11636.36	13750.00	8000.00	64500.00
	17625.00	21166.67	9625.00	8000.00	14333.33	14555.56	4115.38	1352.27	7000.00	11200.00

Table 2. Core battery parameters: R and C table of data, Cell limits.

The built-in PID tuner in Simulink, shown in Figure 3, cannot linearize the circuit; therefore, circuit tuning is necessary.

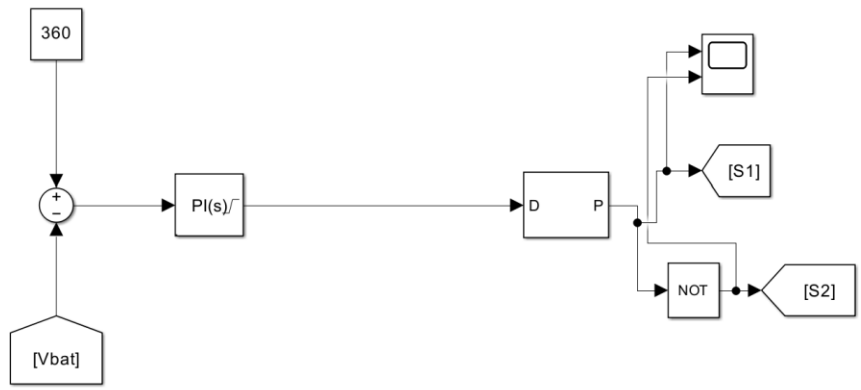

Figure 3. PID tuner from Simulink

By analyzing the transfer functions of converters and the battery, a manual trial-and-error tuning approach can be employed.

At this point, a Long Short-Term Memory (LSTM) neural network enables Artificial Intelligence to predict potential thermal runaway events. The objective of the AI application is to assess the accuracy of the input data to establish repeatability in the control system, thereby eliminating the need for trial-and-error techniques. Future work will need real-time data collected from EV operations.

Artificial Intelligence.

A Long Short-Term Memory (LSTM) neural network, which is used in artificial intelligence, is then employed to predict potential temperature runaway events [18]. The LSTM network is trained on real-time voltage, current, and surface-temperature data generated by Simulink simulations for our application. The Simulink outputs were cross-checked against data from the literature, which was itself validated using an experimental setup [15]. Further development will require data collected from an electric vehicle (EV) in operation, as this methodology relies on temperature trends. Further, a diagnostic module would analyze these predictions to issue early warnings.

The real-time data used to train the AI scheme for open-circuit voltage, series resistance, and state of charge (SOC) are shown in Table 1.

AI Algorithm, numerical results, and conclusions.

The provided algorithm to students allowed them to focus their critical thinking on the project's complexity. At this stage, students consolidated the basic principles of the Electric Circuit Model (ECM) to the electric vehicle (EV) state of charge (SOC), and used Simulink to estimate the Equivalent Circuit Battery Block (ECBB) data, the critical parameter being the battery temperature of operation that must be kept within the safe recommended limits to avoid potential temperature runaway events. This is the data used to train the AI algorithm. The authors integrated pedagogical techniques to help students find a tangible solution.

```
# Training an AI model with data in Python involves several key
steps, generally following a machine learning pipeline
must
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Load the Drive helper and mount
from google.colab import drive

# Prompt for Authorization
drive.mount('/content/drive', force_remount=True)
!ls drive/MyDrive/temp.csv
df_raw = pd.read_csv('drive/MyDrive/temp.csv')

df_raw.info()
# Load the CSV made from the Simulink table data

# Parse the Simulink-style table strings into a flat dataset
# The columns in the strings correspond to Temperatures: [0, 10,
25, 45]
temp_breakpoints = [0, 10, 25, 45]
parsed_data = []

# Iterate through each row (which represents a specific SOC)
for index, row in df_raw.iterrows():
    soc = row['state of charge'] # I accidentally added a space
in the column name in the CSV oopsies :)

    # Convert space-separated strings to number lists
    r0_values = [float(x) for x in row['series resistance table
data'].strip().split()]
    ocv_values = [float(x) for x in row['open circuit voltage
table data'].strip().split()]

    # Match values to their temperature
    for i, temp in enumerate(temp_breakpoints):
```

```
        parsed_data.append({
            'Temperature': temp,
            'SOC': soc,
            'R0': r0_values[i],  # Series Resistance
            'OCV': ocv_values[i] # Open Circuit Voltage
        })

# Create the cleaned dataframe
data = pd.DataFrame(parsed_data)

# Separate features (X) and target variable (y)
# We use R0 and OCV because they are the only parameters in the
simulink table data (very weird)
X = data[['R0', 'OCV', 'SOC']]
y = data['Temperature']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# 2. Model Selection
model = RandomForestClassifier(n_estimators=100,
random_state=42)

# 3. Model Training
model.fit(X_train, y_train)

# 4. Model Evaluation
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print("Parsed Data Sample:")
print(data.head())
print("-" * 30)
print(f"Model Accuracy: {accuracy}")
print(f"Predicted Temperatures: {y_pred}")
print(f"Actual Temperatures:    {y_test.values}")
```

```
Parsed Data Sample:
Temperature  SOC      R0     OCV
```

```
0           0  0.1  0.0975  360.0
1          10  0.1  0.0929  359.0
2          25  0.1  0.0532  358.0
3          45  0.1  0.0337  357.0
4           0  0.2  0.0913  360.0
  -----------------------------

       Model Accuracy: 0.75

Predicted Temperatures: [ 0 10 45  0]
Actual Temperatures:    [ 0 10 45 10]
```

The AI model's accuracy is 75%, which is reasonable for a small dataset of only a few points. It could achieve higher accuracy by expanding the number of temperature points and more SOC values, as AI models struggle with small datasets.
It also evaluated whether the predicted temperatures would fall within the safety margins, set at 10 °C to 45 °C. This also resulted in 75% accuracy, due to the small dataset. Because the use of AI was intended to demonstrate its capabilities to students, no further attempts were made to improve the outcomes.

In conclusion, by employing the well-established pedagogical methodologies of active learning, student integration, and problem-based learning, as well as multidisciplinary critical thinking, the students were notably engaged with this complex multidisciplinary engineering topic, which would otherwise have been very challenging for an undergraduate audience. Multiple student comments indicate that the pedagogical approach resonated with their performance. "Our professor regularly interacted with us in class, and he always created a welcoming environment that encouraged us to ask questions. The research papers he shared for the project were excellent, and the discussion around them was very insightful. The course introduced us to industry-relevant tools like AI, enabling us to model electric vehicles' (EVs) thermal management systems effectively. The professor invested significant effort in integrating real-world aspects into the course, making our learning experience both practical and forward-looking. "

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