Title of Project: Neuro-fuzzy to estimate SOC in BMS

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Abstract

To avoid battery failure when operating, a BMS is used to monitor the battery parameters and protect it form overcharging and over-discharging. In this project a BMS was proposed using neuro-fuzzy logic to estimate the SOC of the battery. This BMS was designed using the knowledge acquired from literature. This circuit was simulated use TinkerCAD to test the software used for the overcharge and over-discharge protection system that is used in the Arduino to monitor the batteries. The results of the simulation were then compared with experimental results to confirm the results and to check that the parameter calculated by the Arduino concord with the values measured with a multimeter. The data acquired by the by the testing of the batteries was then used to train the neuro-fuzzy. The neuro-fuzzy estimated SOC values which were then compared with the calculated values to get an approximation of the accuracy of the model. In this case, the error range was 0.536. A two-input neuro-fuzzy was made by using the current and voltage data as the parameters instead of just voltage. The estimation of SOC values of this model were then compared with the values from the previous model to check the accuracy. The second model had an error of 0.592.

Introduction

Due to the increase in EV use, the demand for Lithium-ion batteries has increased since is the most common type of battery used for this type of application due to their low self discharge rate, high energy density, long life cycles, and high voltage of this type of batteries. One of best ways to increase the efficiency and sustainability of EV is by using BMS to protect and monitor the batteries. This is because it allows the batteries to have longer life cycles as the BMS allows them to operate in optimal state increasing the autonomy of the EV and reducing the amount of battery used per year as the cells will be operational for longer periods of time. SOC estimation allows one to achieve an approximation of the power left in the battery pack thereby allowing the EV to warn the user when to recharge. The user can go to the closest charging station with the remaining power. Therefore, SOC is essential for the increase in efficacy and sustainability of EV.

Result and Analysis

The results achieved in this project are shown in figure 4 to 7 and Table 1 and 2. Figure 4 shows the discharge curve of the voltage value. The correlation between the open circuit voltage and SOC is shown, this correlation is used to estimate the SOC using a neuro-fuzzy. Figure 5 shows the current values and how the error was reduced using exponential smoothening. Figure 6 and table 1 shows the estimated values of the neuro-fuzzy when using voltage and current as the input values to estimate SOC. Comparing these values with the calculated values SOC shows the accuracy of the model giving an average error of 0.592. In figure 7 and table 2 the values estimated by the neuro-fuzzy when using only voltage as the input is shown. Here, the values are also compared with the calculated values to show the accuracy of the model giving an average error of 0.536.

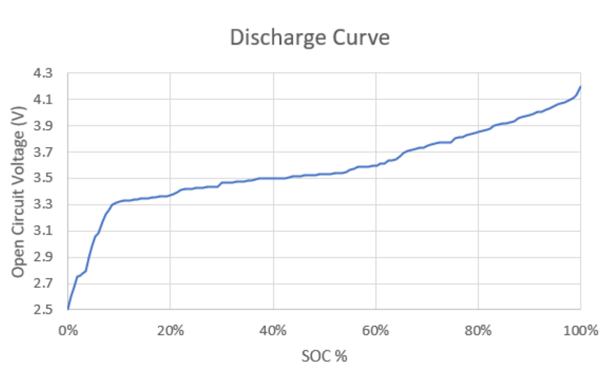

Figure 4

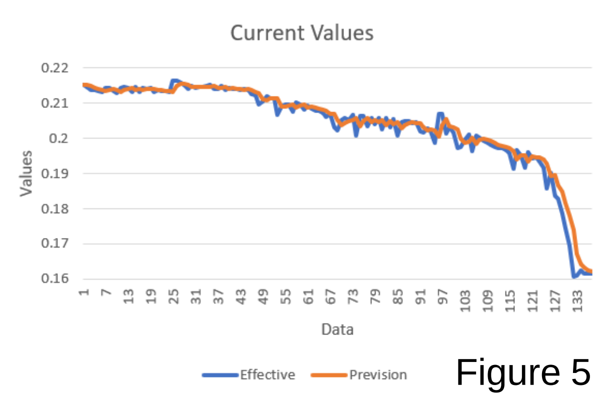

Figure 5

Current (A)	OVC (V)	Calculated SOC %	Two input neuro-fuzzy estimated SOC	Error	Average Error
0.2151	4.131	99	98.7	0.3	0.592
0.2143	3.984	90	90.7	-0.7	
0.2163	3.853	80	80.6	0.6	
0.2137	3.75	70	70.8	-0.8	
0.2114	3.594	60	59.3	0.7	
0.2074	3.534	50	49.7	0.3	
0.2039	3.497	40	39.2	0.8	
0.2028	3.464	30	30.5	0.5	
0.2002	3.369	20	19.2	0.8	
0.1942	3.325	10	10.7	-0.7	
0.1617	2.602	1	0.693	0.31	

Table 1

OVC	Calculated SOC	1 input neuro-fuzzy estimated SOC	Error	Average Error
4.131	99	98.5	0.5	0.536
3.984	90	90.7	-0.7	
3.853	80	79.1	0.9	
3.75	70	70.4	-0.4	
3.594	60	59.2	0.8	
3.534	50	49.8	0.2	
3.497	40	40.1	-0.1	
3.464	30	29.4	0.6	
3.369	20	19.4	0.6	
3.325	10	10.2	-0.2	
2.602	1	1.09	-0.9	

Table 2

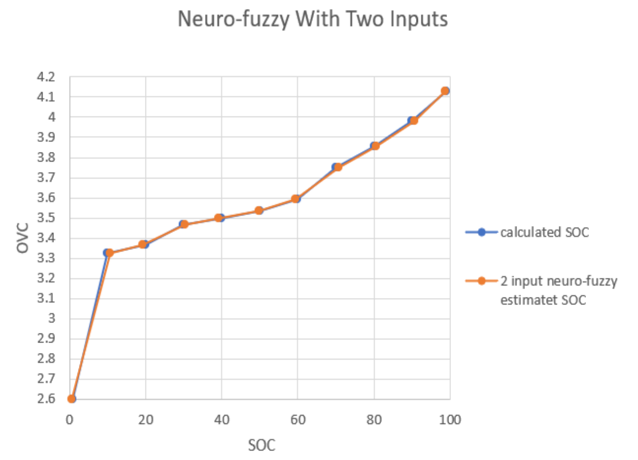

Figure 6

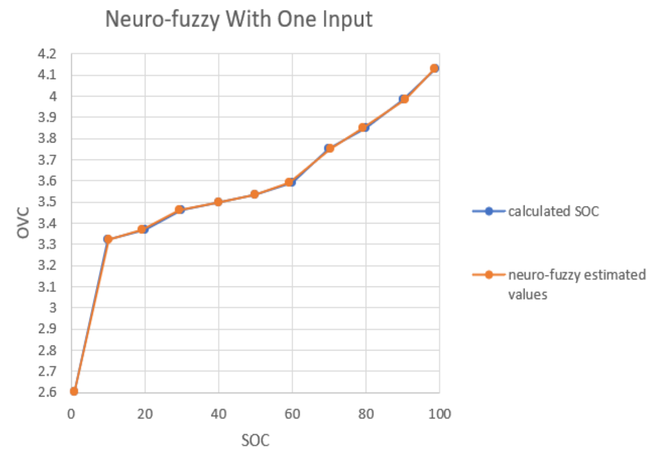

Figure 7

Aims and Objectives

Aims

The aim of this project is to increase the efficiency of EV using a BMS and SOC estimation

Objectives

- Design the BMS
- Simulation
- Compare the simulation parameters with measured parameters
- Research components
- build circuit
- Embed neuron-fuzzy in the Arduino
- Evaluate result
- Present findings

Methodology and Implementation

before starting the designing process for the proposed BMS, it is essential to understand the different tasks the BMS must perform and the parameters being monitored. A block diagram was made (figure 1) to show the concepts of the BMS proposed in this project. To understand the task that the software is implemented in, a flow chart (figure 2) was made to show how the Arduino must perform. All the processes executed by this code to properly monitor the parameter of the batteries is shown. The code used in the Arduino was tested using TinkerCAD for the simulation. To confirm the simulated result, they were compared with the practical results using the circuit design shown in figure 3. The practical values were then used for training the neuro-fuzzy to estimate SOC

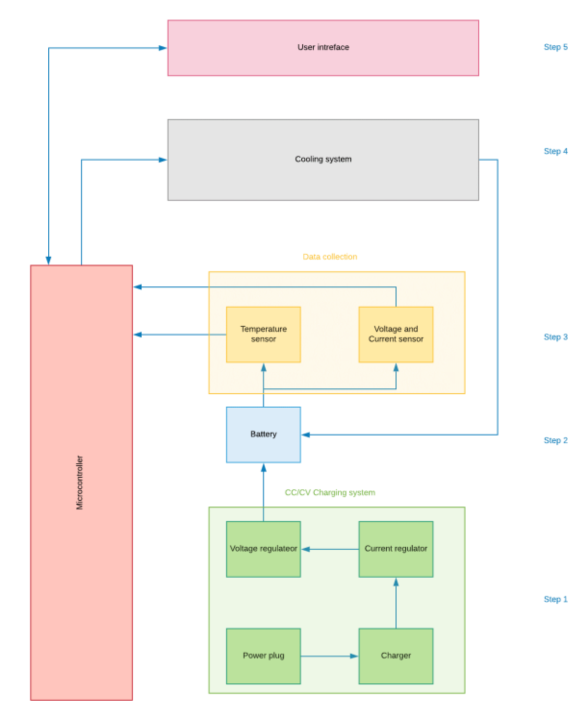

Figure 1

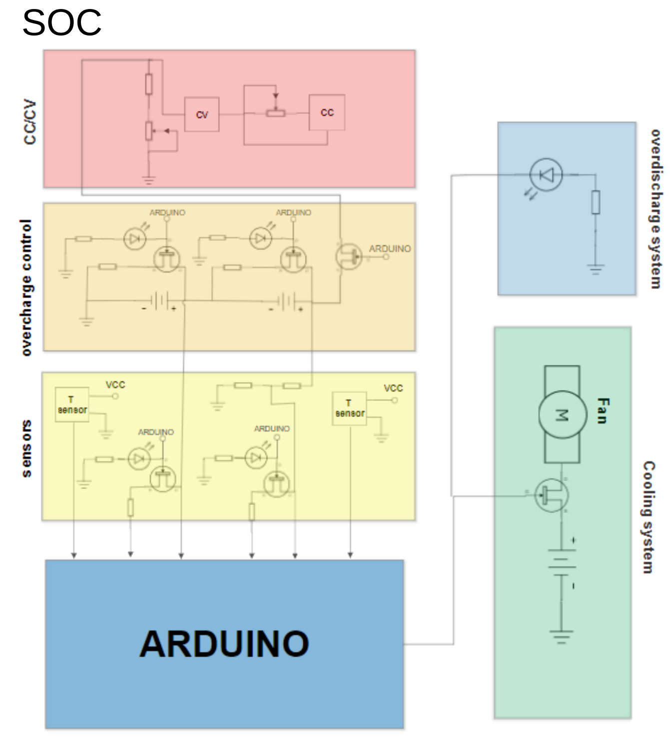

Figure 3

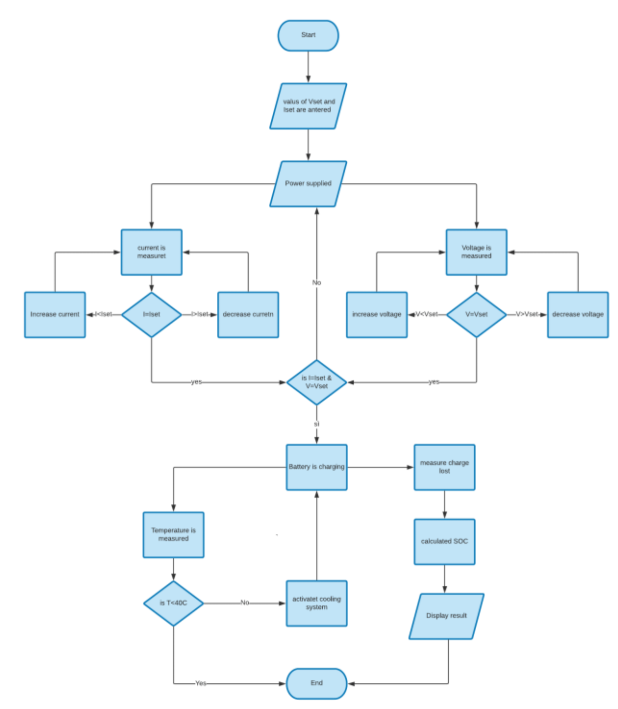

Figure 2

Conclusions

Based on the analysis of the data that was generated by the BMS proposed with a neuro-fuzzy SOC estimation, this report shows that the method for estimation of SOC is relatively accurate when compared to other methods reviewed in the literature [1,2,3]. The method used in the paper is most accurate when the battery is at its optimum within a temperature range of 10 and 40 degrees Celsius. Here, the temperature has a minimal effect on the discharge curve. The correlation between SOC and open voltage circuit is affected by temperature. However, this neuro-fuzzy model does not take into account temperature, so the model is not able to compensate for the temperature changes that it has on the discharge curve. This model also does not account for state of health since not enough discharge cycles were able to be performed to obtain substantial data to estimate the correlation between internal resistance of the batteries and loss of capacity. This made the neuro-fuzzy model less accurate as more batteries are used causing the lowering of the state of health. For future works, implementing a estimation method for the state of health of the battery would be essential to increase and maintain the accuracy of the neuro-fuzzy over time, allowing wireless connection to the user, and accounting for temperature in the fuzzy model so that its accuracy doesn't vary with changes in temperature.

References

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