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Lithium-Ion Battery Classification and Detection Using an Optimal Machine Learning Algorithm

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ABSTRACT

In today's civilization, lithium-ion batteries (LIBs) are essential energy storage technologies. In terms of energy density, power density, cycle life, safety, etc., the performance and cost are still unsatisfactory. Traditional "trial-and-error" procedures necessitate a large number of time-consuming trials to further enhance battery performance. The End-of-life (EOL) LIBs come in a variety of shapes and sizes, which makes it difficult to automate a few unit processes (such cell-level disassembly) of the recycling process. Meanwhile, LIBs contain dangerous and combustible components, posing serious risks to human exposure. In this paper, we anticipate the various crystal system types based on the system's LIB using an optimal machine learning (OML) approach.

Keywords : LIB, Rediction, Battery Management System, Python Programming Language, Jupyter Notebook.

I. INTRODUCTION

Electric systems like electric vehicles (EVs), storage power plants, home appliances, and portable electronics are increasingly using rechargeable batteries [1]. The most effective way to lessen reliance on fossil fuels for transportation and slow down global warming may be EVs [2]. One of the most widely used rechargeable batteries is the LIB, which serves as a significant electrochemical energy storage system (EESS) for electric vehicles. Due to its exceptional benefits, LIBs have been used in a variety of applications. These benefits include high single cell voltage, superior energy density, extended lifetime, low self discharge, and wide temperature range [3] [4] [5].

LIBs must function for a lengthy period of time [6] [7]. The lifespan of battery-powered sensor nodes has been maximised using a number of different solution strategies. These include redundant node placement and storage, routing, and data dissemination protocols, adaptive sensing rates, tiered system designs, and coverage assurances [8]. The lifetime of a sensor node remains bounded and finite [9] despite the fact that all of the aforementioned strategies optimise and adjust energy usage to maximise it. The aforementioned methods aid in extending the lifespan of the application and/or the duration between battery changes, but they do not aid in removing energy-related inhibitors [10].

The structure of this paper is as follows: The works connected to our suggested method are covered in Section 2. The proposed approach is thoroughly covered in Section 3. The simulation results of our suggested strategy are covered in Section 4. The main conclusion of this essay is stated in section 5.

II. RELATED WORK

To reduce overall costs and CO2 emissions, Li Guoet al. [11] introduced a two-stage optimal planning and design strategy for combined cooling, heat, and power (CCHP) microgrid systems. In the first step, the optimal design issue, which included the optimisation of equipment type and capacity, was solved using a multi-objective genetic algorithm based on non-dominated sorting genetic algorithm-II (NSGA-II). The optimal dispatch problem was solved using the mixed-integer linear programming (MILP) technique in the second step.

In order to reduce the life cycle cost of a hybrid, renewable energy based microgrid, Omar Hafez and Kankar Bhattacharya [12] presented a strategy. The four choices listed by the authors—diesel-only, entirely renewable, diesel-renewable mixed, and an external grid-connected microgrid configuration—were used to compare the operating performance and life cycle costs.

An ideal planning of the interconnected network of several microgrids was provided by Liang Cheet al. [13]. For the best planning of connectivity among microgrids using variable renewable energy sources, the authors had developed a probabilistic minimal cut-set-based iterative method.

A multi-objective stochastic optimal planning approach and a chance-constrained programming model were presented by Wenjian Liu et al. [14] with the goal of achieving economic and environmental advantages while minimising overall costs and CO2 emissions. To analyse the time series data, the Markov transition probability matrix is employed.

In a multi-objective optimisation model that can incorporate the results of a life cycle estimation of the examined technology, Di Zhang et al. [15] proposed the ideal design of microgrids with CHP (Combined Heat and Power) units, which is the collection of the proton exchange membrane (PEM) fuel cells used to address the environmental and economic ability.

III. PROPOSED SYSTEM

In portable electronics, electric vehicles, and military and space applications, LIB rechargeable batteries are most frequently used. Our suggested approach suggests using the OML algorithm to anticipate the various battery crystal kinds of lithium ion batteries. Applying preprocessed datasets to it and using it to train our model, we are able to predict the various battery crystal types used in LIB. When testing the model solely after the training process, we may evaluate the battery life and obtain accuracy metrics by employing the trained model.

A. Preliminaries

We simulate a general LIB that enables our model to harvest energy when it is available and use it afterwards.

$$B_t = B_0 + \sum_{t' \le t} \varepsilon \left(C_{t'} - D_{t'} \right) \qquad (1)$$

LIB is categorized by its efficiency ε, which is the fraction of energy recuperated from the total energy input. The state of charge of the battery at time step t, B_t, is represented in terms of the initial charge B_0 the efficiency ε, and the energy used for charging and discharging in each time step $t' \le t$ denoted by $C_{t'}$ and $D_{t'}$, respectively

B. Problem formulation

In order to optimally size various system components including LIB capacity $G_{\max}$ (kW_P), battery Storage capacity S_c (kWh) and conductor size Con_{size} (AWG) for minimum cost of installation.

$$\min_{G_{\max}, S_c, Con_{size}} \left[\sum_{t=1}^{T} G_{\max}\partial_1 + S_c\partial_2 + Con_{size}\partial_3 \right] \quad (2)$$

Constraints: Due to systemic technological, socioeconomic, legal, or physical limits, the range of the choice variables is limited. The technological aspects of battery and diesel operation and demand and supply matching provide the limits in the proposed approach.

$$G_{\max} \ge 0, S_c \ge 0; \forall T \quad (3)$$

$$B_E \ge SOC_{\min}.S_c \ ; \forall T \quad (4)$$

$$\eta So(t) = SL_E(t) + BL_E(t) \quad ; \forall T \quad (5)$$

$$\Delta B_E = B_E(t) - B_E(t-1)$$

$$= \eta_B \ SB_E(t) - BL_E(t) \quad ; \forall T \quad (6)$$

(3) establishes the load limits so that the load demand must always be satisfied by LIB output. Load restrictions' linearization does not result in a material loss of precision.

$$\sum_{t=1}^{T}\sum_{i=1}^{N} \frac{Power_i(t)}{\eta_i}\Delta t + \sum_{t=1}^{T} Power_{loss}\Delta(t) = SL_E(t) + BL_E(t); \forall T$$

(6)

The optimal LIB size $G_{\max}$ is determined by the maximum output power produced by LIB. Similarly, optimal battery size S_c is determined by the maximum energy state attained by the battery, therefore (5) and (6) dictate the equality constraints associated with the objective function for the optimal sizing of LIB.

$$G_{\max} = \max(G) \quad ; \forall T \quad (7)$$

$$S_c = \max(B_E) \quad ; \forall T \quad (8)$$

C. Optimal ML algorithm

OML is a straightforward concept, is simple to implement, and converges quickly. In order to assign one curve, the convergence factor must be changed during the optimisation process. The formula for the change of convergence factor (CF) is:

$$P(loop_i) = P_1 + \left[(1-P_1)loop_i^{\,power} - 1*(loopsnumber)^{power} - 1 \right]$$

(9)

Where P is the predefined probability, P_1 is the convergence factor of the first loop, $loop_i$ shows the number of current loops. A system simulation approach is used as the first stage in the optimal sizing methodology to determine whether a system design with a specific number of system devices is appropriate. One possible formulation of the objective function is:

$$Objective\ Function = MIN.TYPE\ \left[Costs(type)_{no.oftypes}\right] + \min_{k,\forall t \in [t_0,T]} \left[O\cos t\right](no, type(T, nooftype)) \quad (10)$$

The OML algorithm's steps can be described as follows:

Step 1: Start the problem's input data and the optimisation algorithm's information. This information for LIB comprises load values, purchasing and selling prices, etc. The initial population size, the termination criterion, and other information are also included in the algorithm parameters.

Step 2: We should use a penalty factor to convert the limited optimisation problem into an unconstrained one to ensure that all equality and inequality constraints are satisfied.

Step 3: Generate the first details of the algorithm and select the dolphin's places at random.

Step 4: Using the dolphin rules, calculate the cumulative fitness by applying the predesignate fitness to the alternatives chosen for each variable and its neighbours.

Step 5: Calculate the objective function. It should be highlighted that the problem is resolved using the scenario-based approach described above.

Step 6: Divide the remaining probability across all remaining options and equate the probability of the best site to the predefined possibility value in the current loop.

Step 7: Visit the locations in the following loop and update the locations.

IV. Experimental Setup & Results

The hardware and software requirements for the system that we suggest are covered in this section of the technical specs. We have additionally included the experimental results in this section.

Table 1 : Hardware & Software Requirements

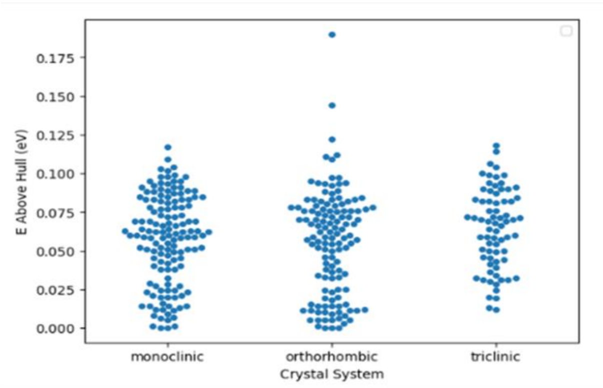
CPU type	I5
Ram size	4GB
Hard disk capacity	80 GB
Keyboard type	Internet keyboard
Monitor type	15 Inch colour monitor
CD -drive type	52xmax
Operating System	Windows 7or later
Simulation Tool	Anaconda (Jupyter notebook)
Documentation	Ms – Office
programming language	python

4.1 Dataset

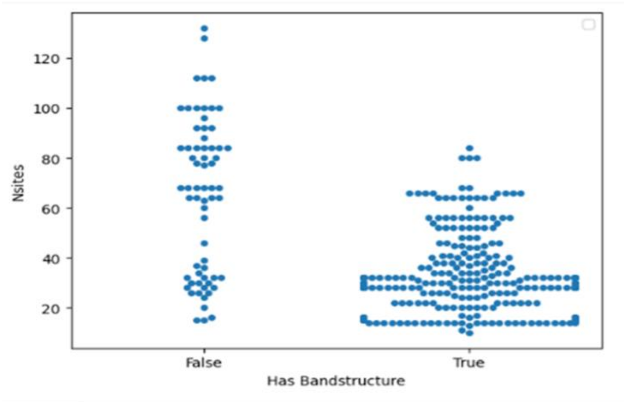
To create useful artificial intelligence (AI) from the data we collect. Data tables are shown as CSV text files with comma delimiters. Although this file format makes it simple to get the data table into a number of programmes, it is recommended to see them in a programme that makes it simple to edit data that is organized in columns. Here, we can gather data in the system's crystal dataset in the CSV format based on LIB. In this case, we make use of data from our datasets' rows and columns. Here, we make use of the system's 11 columns and roughly 400 rows.

4.2 Experimental Results

A swarm plot is another way of plotting the distribution of an attribute or the joint distribution of a couple of attributes. Figure 1 shows the swarm plot of energy band structure of LIB.



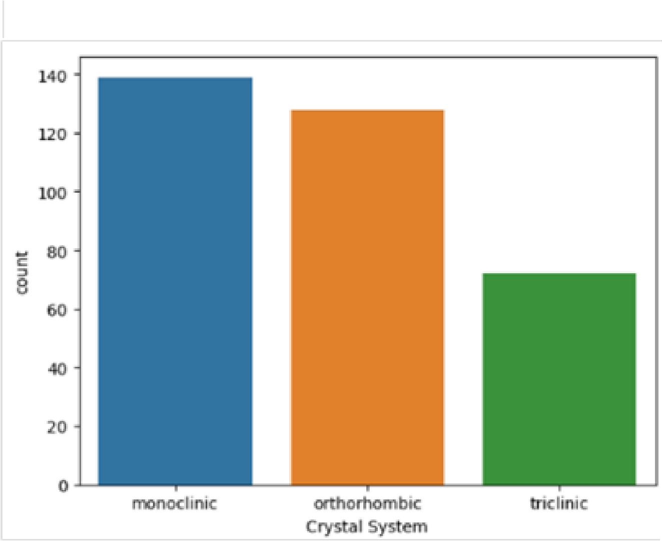
(a)



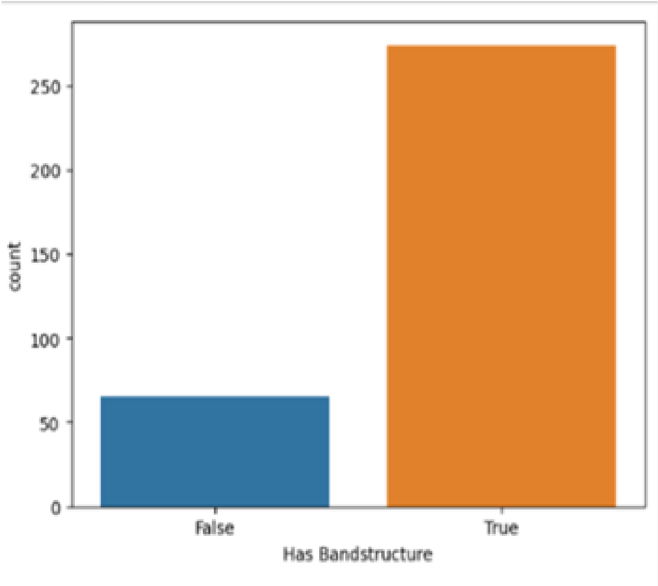
(b)

Figure 1: Swarm plot

A count plot can be thought of as a histogram across a categorical, instead of quantitative, variable. Figure 2 shows the count plot of LIB.



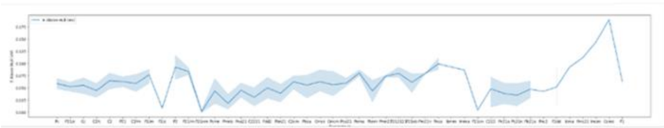
(a)



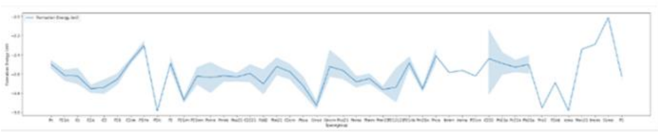
(b)

Figure 2: Count Plot

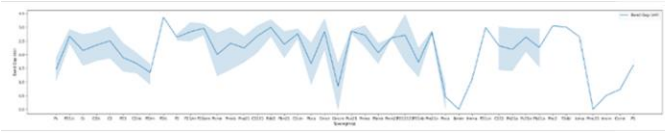
The battery storage capacity of LIB in different state of phases is shown in figure 3



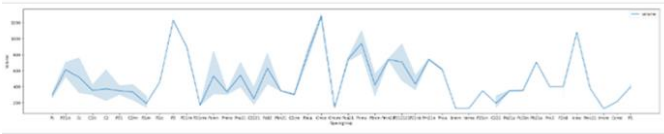
(a)



(b)



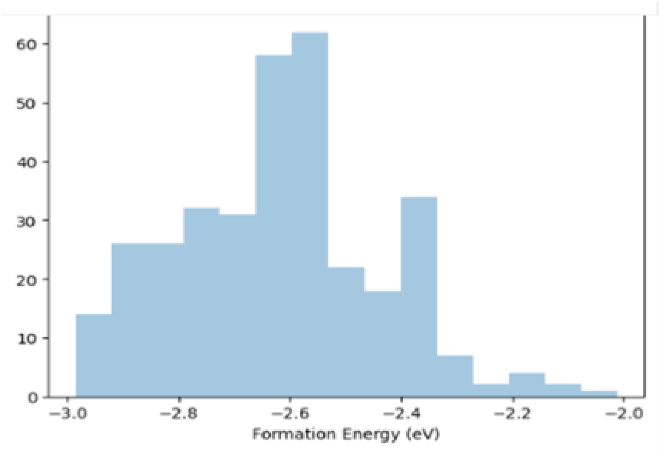
(c)



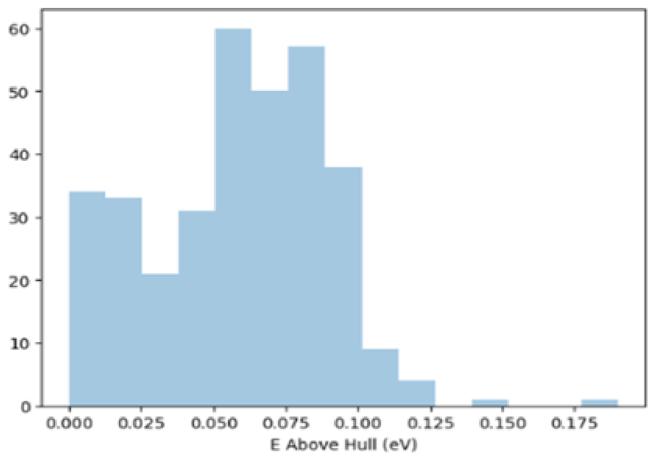
(d)

Figure 3 : Line plot that shows the battery storage capacity of LIB in different states

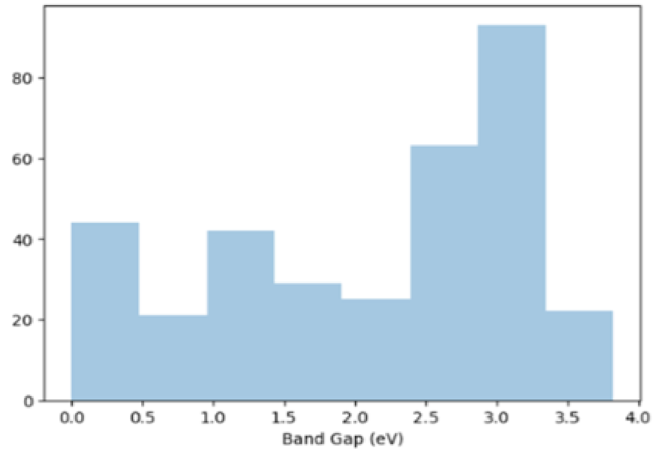
A distribution plot usually depicts the data distribution variation in python. Figure 4 shows the energy distribution variation in LIB.



(a)



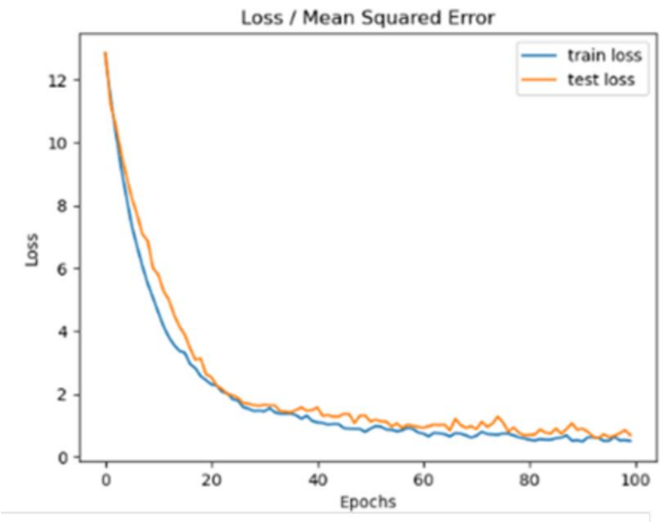
(b)



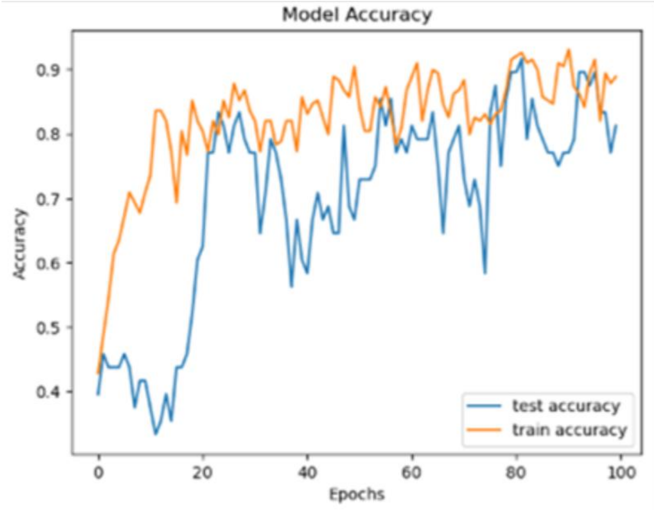
(c)

Figure 4: Energy distribution variation in LIB

a classification method that, depending on the weights of the input features, separates a class into positive and negative values. The objective of classification is to identify the decision boundary that divides the dataset into various classes. According to the many crystal systems employed in our LIB, we categorize the facts in our article. Here, we classify our system using monoclinic, orthorhombic, and triclinic data. Figure 5 displays the OML algorithm's accuracy and loss throughout training and testing.



(a)



(b)

Figure 5 : Loss and Accuracy during training and testing process of OML algorithm

From figure 5, we can analyze datasets that classify the different types of crystal system and predict the LIB with high accuracy. Finally, it is observed that the proposed OML algorithm is best to calculate based on prediction performance accuracy score of the system.

V. CONCLUSION

An innovative mathematical model of a LIB array is originally presented in this study. With the proposed OML method that is employed in this work, the model that would predict the different types of battery crystals based on LIB performs better. Algorithms for machine learning are in line with recent advances in artificial intelligence. The development of many ML models that are broadly applicable to a variety of prediction data types in our system will be the future focus of data-driven LIB based prediction.

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