



Battery Management System using Artificial Intelligence and Machine Learning

Potnuru Dileep, Vasetti Krishna Rao, Tammineni Manasamitra, Uttaravalli Vasu.

Student, Rajam, Vizianagaram, 532127, India.

ABSTRACT

The Battery Management System (BMS) efficiently monitors and controls key parameters. Enhancing safety and longevity, BMS ensures optimal state-of-charge and overall battery health[1]. The presented research integrates a subtractive clustering-based neuro-fuzzy system into a Battery Management System (BMS). The BMS oversees an electric vehicle's battery, managing factors like current, temperature, and power. The proposed SOC estimation method enhances BMS accuracy, addressing monitoring and safety concerns[5]. the state of charge, contributing to improved overall battery performance and safety in electric vehicles. State of Charge (SoC) is a critical parameter in battery management, representing the remaining charge within a battery as a ratio of residual capacity to nominal capacity[6]. In the context of Li-ion batteries, SoC estimation is vital for assessing an electric vehicle's driving range and ensuring proper battery pack balance. Traditional methods like open circuit voltage and coulomb counting face challenges, leading to the adoption of sophisticated techniques such as neural networks. This work emphasizes the importance of accurate SoC estimation, especially in dynamically changing conditions, and highlights the role of advanced machine learning, particularly Feedforward Neural Networks and Deep Feedforward Neural Networks, in improving SoC estimation accuracy.

Keywords: State of charge (SOC), State of Health (SOH), Temperature Prediction, Li – ion Battery, Artificial neural network.

Introduction

Lithium-ion batteries are popular for portable electronics and zero-emission vehicles [6-7]. Electric vehicles (EVs) are recognized as the best alternative to fuel automobiles. Li-ion batteries are the preferred energy storage device for EVs. Battery management systems (BMS) are necessary for monitoring battery states. State of Charge (SOC) estimation is critical for battery management. SOC is the ratio of remaining available capacity to reference capacity [8 9]. Accurate state of charge (SOC) estimation is crucial for electric vehicles [10]. 1.1 State of Charge SOC (State of Charge) determination and controlling is critically important for electric vehicles (EVs) [5-6]. Accurate measurement of battery state (SOC) provides drivers with an indication of the available runtime of the vehicle. SOC determination helps in avoiding detrimental situations such as overcharging or over discharging, which can reduce the useful lifetime of a power battery[6].Overcharging can lead to excessive heat generation and chemical reactions within the battery, which can cause damage and reduce its overall capacity[7].Over discharging can lead to a decrease in battery performance and capacity, reducing the range and efficiency of the EV[7].By accurately determining and controlling the SOC, EV drivers can optimize the use of their battery and ensure its longevity[8]. State of Charge (SoC) is a critical parameter in battery management, representing the remaining charge within a battery as a ratio of residual capacity to nominal capacity [5]. In the context of Li-ion batteries, SoC estimation is vital for assessing an electric vehicle's driving range and ensuring proper battery pack balance [5]. Traditional methods like open circuit voltage and coulomb counting face challenges, leading to the adoption of sophisticated techniques such as neural networks. This work emphasizes the importance of accurate SoC estimation, especially in dynamically changing conditions, and highlights the role of advanced machine learning, particularly Feedforward Neural Networks and Deep Feedforward Neural Networks, in improving SoC estimation accuracy [6]. 1.2 State of Health A Battery Management system (BMS) is like the brain of a rechargeable battery. It helps the battery work better and last longer. Now, imagine if this brain could learn and make smart decisions on its own using a kind of smart technology called Artificial Intelligence (AI) and Machine Learning (ML)[5]. One of the important things the Battery Management System (BMS) brain can learn is the "State of Health" (SOH) of the battery. SoH like checking how fit and healthy the battery is[10]. 1.3 Artificial neural network Artificial neural network (ANN) is a machine learning technique inspired from human brain structure.

ANN are greatly known for function approximation and regression problems. In general,[11] Artificial neural network is a web of interconnected entities called nodes, creating an input layer, one or more hidden layers and an output layer. Each node is connected to each other with a specific weight threshold. Each node has an activation function $f(x)$ which is a fixed nonlinear function used to compute the output.[12] The individual node is activated and pass by the data to the next layer node, only if the calculated output is above the threshold, otherwise no data is sent to the next layer node. The output value of Y of each neuron can be expressed as $Y = F(\sum_i P_i W_{ij} + b_j)$ [11] where Y is the output value, F is the activation function, P is the input vector, W is the weight value, b is the biases value, i and j are input number vector and neuron number respectively. There are three commonly used activation functions in the nodes which are logistic function, hyperbolic tangent function, and ReLU function. Logistic function also known by sigmoid function can be presented as follows

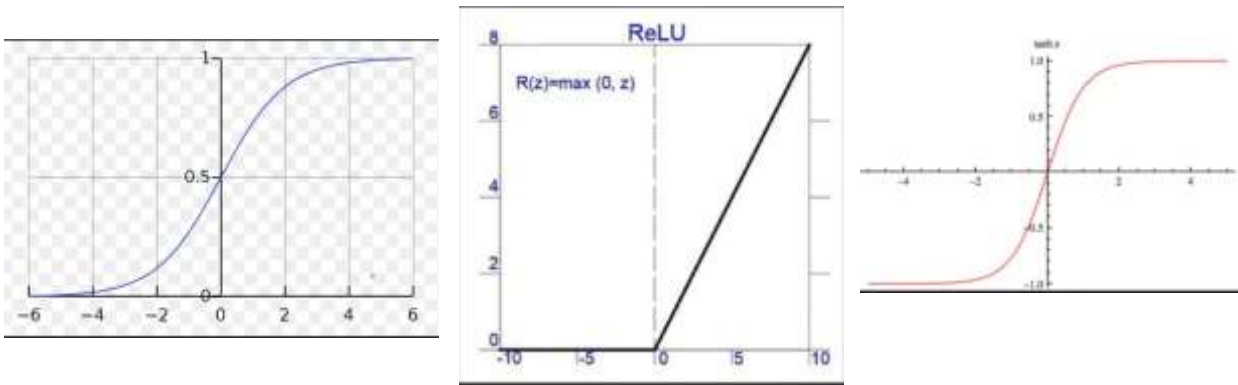
$$f(x) = \frac{1}{1 + e^{-x}}$$

As shown in Fig. 5, the sigmoid function saturates and becomes less responsive at higher and lower values of x , while it becomes more sensitive near the value of $x = 0$ [11].

Hyperbolic tangent function also known by tanh function and it can be presented in equation below.

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

The function can be presented in the Fig. 6. The tanh function is similar to the sigmoid function, but tanh function is centered at 0 rather of that of sigmoid where it is centered at 0.5 which makes learning a little bit easier.



ReLU function is a rectified linear function typically used in all hidden layers as a default activation function. ReLU function will activate the node if the input is positive, otherwise it will output 0. Fig. 6. Tanh function. Fig. 4. ReLU function.

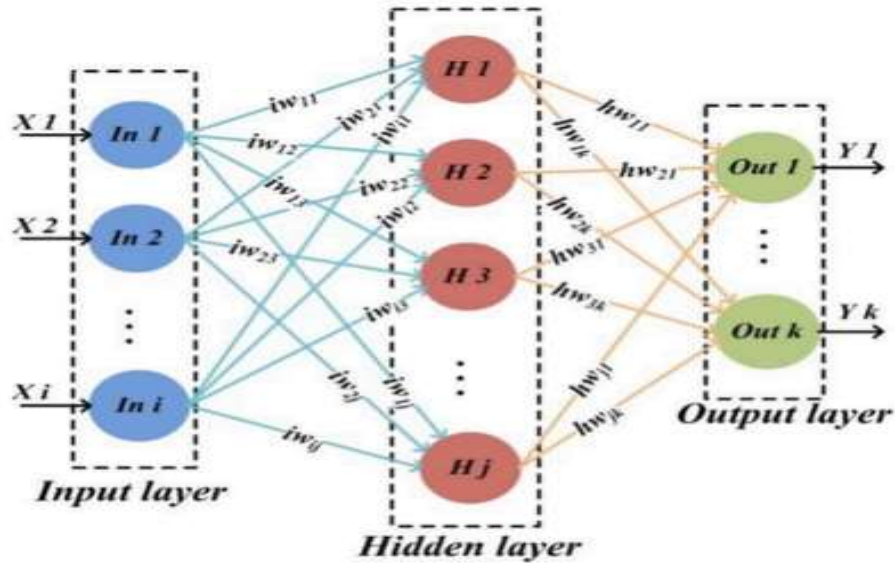
ReLU can be presented in form of the equation below.

$$\text{ReLU}(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{otherwise} \end{cases}$$

The function is presented in the Fig. 4. The output of the function is zero when the value of x is negative and it is linear when it is positive [12].

1.4 Architecture of ANN

An ANN model is a multi-layered network comprising multiple neurons with one input layer, one or more hidden layers, and one output layer.[15] The Back propagation (BP) neural network exhibits a strong nonlinear mapping ability as a feedforward ANN. Therefore, we used the BP neural network for training and testing and selected the sigmoid as the activation function.



The Levenberg–Marquardt algorithm was used as the learning algorithm due to its fast convergence. The learning rate was set to 0.01. There are no universal rules for selecting the number of hidden layers and neurons [13]. We employed the trial-and error method to determine the architecture of the ANN model by creating and training networks with different architectures and implementing independent tests. The first choice for the number of hidden layers was one, and that for the number of neurons was in the range of 1–20. Lastly, [4] we selected the architecture with a smaller test root mean square error (RMSE) and fewer hidden layers and neurons for each case.

1.5 Data-driven authentication parameters

The parameters for an electrochemical model for lithium-ion batteries are derived by physical particles on experimental data. Some measures on time and cost intensive, accuracy, temperature. The novel learns about metaheuristic algorithm on electrochemical models[16].

Metaheuristic algorithm

A metaheuristic algorithm refers to a higher-level strategy designed to guide and control the exploration of solutions in order to efficiently find high quality solutions. These algorithms are problem solving techniques that can be applied across a range of problems[16].

Metaheuristic algorithms follow a process of refinement exploring and enhancing solutions to gradually improve their quality over time. The main objective of these algorithms is to explore the solution space avoiding the trap of getting stuck, in optima and instead finding near optimal or optimal solutions. Metaheuristics are designed with the ability to adapt to the characteristics of each problem they encounter. They can adjust their search strategy based on the landscape of the problem at hand. Metaheuristics rely on heuristics – rules or strategies – that provide

guidance throughout the search, for solutions even if they cannot guarantee finding the best solution. Metaheuristic algorithms can be applied to types of optimization problems, including optimization, continuous optimization and multi objective optimization.

Some examples of algorithms include that Genetic Algorithms (GA) Inspired by the concept of selection GA operates on a population of solutions gradually evolving them over generations using genetic operators such as crossover, mutation and selection. Simulated Annealing (SA) Taking inspiration from the annealing process in metallurgy SA starts with a solution. Allows for the acceptance of worse solutions with decreasing probability in order to avoid getting stuck in local optima.

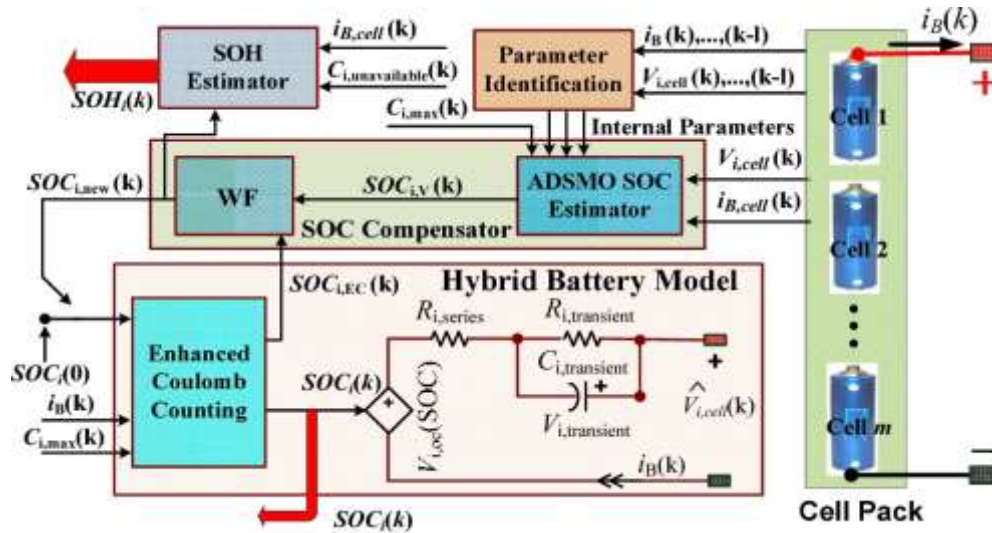


Fig 5: Data-driven authentication

We can utilize algorithms to find the charging and discharging patterns, for batteries. The ultimate goal is to maximize energy efficiency minimize charging time or evenly distribute the load on battery cells[17]. By optimizing these cycles, we can effectively manage the SOC of the battery thereby avoiding overcharging or deep discharging that may harm its health.

Battery health is often measured by its cycle life, which refers to the number of charge/discharges cycles a battery can undergo before experiencing capacity degradation. Metaheuristics play a role, in developing charging and discharging strategies that aim to prolong a battery’s cycle life[17]. This involves avoiding SOC levels and ensuring utilization of battery cells. These applications demonstrate how metaheuristic algorithms contribute to managing SOC levels and improving battery health[16].

Many optimization algorithms take factors into consideration. When it comes to batteries temperature plays a role, in determining both the state of charge (SOC) and overall health. Designing optimization algorithms that factor in temperature constraints can help guide the charging and discharging processes to operate within temperature limits that promote battery lifespan. Some optimization algorithms can be combined with models for estimating the state of charge (SOC). These models utilize information, like current, voltage and temperature to approximate the SOC of the battery. By optimization of charge and discharge to estimate accurate SOC, the battery management system to enhance battery health and make more informed decisions.

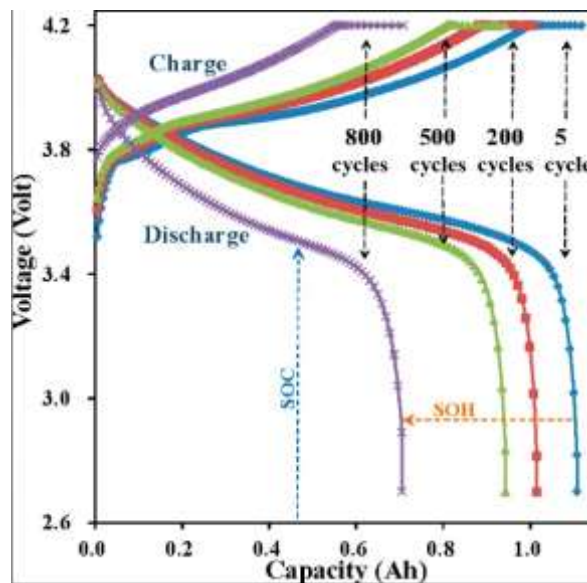


Fig 6: Extend the life cycle

In multi cell battery, metaheuristics algorithm is applied to control or balance the voltage on individual cells. Balancing of cells is more crucial to prevent over discharging/ overcharging of specific cells to increase battery health. It contributes to extend the life cycle and ensures unnecessary stress of battery. Metaheuristic algorithm is used to distribute loads for power consumption. It can be adaptive and adjust their strategies on real time changing conditions. This can assist to utilize maximum battery capacity without compromising its health. This involves optimizing the state of charge (SOC) levels during charging and discharging to make the most effective use of available energy.

1.5 Applications:

Electric Vehicles:

In the realm of electric mobility, AI and ML in Battery Management Systems optimize the performance and life span of electric vehicles batteries. Predictive analytics help estimate State of Charge (SOC) accurately, allowing for efficient energy use and range prediction. Adaptive charging strategies based on machine learning contribute to longer battery life, addressing a critical aspect of Electric Vehicles sustainability.

Renewable Energy Storage:

Battery System play a crucial role in storing energy generated from renewable source like solar and wind. AI and ML enhance the efficiency of these storage system by predicting energy demand, optimizing charge-discharge cycles, and adapting to variable renewable energy inputs. This contributes to grid stability and promotes the integration of renewable energy into power grid.

4. Conclusion:

In the changing field of battery technology, the combination of Artificial Intelligence (AI) and Machine Learning (ML), in Battery Management Systems (BMS) has become a game changer. The key aspects of State of Charge (SOC) and State of Health (SOH) are vital in determining the effectiveness and durability of batteries and the integration of technologies has completely transformed our understanding and management of these factors[6]. Traditionally estimating SOC relied on algorithms that often failed to capture the dynamics of battery behaviour. However, with the introduction of AI and ML SOC monitoring has reached a level of precision. Algorithms, those inspired by networks similar to the human brain now analyse a wide range of influencing factors such as temperature charging/discharging rates and historical usage patterns. This allows for real time adaptation to charging conditions resulting in accurate predictions for SOC. The intelligence embedded within a Battery Management System also extends to comprehending the battery's health or SOH. Acting like a doctor the BMS utilizes AI and ML techniques to assess the battery's fitness. This proactive approach enables identification of issues ultimately contributing to optimal performance and an extended lifespan. Artificial Neural Networks (ANN) play a crucial role in this paradigm shift. With their ability to process large datasets and learn complex models, ANN ensures accurate predictions of battery temperature[14]. This not only enhances the BMS's decision-making capabilities but also improves the overall efficiency of the battery system. Moreover, the incorporation of metaheuristic algorithms such as Genetic Algorithms and Simulated Annealing further optimizes charging and discharging patterns[16]. By maximizing energy efficiency and evenly distributing the load on battery cells, these algorithms actively contribute to the effective management of SOC, ultimately enhancing battery health[17].

References

- [1] F. Duffner, N. Kronemeyer, J. Tübke, J. Leker, M. Winter, R. Schmich, Postlithium-ion battery cell production and its compatibility with lithium-ion cell production infrastructure, *Nat. Energy* 6 (2) (2021) 123–134, <http://dx.doi.org/10.1038/s41560-020-00748-8>.
- [2] C.P. Grey, D.S. Hall, Prospects for lithium-ion batteries and beyond—a 2030 vision, *Nature Commun.* 11 (1) (2020) 1–4, <http://dx.doi.org/10.1038/s41467-020-19991-4>.
- [3] C. Xu, Q. Dai, L. Gaines, M. Hu, A. Tukker, B. Steubing, Future material demand for automotive lithium-based batteries, *Commun. Mater.* 1 (1) (2020) 1–10, <http://dx.doi.org/10.1038/s43246-020-00095-x>.
- [4] A. Manthiram, An outlook on lithium ion battery technology, *ACS Central Sci.* 3 (10) (2017) 1063–1069, <http://dx.doi.org/10.1021/acscentsci.7b00288>.
- [5] Fang YJ. Wong. electric vehicles to hit 1 million by 2020: report. 2010. Available from: <http://www.reuters.com/article/retire-us-autos-china/idUSTRE69F0J8201010161>.
- [6] White CD, Zhang KM. Using vehicle-to-grid technology for frequency regulation and peak-load reduction. *J Power Sources* 2011;196(8):3972e80.
- [7] Di Silvestre ML, et al. An optimization approach for efficient management of EV parking lots with batteries recharging facilities. *J Ambient Intelligence Humanized Comput* 2013;4(6):641e9.
- [8] Plett GL. Extended Kalman filtering for battery management systems of LiPB based HEV battery packs: Part 2. Modeling and identification. *J Power Sources* 2004;134(2):262e76.
- [9] X. Hu, C. Zou, C. Zhang, Y. Li, Technological developments in batteries: a survey of principal roles, types, and management needs, *IEEE Power Energy Mag.* 15 (5) (2017) 20–31.
- [10] A. Emadi, *Advanced Electric Drive Vehicles*, CRC Press, New York, 2015.
- [11] Ahmad Al Miaari a, Hafiz Muhammad Ali a,b,* a Mechanical Engineering Department, King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia b Interdisciplinary Research Center for Renewable Energy and Power Systems (IRC-REPS), King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia.

-
- [12] Renfeng Cao, Xingjuan Zhang and Han Yang ,School of Aeronautic Science and Engineering, Beihang University, Beijing 100191, China, Correspondence: yang_han@buaa.edu.cn.
- [13] Yuanlong Wang, Xiongjie Chen, Chaoliang Li, Yi Yu, Guan Zhou, ChunYan Wang, Wanzhong Zhao College of Energy and Power Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, Jiangsu, Peoples' Republic of China.
- [14] Zhang, G.; Eddy Patuwo, B.; Hu, M.Y. Forecasting with Artificial Neural Networks: The State of the Art. *Int. J. Forecast.* 1998, 14,35-62.
- [15] Levenberg, K., 1944. A method for the solution of certain non-linear problems in least squares. *Q. Appl. Math.* 2 (2), 164–168. <http://dx.doi.org/10.1090/qam/10666>.
- [16] eihan Li, Iskender Demir, Decheng Cao, Dominik Jost, Florian Ringbeck, Mark Junker, Dirk Uwe Sauer , Energy storage materials of Data-driven electrochemical model of Lithium-ion batteries with artificial intelligence,2022,557-570.
- [17] Tejs Vegge, Jean-Marie Tarascon, and Kristina Edstrom on Toward Better and Smarter Batteries by Combining AI with Multisensory and Self-Healing Approaches,2021, DOI: 10.1002/aenm.202100362.