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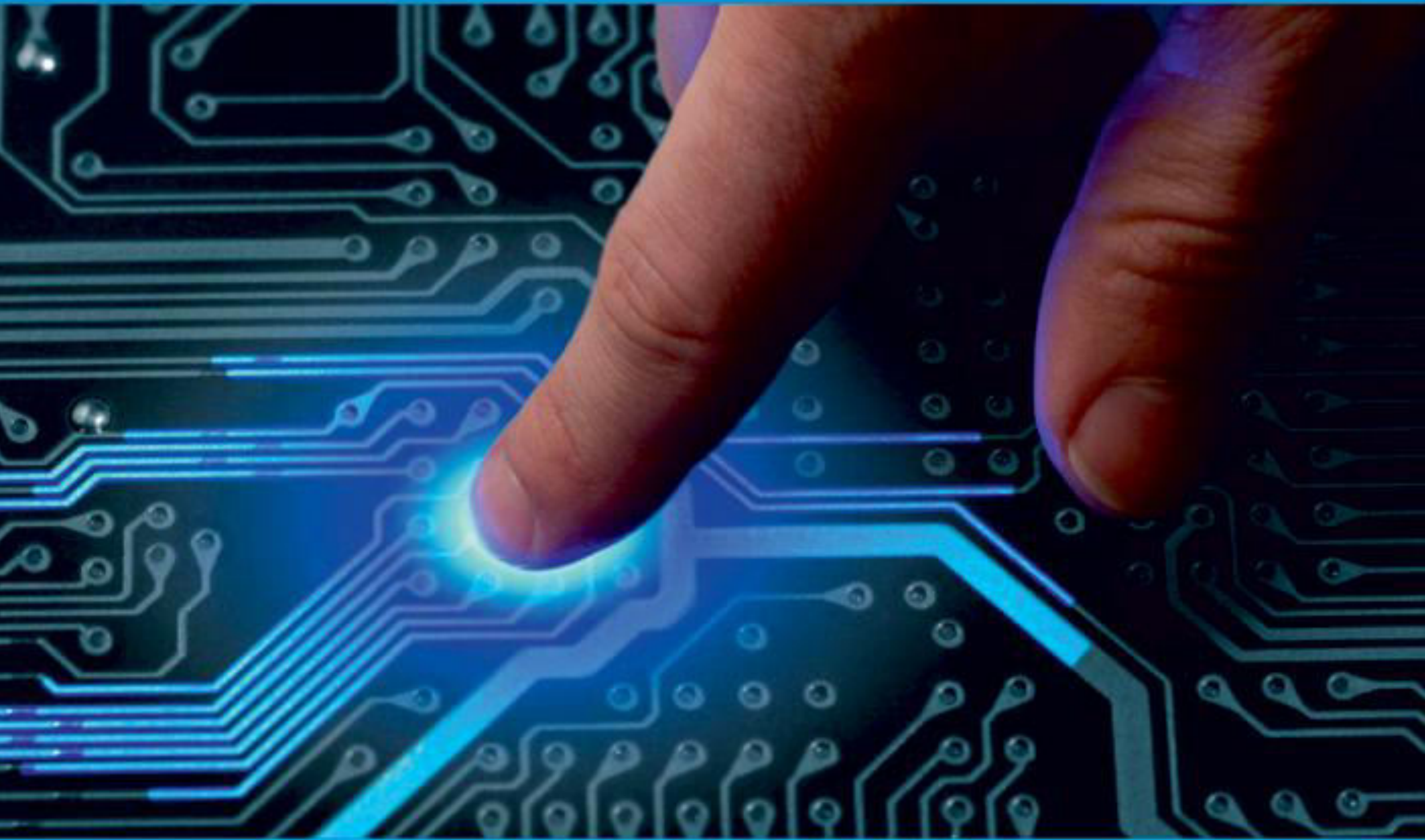

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Machine Learning Applied to Electrified Vehicle Battery State of Charge and State of Health Estimation

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ABSTRACT: Machine learning is a specific application of artificial intelligence that allows computers to learn and improve from data and experience via sets of algorithms, without the need for reprogramming. In the field of energy storage, machine learning has recently emerged as a promising modeling approach to determine the state of charge, state of health and remaining useful life of batteries. To cope with the new transportation challenges and to ensure the safety and durability of electric vehicles and hybrid electric vehicles, high performance and reliable battery health management systems are required. The Battery State of Health (SOH) provides critical information about its performances, its lifetime and allows a better energy management in hybrid systems. In this paper, we used CNN algorithm for battery life prediction and state of charge estimation.

KEYWORDS: CNN, Machine learning, vehicle battery,

I. INTRODUCTION

Electric vehicles (EVs) are considered as future cars to solve oil dependency and environmental problems. However, the spread of EVs is limited by high price, long charging time, few charging stations and limited driving range. The limited driving range and long charging time may lead to "range anxiety", which can be explained as the drivers' concern of not reaching the destination during driving. Range anxiety is considered as one of the major factors that affect the acceptance of electric vehicles. Apart from a bigger battery, an accurate range estimation system is necessary to solve range anxiety. However, the prediction of the remaining range is complicated, because it is dependent on some stochastic factors such as vehicle characteristics, driving behaviour, traffic state, road topography and weather condition. Several studies have been performed to predict the remaining driving range of EVs. They mainly focus on predicting the driving speed [2-4] and obtaining the traffic information and road topography information.

The limited driving range is considered as a significant barrier to the spread of electric vehicles. One effective method to reduce "range anxiety" is to offer accurate information to the driver on the remaining driving range. However, the energy consumption during driving is largely determined by driving behaviour, road topography information and traffic situation, which are hard to predict. Global warming has led to more severe regulations on CO2 and pollutant emissions. In these circumstances, Hybrid Electric Vehicles (HEVs) and Electric Vehicles (EVs) have been introduced. EVs are considered as a solution to the above issue since it offers a zero emissions alternative. Besides, EVs are cheaper to recharge as electricity is cheaper than fuel. It is also possible to recover some energy from regenerative braking with EVs thanks to electric motors reversibility. Along with HEVs, it is a solution for car manufacturers to reduce the average emissions of their fleet to meet the regulations and hence avoid paying taxes.

II. LITERATURE SURVEY

In [1], a survey of battery state estimation methods based on ML approaches such as feedforward neural networks (FNNs), recurrent neural networks (RNNs), support vector machines (SVM), radial basis functions (RBF), and Hamming networks is provided. Comparisons between methods are shown in terms of data quality, inputs and outputs, test conditions, battery types, and stated accuracy to give readers a bigger picture view of the ML landscape for SOC and SOH estimation. Additionally, to provide insight into how to best approach with the comparison of different neural network structures, an FNN and long short-term memory (LSTM) RNN are trained fifty times each for 3000 epochs.

In [2], an SOC and SOH co-estimation scheme is proposed based on the fractional-order calculus. First, a fractional-order equivalent circuit model is established and parameterized using a Hybrid Genetic Algorithm/Particle Swarm Optimization method. This model is capable of predicting the voltage response with a rootmean-squared error less than

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10 mV under various drivingcycle-based tests. Comparative studies show that it improves the modeling accuracy appreciably from its second- and thirdorder counterparts. Then, a dual fractional-order extended Kalman filter is put forward to realize simultaneous SOC and SOH estimation.

In [3], initially different types of batteries used in the EVs and HEVs are investigated, according to the latest battery management systems (BMS). Li-Ion batteries are a popular source of EVs and HEVs because of their long-life span, high energy and power density, and good charging and discharging performance. However, there remain some issues associated with the deployment of Li-ion batteries, such as complex electrochemistry, degradation, and inaccurate battery health estimation. The latest techniques for the estimation of the battery state of health (SOH) are reviewed in a comparative table.

In [4], a new reduced-decoupling SOC and SOH co-estimation algorithm based on convex optimization is proposed. This scheme estimates the battery SOC from the battery model and does not require the classic coulomb-counting method. Therefore, it can decouple the capacity estimation from the SOC estimator and reduce the strong interaction existing in conventional co-estimation methods. Besides, all state variables can be solved together by one estimator, which is straightforward and avoids the complicated observer network. Owing to the decoupling design, the stability of the proposed method becomes more intuitive and can be always guaranteed according to the convexity analysis without using other stabilizing approaches.

In [5], a detailed assessment of optimizationdriven moving horizon estimation (MHE) framework by means of a reduced electrochemical model is pursued. For State-of-Charge (SOC) estimation, the standard MHE and two variants in the framework are examined by a comprehensive consideration of accuracy, computational intensity, effect of horizon size, and fault tolerance. A comparison with common extended Kalman filtering (EKF) and unscented Kalman filtering (UKF) is also carried out. Then, the feasibility and performance are demonstrated for accessing internal battery states unavailable in equivalent circuit models (ECMs), such as solid-phase surface concentration and electrolyte concentration.

In [6], two new approaches are suggested to enrich the existing solutions. To that extent, capacity fading is studied using exchanged energy during charging events. What's more, power fading is assessed using direct current resistance (DCR) and voltage measurement at the beginning of charge events. Both solutions produce reliable state of health measurements SoH with significantly good accuracy.

In [7], by proposing a constant temperature constant-voltage (CT-CV) charging technique, considering cell temperature as a key degradation metric, gap between charging techniques that use instantaneous cell voltage and/or temperature to modulate the charging current magnitude is minimized. The proposed CT-CV charging scheme employs a simple and easy-to-implement proportional-integral-derivative (PID) controller aided by a feed-forward term. The charging current is dynamically adjusted in response to the battery temperature, which indirectly reflects its aging and thermal environment.

In [8], a fast charging technique for a grid-tied, cascaded H-bridge (CHB) converter based charging station is developed. A controller is designed to achieve constant current constant voltage (CC-CV) charging for all of the cells of the CHB converter. As proven in this paper, to achieve fast charging, the effects of internal resistance and polarization parameters of battery should be compensated. To reach this goal, the internal resistance and polarization parameters of battery are estimated based on the initial fast measurements before formal battery charging. The estimated parameters can increase the constant current charging duration for Li-Ion batteries so the charging speed is improved.

In [9], constant voltage is kept across the battery. And it draws higher current but Li-ion cells have 4.2+/-50mV as nominal set-point voltage and allowable charging current is 1C .This process of charging is chosen for Pb-acid batteries as each individual cell balance the charge between them .The lead acid cells used for cars and backup power systems. The disadvantage of this technique is battery does not charge fully and time required for charging is more than 2 hours.

In [10], a particle swarm optimization algorithm to search for an optimal five-stage constant-current charge pattern is proposed. The goal is to maximize the objective function for the proposed charge pattern based on the charging capacity, time, and energy efficiency, which all share the same weight. Firstly, an equivalent circuit model is built and battery parameters are identified. Then the optimal five-stage constant-current charge pattern is searched using a particle swarm optimization algorithm. At last, comparative experiments using the constant current-constant voltage

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(CC-CV) method are performed. Although the charging SOC of the proposed charging pattern was 2.5% lower than that of the CC-CV strategy, the charging time and charging energy efficiency are improved by 15.6% and 0.47% respectively.

III. PROPOSED METHOD

Lithium-ion batteries have emerged as the state-of-the-art energy storage for portable electronics, electrified vehicles, and smart grids. An enabling Battery Management System holds the key for efficient and reliable system operation, in which State-of-Charge (SOC) estimation and State-of-Health (SOH) monitoring are of particular importance. In this article, an SOC and SOH co-estimation scheme is proposed based on the CNN algorithm.

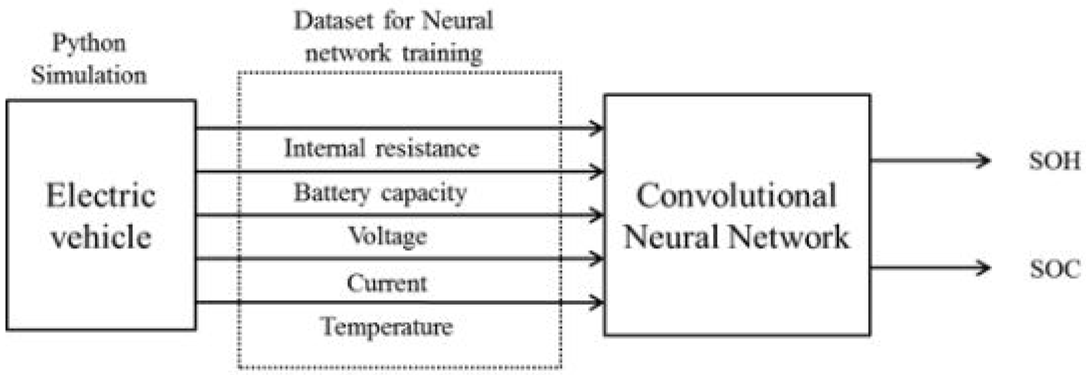

Fig 1 block diagram of proposed system

An accurate estimation of the SOC is crucial to improve vehicle performance, safety, passenger comfort, andto minimize costs associated with over design or oversizingof the pack.Due to the strong dependence of SOC estimation on battery capacity, the insufficient precision of capacity diagnostic may further reduce the SOC estimation accuracy. An effective approach is to measure different associated parameters of the battery. These include current, voltage and temperature of the battery, where for SOH estimation internal resistance and the battery capacity are direct standards. Dataset of internal resistance of battery, capacity, voltage, current and temperature is feed to CNN for training (shown in fig). Parameters of test electric vehicle is fed to system, CNN compares test electric vehicle data with parameters from dataset and estimates SOH (state of Health) and SOC (State of charge) of battery.

Algorithm – CNN

Neural networks are a set of algorithms, modeled loosely after the human brain, that are designed to recognize patterns. They interpret sensory data through a kind of machine perception, labeling or clustering raw input. The patterns they recognize are numerical, contained in vectors, into which all real-world data, be it images, sound, text or time series, must be translated.

Neural networks help us cluster and classify. You can think of them as a clustering and classification layer on top of the data you store and manage. They help to group unlabeled data according to similarities among the example inputs, and they classify data when they have a labelled dataset to train on. (Neural networks can also extract features that are fed to other algorithms for clustering and classification; so you can think of deep neural networks as components of larger machine-learning applications involving algorithms for reinforcement learning, classification and regression.)

Deep learning maps inputs to outputs. It finds correlations. It is known as a “universal approximator”, because it can learn to approximate an unknown function f(x) = y between any input x and any output y, assuming they are related at all (by correlation or causation).

1) Classification

All classification tasks depend upon labeled datasets; that is, humans must transfer their knowledge to the dataset in order for a neural network to learn the correlation between labels and data. This is known as supervised learning.

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- Detect faces, identify people in images, recognize facial expressions (angry, joyful)
- Identify objects in images (stop signs, pedestrians, lane markers…)
- Recognize gestures in video
- Detect voices, identify speakers, transcribe speech to text, recognize sentiment in voices
- Classify text as spam (in emails), or fraudulent (in insurance claims); recognize sentiment in text (customer feedback)

Any labels that humans can generate, any outcomes that you care about and which correlate to data, can be used to train a neural network.

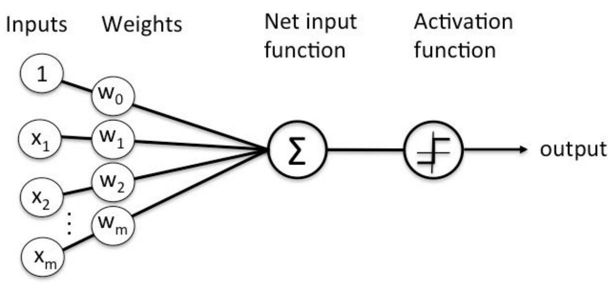
2) Clustering

Clustering or grouping is the detection of similarities. Deep learning does not require labels to detect similarities. Learning without labels is called unsupervised learning. Unlabeled data is the majority of data in the world. One law of machine learning is: the more data an algorithm can train on, the more accurate it will be. Therefore, unsupervised learning has the potential to produce highly accurate models.

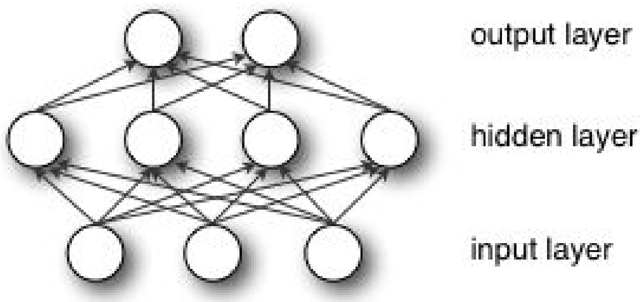
- Search: Comparing documents, images or sounds to surface similar items.
- Anomaly detection: The flipside of detecting similarities is detecting anomalies, or unusual behavior. In many cases, unusual behavior correlates highly with things you want to detect and prevent, such as fraud.

3) Neural Network Elements

Deep learning is the name we use for "stacked neural networks"; that is, networks composed of several layers. The layers are made of *nodes*. A node is just a place where computation happens, loosely patterned on a neuron in the human brain, which fires when it encounters sufficient stimuli. A node combines input from the data with a set of coefficients, or weights, that either amplify or dampen that input, thereby assigning significance to inputs with regard to the task the algorithm is trying to learn; e.g. which input is most helpful is classifying data without error? These input-weight products are summed and then the sum is passed through a node's so-called activation function, to determine whether and to what extent that signal should progress further through the network to affect the ultimate outcome, say, an act of classification. If the signals pass through, the neuron has been "activated."



A node layer is a row of those neuron-like switches that turn on or off as the input is fed through the net. Each layer's output is simultaneously the subsequent layer's input, starting from an initial input layer receiving your data.



Pairing the model's adjustable weights with input features is how we assign significance to those features with regard to how the neural network classifies and clusters input.

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Deep-learning networks are distinguished from the more commonplace single-hidden-layer neural networks by their depth; that is, the number of node layers through which data must pass in a multistep process of pattern recognition.Deep-learning networks perform automatic feature extraction without human intervention, unlike most traditional machine-learning algorithms. Given that feature extraction is a task that can take teams of data scientists years to accomplish, deep learning is a way to circumvent the chokepoint of limited experts. It augments the powers of small data science teams, which by their nature do not scale.

When training on unlabeled data, each node layer in a deep network learns features automatically by repeatedly trying to reconstruct the input from which it draws its samples, attempting to minimize the difference between the network's guesses and the probability distribution of the input data itself. Restricted Boltzmann machines, for examples, create so-called reconstructions in this manner.

Deep-learning networks end in an output layer: a logistic, or softmax, classifier that assigns a likelihood to a particular outcome or label. We call that predictive, but it is predictive in a broad sense. Given raw data in the form of an image, a deep-learning network may decide, for example, that the input data is 90 percent likely to represent a person.

Artificial Intelligence has been witnessing a monumental growth in bridging the gap between the capabilities of humans and machines. Researchers and enthusiasts alike, work on numerous aspects of the field to make amazing things happen. One of many such areas is the domain of Computer Vision.The agenda for this field is to enable machines to view the world as humans do, perceive it in a similar manner and even use the knowledge for a multitude of tasks such as Image & Video recognition, Image Analysis & Classification, Media Recreation, Recommendation Systems, Natural Language Processing, etc. The advancements in Computer Vision with Deep Learning has been constructed and perfected with time, primarily over one particular algorithm — a Convolutional Neural Network.

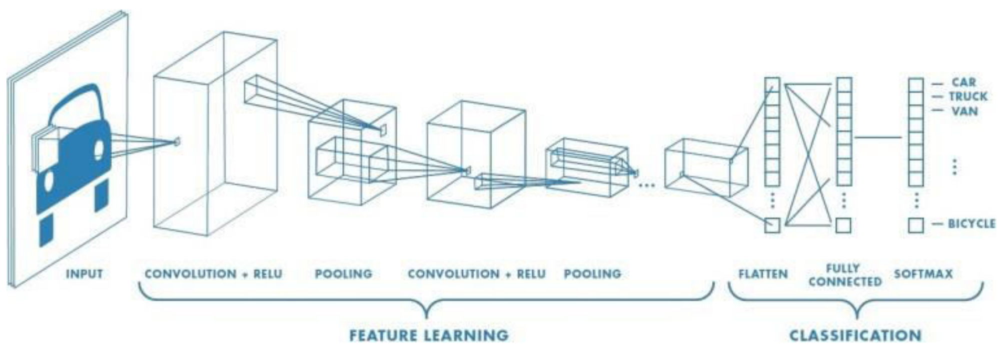

Fig 2 *architect CNN*

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.

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IV. RESULTS

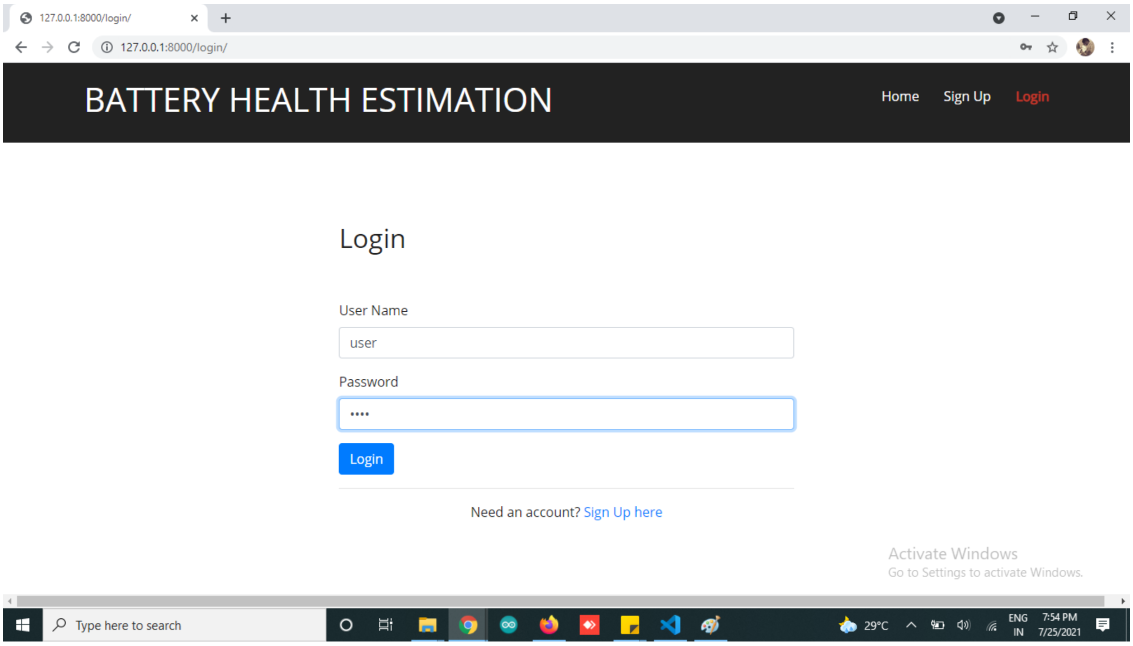

Fig 3. Login

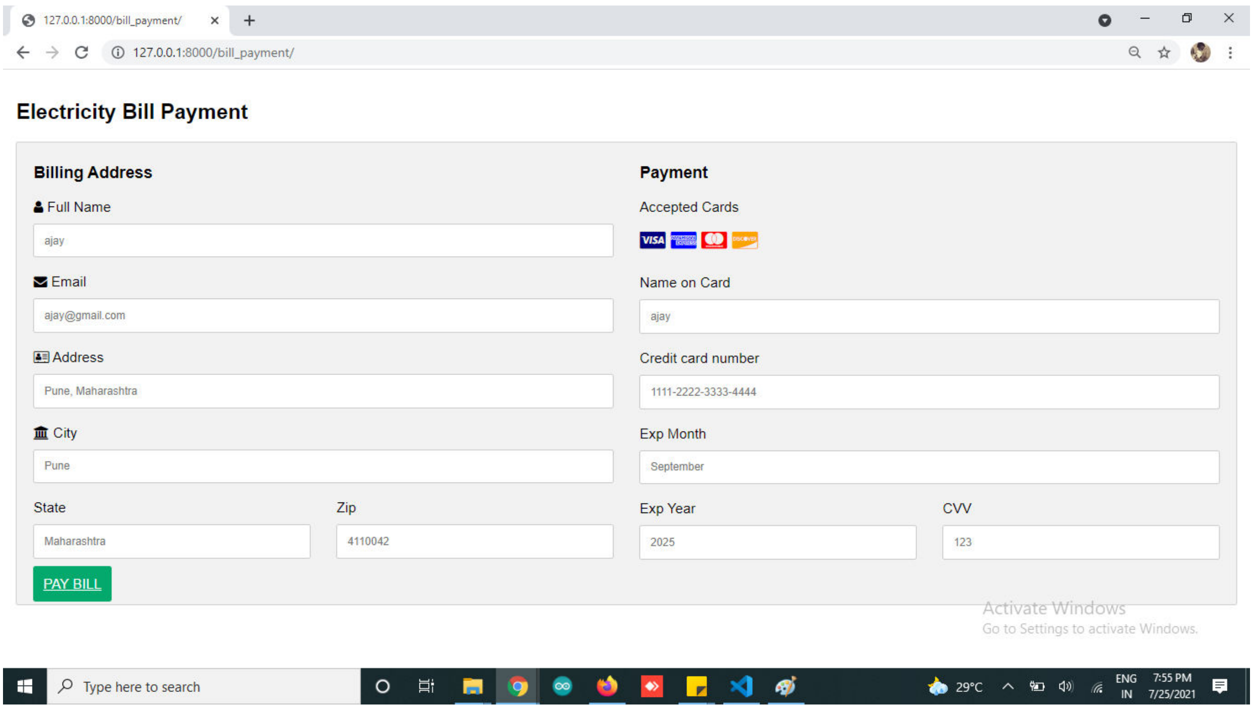

Fig 4.Bill Payment

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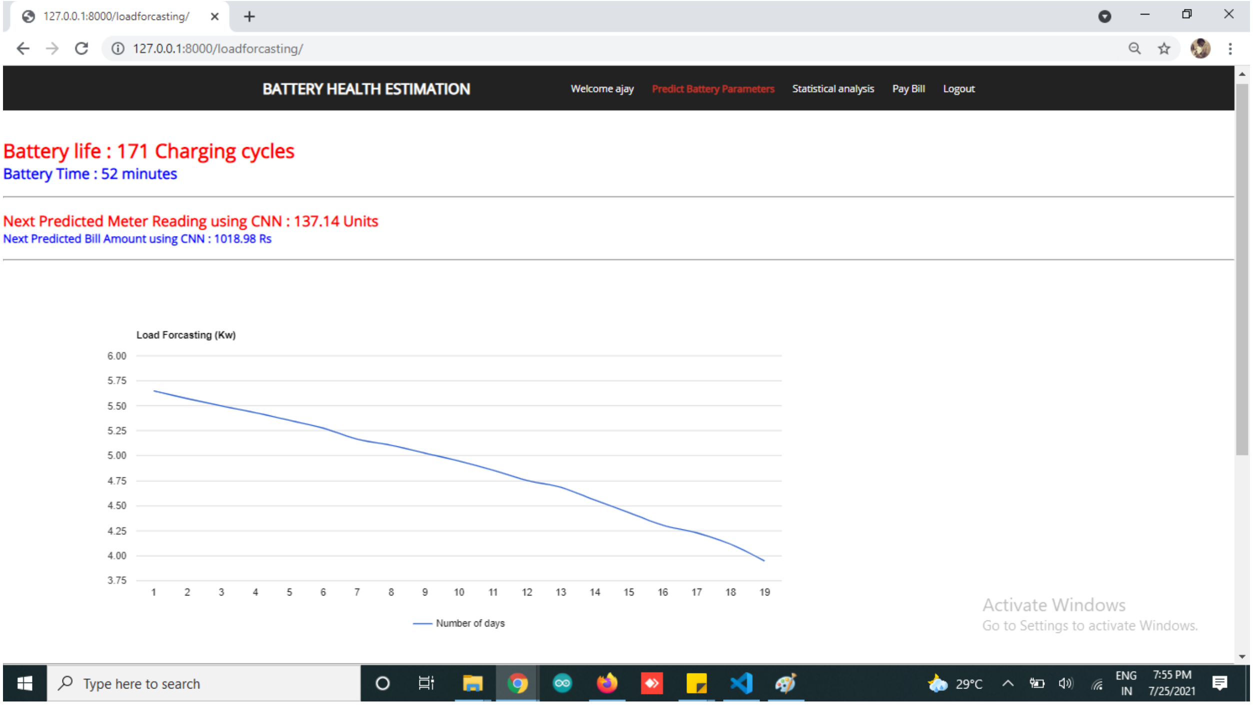

Fig 5.Result

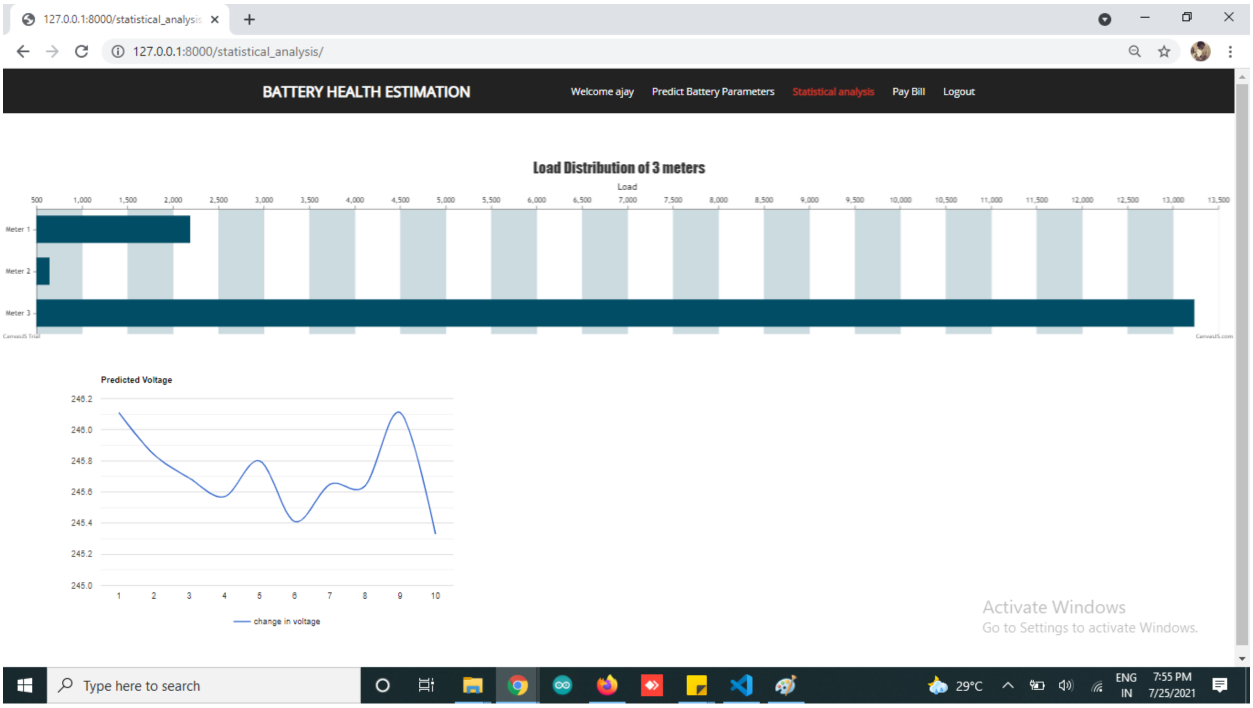

Fig 6.Graph

V. CONCLUSION

SOC and SOH estimation is of a great importance when developing a battery management system; they provide an overview of the short- and long-term state of the battery. The paper proposes a new SOC and SOH co-estimation method with reduced coupling based on convex optimization. Since the energy storage systems have been

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highlighted in portable electronics and hybrid electric vehicle applications, the estimate accuracy of SOC becomes increasingly important. In recent years, many scholars have done a lot of research on SOC estimation.

REFERENCES

1. Vidal, Carlos; Malysz, Pawel; Kollmeyer, Phillip; Emadi, Ali (2020). Machine Learning Applied to Electrified Vehicle Battery State of Charge and State of Health Estimation: State-of-the-Art. IEEE Access, (), 1–1. doi:10.1109/ACCESS.2020.2980961
2. Xiaosong Hu, Hao Yuan, ChangfuZou, Zhe Li and Lei Zhang (2018). Co-Estimation of State of Charge and State of Health for Lithium-Ion Batteries based on Fractional-order Calculus. IEEE Transactions on Vehicular Technology, (), 1–1. doi:10.1109/tvt.2018.2865664
3. Shah, Fawad Ali; Shahzad Sheikh, Shehzar; Mir, UmerIftikhar; OwaisAthar, Syed (2019). [IEEE 2019 International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET) - Istanbul, Turkey (2019.8.26-2019.8.27)] 2019 International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET) - Battery Health Monitoring for Commercialized Electric Vehicle Batteries: Lithium-Ion. , (), 1–6. doi:10.1109/PGSRET.2019.8882735
4. Xiao, Dianxun; Fang, Gaoliang; Liu, Sheng; Yuan, Shaoyi; Ahmed, Ryan; Habibi, Saeid; Emadi, Ali (2020). Reduced-Coupling Co-Estimation of SOC and SOH for Lithium-Ion Batteries Based on Convex Optimization. IEEE Transactions on Power Electronics, (), 1–1. doi:10.1109/TPEL.2020.2984248
5. Hu, Xiaosong; Cao, Dongpu; Egardt, Bo (2017). Condition Monitoring in Advanced Battery Management Systems: Moving Horizon Estimation Using a Reduced Electrochemical Model. IEEE/ASME Transactions on Mechatronics, (), 1–1. doi:10.1109/tmech.2017.2675920
6. Mawonou, KodjoSenouRodolphe; Eddahech, Akram; Dumur, Didier; Godoy, Emmanuel; Beauvois, Dominique (2019). [IEEE IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society - Lisbon, Portugal (2019.10.14-2019.10.17)] IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society - Charge analysis for Li-ion battery pack state of health estimation for electric and hybrid vehicles. , (), 5915–5920. doi:10.1109/IECON.2019.8926645
7. Patnaik, Lalit; Jaya Sai, Praneeth; Williamson, Sheldon S. (2018). A Closed-loop Constant-temperature Constant-voltage Charging Technique to Reduce Charge Time of Lithium-ion Batteries. IEEE Transactions on Industrial Electronics, (), 1–1. doi:10.1109/TIE.2018.2833038
8. Moeini, Amirhossein; Wang, Shuo (2018). [IEEE 2018 IEEE Applied Power Electronics Conference and Exposition (APEC) - San Antonio, TX, USA (2018.3.4-2018.3.8)] 2018 IEEE Applied Power Electronics Conference and Exposition (APEC) - Design of fast charging technique for electrical vehicle charging stations with grid-tied cascaded H-bridge multilevel converters. , (), 3583–3590. doi:10.1109/APEC.2018.8341621
9. YahuiJia; Xiaofei Li; Lin Sang; Ke Wang, "Research on Constant Voltage Output Optimization Method for EV Dynamic Wireless Charging System", 2020 8th International Conference on Power Electronics Systems and Applications (PESA), DOI: 10.1109/PESA50370.2020.9343964
10. Wang, Yixiao; Li, Yong; Jiang, Li; Huang, Yuduo; Cao, Yijia (2019). PSO-based optimization for constant-current charging pattern for li-ion battery. Chinese Journal of Electrical Engineering, 5(2), 72–78. doi:10.23919/CJEE.2019.000013

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