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BATTERY MODELLING APPROACHES FOR ELECTRIC VEHICLES: A SYSTEMATIC REVIEW

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Abstract— **In order to address issues with a sustainable energy supply and environmental pollution, electric and hybrid electric cars are quickly gaining acceptance as effective methods of decarbonizing the transportation industry. It is crucial to establish a proper battery model that accurately predicts battery behavior under varied operating scenarios to prevent operating batteries dangerously and create good regulating algorithms and maintenance plans. The battery model systems must be aware of two crucial internal parameters: state of charge (SoC) and state of health (SoH). A battery model uses approaches such as adaptive observers to understand these internal states. This review paper offers a thorough analysis of battery modelling techniques. Different modelling techniques are examined, and the mechanism and features of Li-ion batteries are described. A thorough examination of the modelling process is offered, considering that analogous electric circuit models are the ones most frequently utilized in the battery management system.**

Keywords— **Battery modelling, Li-ion battery, State of Charge, Kalman Filter, Coulomb Counting.**

I. INTRODUCTION

Fossil fuels (oil, gas, and coal) account for about 65 percent of the energy produced today and the majority of the power required by civilization [1]. The primary issue is the rising pollution, fueling a faster rate of climate change every day. The cost of extracting these fuels will rise shortly, and the natural reserve will run out. Utilizing power produced by renewable energy sources is a close-by choice to assure a bright future. As an illustration, consider solar power systems, wind power systems, smart grids, and electric vehicles. Additionally, as some of these devices utilize energy storage, the main issue is the battery's power capacity, efficiency, and charging techniques [2]. Since these system properties vary for each of them, the suggested study contains a description and comparison of the critical features of the most popular batteries.

A crucial problem is the measurement and prediction of the behavior of battery-based energy storage systems using simulations of the battery's charge and discharge cycles. Its state of charge (SOC), state of health (SOH), and state of function (SOF) should all be estimated [3]–[6]. These states can be measured theoretically, for instance, by using an electrical model and an Extended Kalman Filter (EKF). As a result, the accuracy of the battery model is dependent on the method's accuracy, which in this case uses EKF [7]-[8]. The most appropriate battery model for a particular application can be determined by studying and reviewing the most popular battery models. After that, this study offers a thorough review and analysis of the primary battery types and electrical models employed to predict the various states of a battery system. It should be noted that different applications typically have distinct modelling needs. However, the following factors [1] can typically be used to evaluate battery models:

1) Accuracy: How closely does the model's output correspond to the battery's actual output in practical applications?
2) Configuration effort: How many variables does the model contain? Is it necessary to have in-depth battery chemistry expertise to obtain the parameters?
3) Computational complexity: How long does the simulation take?
4) Interpretability: Can the model be used to develop battery management strategies by offering a qualitative understanding of the behaviour of batteries?

Batteries

By converting chemical energy into electrical energy and moving electrons from the cathode to the anode during the discharging process and vice versa during the charging phase, batteries are devices that can store energy. Two main categories of batteries are mentioned in the literature: primary and secondary. Primary batteries cannot be refilled because of the irreversible chemical deterioration during the discharging process. However, in the case of secondary batteries, the chemical deterioration that occurs during the discharging process is reversible, and the materials used to construct the battery can be restored to their charging qualities by applying a reverse current to it [9].

A. Battery configuration

An electrochemical cell, which serves as the primary component of a general battery structure, is constructed using materials for the anode and cathode and produces oxidation and reduction, respectively [9]-[10]. The anode and cathode terminals of the battery's cells are connected after the electrodes, which can be implemented using conductive materials. Additionally, the electrolyte, a chemical solution in which the electrochemical cells are submerged, enables the transfer of electrons between the cells during the chemical reaction. In order to prevent short circuits, the anode and cathode electrodes are separated from the cell and one another by separators, which are sheets of porous and insulating material.

B. The battery's principal properties

The following list summarizes a generic battery's key features [11]. The amount of energy, expressed in Wh and calculated by multiplying the output voltage by the maximum deliverable current, is the energy storage capacity created by the electrochemical reaction [12]. The maximum deliverable current is the most significant amount of Ah a battery can provide to a load. The internal resistance, which is only a few ohms and is carefully designed by the manufacturer, is another crucial feature. This is produced by the electrolyte and separators' physical characteristics and chemical makeup. The percentage of the total battery capacity consumed during a discharge operation is known as the discharge depth. Shorter charge/discharge cycles result in longer service life because they create shallow discharges (less than 20%) or deep discharges (up to 80%) of the nominal capacity. The number of charge-discharge cycles a battery can withstand before experiencing appreciable detrimental impacts on its performance is the lifespan [13]. The battery's energy progressively evaporates over time, known as the self-discharge parameter. The memory effect measures the maximum battery capacity, which can diminish for three primary reasons: an incomplete charge, staying discharged for an extended period, or remaining idle for an extended period.

C. Open-Circuit Voltage (OCV)

Battery OCV is the terminal voltage at which the battery has reached internal equilibrium when there is no load. The hysteresis effect, which affects battery OCV, depends on the SOC, temperature, and prior charging/discharging history. SOC primarily affects battery OCV. Without considering additional influences, such as temperature and the hysteresis effect, OCV is a non-linear monotonous function of SOC. A lookup table that uses the linear interpolation method to calculate the values within each interval might be used to explain this relationship. Unless there are high-temperature circumstances, temperature influence on OCV is often minimal compared to SOC. The hysteresis effect occurs when, even after enough relaxation time, the battery relaxes to a voltage value more significant than the OCV for a given SOC while charging and to a lower value than the OCV for that SOC when discharging.

D. Impact of temperature

Battery capacity [10] and battery OCV [11] are also impacted by temperature. The typical temperature for measuring battery-rated capacity is 25°C. As the temperature drops, the capacity becomes less and less usable until it may be reduced to a mere 20 degrees Celsius. The internal resistance of the battery is also affected by temperature. The electrons become excited as a battery's internal temperature rises; as a result, the internal resistance falls, and the battery may produce more current. On the other hand, as the temperature drops below -10 C, Li-ion batteries' energy and power capacities often significantly decrease [12]. For developing thermal management algorithms and cooling techniques in EV/HEV applications, a thermal model that can forecast battery temperature under varied charging and discharging scenarios is essential. The battery model can incorporate a straightforward first-order thermal model with just two parameters: thermal capacity and heat conduction coefficient [13]. To describe the temperature effect, researchers have also put out complicated first-principle thermal models [14].

E. Impact of ageing

Whether energy or power capability is essential, a battery's ageing condition can be detected by capacity fading or an increase in internal resistance. Battery end of life is typically described as when the capacity falls below 80% of its nominal capacity. Battery capacity fading is the irreversible capacity decrease after a given duration of storage or use. Researchers have suggested various ageing models for Li-ion batteries. There are two significant forms of battery ageing processes: calendar life (capacity fading due to storage) and cycle (capacity fading due to usage). It is outside the purview of this work to review battery ageing models in depth.

Types of Batteries

The term "battery types" refers to the components or materials that use electrochemistry to store energy [12, 13]. An overview of the various battery types is given in the following sections [14].

A. Lead-Acid battery (Pb-Ac)

Lead dioxide serves as the anode in this battery, and a matrix of lead, sometimes known as sponge lead, serves as the cathode. The electrolyte can be a paste, gel, or liquid (sulfuric acid and distilled water) with a pressure-regulating valve.

- Benefits: Low cost, withstands heavy use, has undergone extensive research, high voltage per cell, permits deep discharge, low self-discharge rate (> 0.1 percent) [15], high efficiency (75–80 percent) [15], and recyclable.

- Drawbacks: Does not support quick charging, is heavy due to the lead, has a poor power density (30 to 50 Wh/Kg) [15], has a short lifespan (typically 500 to 1000 cycles), and may need maintenance.

  Applications include beginning systems, power management, grid stability, and uninterruptible power supply (UPS) systems.

B. Nickel-Cadmium (Ni-Cd)

Batteries made of nickel hydroxide and cadmium have cadmium anodes and cathodes, respectively. Potassium hydroxide is the main component of the electrolyte. Since there is no connection between voltage and charge level, this battery is charged using a constant current method [14].

- Benefits: It is a well-researched technology with good behavior at a range of temperatures (between 40 and 60 °C) [16], the ability to handle overloads that dissipate as heat, a long life cycle (more significant than 3500 cycles, reaching 50 000 cycles only if recharged at 10 percent of the total charge and used continuously) [15], the ability to deliver energy peaks, the ability to handle deep discharges, a small internal resistance, a higher power.
- Drawbacks: The technology is expensive, cadmium is very polluting, degraded using other battery types, suffers from significant self-discharge (10 percent per month) [16], has a low voltage per cell, a significant memory effect, and is susceptible to damage from high temperatures.

Applications include energy management, portable electronics, and backup and energy storage.

C. Nickel Metal Hydride (Ni-MH)

This battery consists of a metal hydride cathode and a nickel hydroxide anode. It is an upgrade or modification of the nickel-cadmium battery. Following are some of its primary traits:

- Benefits: They have all the benefits of nickel-cadmium and a higher energy density (60–120 Wh/Kg) [15], eliminating the memory effect and being cadmium-free, making them less polluting and penalized.
- Drawbacks: A higher rate of self-discharge (15–20 percent per month) [16], an inability to withstand heavy discharges, low voltage per cell, a life expectancy of 300–500 charge cycles [16], a longer charge time than nickel-cadmium, and a lower threshold for forced operation (overloads or complete discharges).

Applications include energy management, energy storage, and backup.

D. Sodium Sulphide (Na-S)

This new technology battery type has a sodium cathode and a Sulphur anode. The electrolyte is an aluminum oxide ceramic composition that serves as a separator and an electrolyte. Its primary attributes are:

- Benefits: Rapid response, prominent energy peaks (reaching 600 percent) [15], and a long lifespan because liquid electrodes are unaffected by temperature fluctuations and do not vibrate or make noise.
- Drawbacks: internal self-overloads can be formed in the cells by operation, raising internal resistance; it must not be entirely discharged and requires control and protection systems.; very high working temperature due to chemical reactions (270°C to 350°C) [15].

Renewable energy sources and energy management are applications.

E. Lithium-ion (Li-ion)

Graphite serves as the cathode, and lithium is the anode in lithium-ion batteries, based on compounds with lithium in both electrodes. Lithium-cobalt oxide, lithium-cobalt phosphate, and lithium-manganese oxide are the most often used types [17]. The conversion of chemical energy to electrical energy occurs during the charge-discharge process, based on the insertion and disinsertion of lithium ions.

- Benefits: A high energy density (75–125 Wh/Kg) [15], lack of memory effect, low self-discharge effect (> 10%), high voltage per cell (3.3–4.0V) [17], long lifespan with effective charge-discharge methods, and high voltage per cell.
- Drawbacks: They need a charging circuit, have a short lifespan of between two and five years [15] regardless of use, have low current peak capacities, are pricey compared to alternative technologies like Pb-Ac, and are sensitive to over-voltage events.

Some critical applications include portable electronics, the auto sector, renewable energy, and energy management.

F. Lithium polymer (Li-Po)

The Li-Po battery is an enhancement or modification of the lithium-ion battery, but its key feature is that the electrolyte is a solid polymer. Because the solid electrolyte takes up less space than the liquid electrolyte, this feature enables the production of small batteries. Its primary attributes are:

- Benefits: Due to the electrolyte, they have a high-power density (more significant than lithium-ion, 130–200 Wh/Kg) [16], a reduced volume, are lighter, have no memory effect, and have a low self-discharge rate.
- Drawbacks: This battery type requires charge regulation, is expensive because the electrolyte lowered conductivity, has a higher internal resistance (which can be handled with gel electrolytes but with a lower power density), and is currently under research.

Applications consist of tiny portable devices.

Types of Battery Models

Theoretical internal parameters like the State of Charge (SOC), State of Health (SOH), State of Function (SOF), open circuit voltage (OCV), the effect of temperature and the effect of ageing or physical parameters like voltage, current, and temperature can be measured or predicted using battery modelling, which can be empirical or analytical [17]–[19]. These help design, manage and optimize Battery Management Systems (BMS), used in portable electronics, backup power systems, electric and hybrid vehicles, and renewable energy systems with energy storage. Battery models can be categorized using the following criteria or goals:

A. Electrochemical model

The kinetics of chemical reactions inside battery cells serve as the foundation for electrochemical models. They are the slowest models because they use nonlinear differential equations, but they are the most accurate models because the simulation is done at the particle level.

B. Mathematical model

This type of model can be analytical or stochastic; the former uses fewer equations to describe the behavior of the battery and presents it as a more straightforward system (e.g., the two-tank model [5]), whereas the latter is based on discrete-time and preserves great precision but is slower and more challenging than the former (e.g., Markov chain [5]).

C. Ageing model

It is based on three key factors: the battery's internal resistance, energy loss, and self-discharge. Where the primary goal is to simulate the phenomenon of battery ageing in the present and the future.

D. Thermal model

It is based on past storage and operating temperature patterns and elements that affect the battery's performance, lifespan, and safety. It enables knowledge of and prediction of the battery's behavior and operation under specific temperature settings [18]-[19].

E. Electric model

These models employ non-linear aspects in some cases and are based on passive electrical parts and power sources to describe the behavior of the battery. In terms of time-benefit compared to the earlier models, these types of models strike a compromise between accuracy and calculation speed [20]–[22].

As a result, the electric or equivalent circuit models will be thoroughly examined in this paper. They are the most popular because of their quick and easy simulation, acceptable high precision in real-time, and the fact that they are the best for connecting to networks or electrical and electronic circuits.

Significane and Criteria of Review

A correct battery model is crucial for forecasting Li-ion battery behavior under various operating settings to prevent improper operations, such as overcharging, deep discharge, and high temperatures. Li-ion cells are widely employed in EV/HEV applications because of their benefits, such as high energy density, high power density, low self-discharge rate, and no memory effect [21-22]. Another indication of this fact is the rise in research articles on this subject. Battery modelling is a powerful tool for predicting and optimizing basic battery parameters such as state of charge, battery lifetime, and charge/discharge behavior. Many different battery models have been produced over the years for various applications. This includes mathematical models, fuzzy models and much more [23]. Hence there is a need for a detailed review paper summarizing the research progress based on the methodologies and architecture used to develop the battery models. Even though there are several review papers in this domain reviewing battery models, they do not cover all aspects of battery modelling like methodology, parameters covered, type of model, validation using the graphical user interface and updating algorithms used.

- Singirikonda et al., 2020 [23] summaries technologies that focus more on the state of charge aspect alone. The proposed paper will cover all factors, including SoC, SoH and other battery parameters.
- Zhang et al., 2014 [24] summaries methodologies used to compare various battery modelling techniques. However, it lacks tables for comparing multiple research articles. This review paper does not review the modelling aspects of the published journals.
- Tamilselvi et al., 2021 [25] only review the mathematical modelling of the battery. The proposed review paper will examine the modelling aspect as well.
- Vykhodtsev et al., 2022 [26] summaries mathematical model aspects of the Li-ion battery model. This document is not covering any estimation techniques that can be used to develop the equivalent model. The proposed paper will cover different modelling methodologies reviewed in other articles.

Considering many published journals on battery modelling, this review paper focuses only on journals on li-ion battery modelling. Also, focusing on battery models which cover the battery parameters like SOH and SOC with graphical user interface developed are considered for the review. A total of 23 papers were shortlisted, as shown in Table I and Figure 1. The significance of a battery model with the graphical user interface is relevant considering the ability to validate the model with actual battery parameters. It also provides an option to validate the developed model and choose to integrate the model developed in hardware in loops setup. This is vital in proving that the model developed is accurate. Battery modelling got a significant boost in publications in

2018 due to the drastic boom in the electric vehicle industry, as shown in Figure 2.

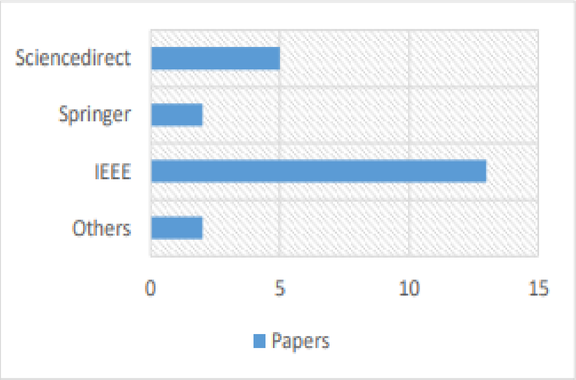


Figure 1. Detailed journal distribution

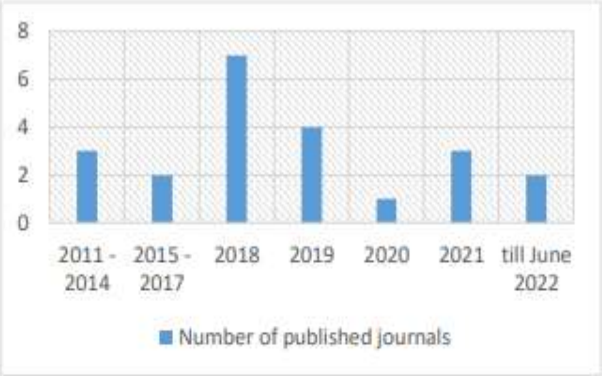


Figure 2. Yearly trend in published journals

Review Methedology

Primary battery modelling covers battery parameters like state of charge and state of health, but most papers focus only on the state of charge. Major battery parameters are charted out as sown in Figure 3. Similarly, other parameters like energy lost at charging are only covered in very few models. Mathematical models are the easiest to design and validate, whereas graphical user interface models are hard to design and validate; hence, they are less popular. Validation of the model developed is vital in proving the model developed is behaving like an actual battery. The validation requires coupling the developed model with the actual battery bank and monitoring the model parameters closely. This is done with the help of software like MATLAB and NI LabVIEW. These characteristics of the papers on battery modelling are discussed and sorted in Table 1. Also, the model uses complex mathematical computations to calculate and predict the performance of the Li-ion battery. This is done using methods like coulomb counting or Kalman filter computational methods. For each iteration, the gain weight factors must be updated after each cycle. Each computational method has its gains and disadvantages. A detailed classification of computational methods is given in Figure 4.

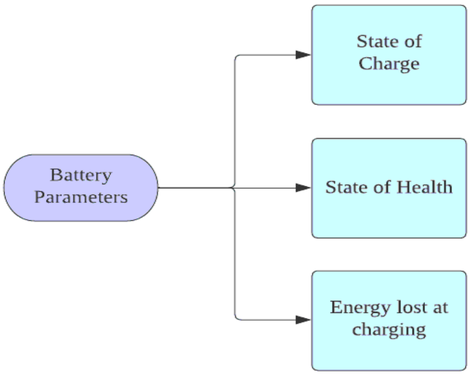


Figure 3. Battery parameters

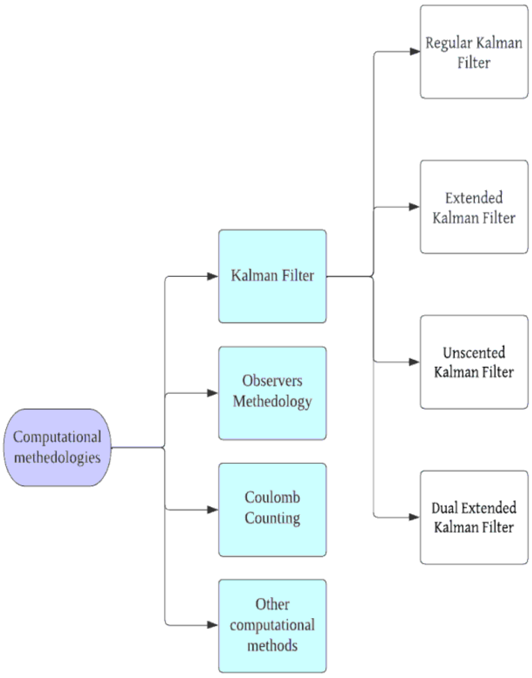
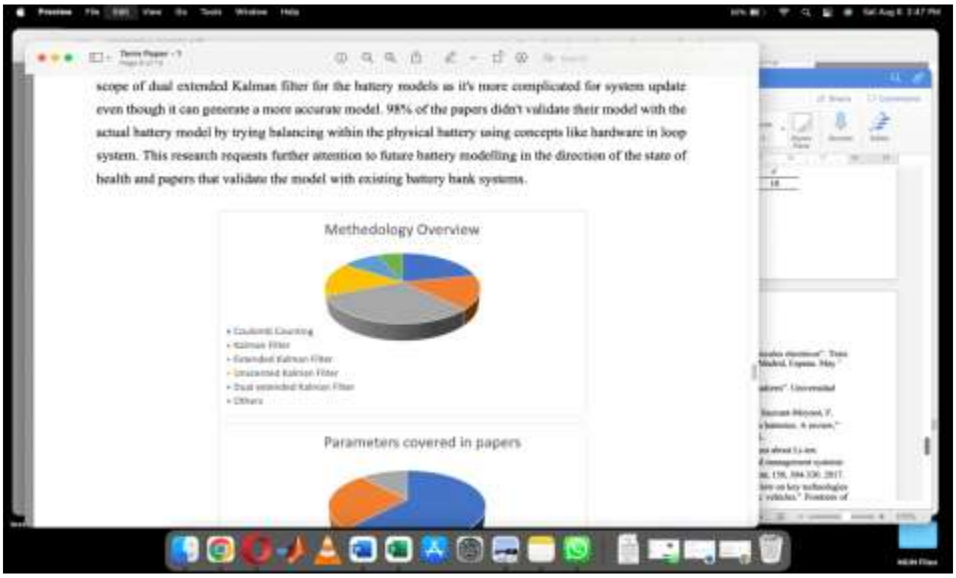


Figure 4. Detailed computational methodologies

Validation of the model developed is vital in proving the model developed is behaving like an actual battery. The validation requires coupling the developed model with the actual battery bank and monitoring the model parameters closely. This is done with the help of software like MATLAB and NI LabVIEW [57]. These characteristics of the papers on battery modelling are discussed and sorted in Table 1. Also, the model uses complex mathematical computations to calculate and predict the performance of the Li-ion battery. This is done using methods like coulomb counting or Kalman filter computational methods. For each iteration, the gain weight factors must be updated after each cycle. Each computational method has its gains and disadvantages. A detailed classification of computational methods is given in Figure 4. It can be noted from Table II that the most popular battery parameter updating methodology is the Extended Kalman filter, followed by Columb counting, as shown in Figure 5. Also, Table I shows that most battery modelling research papers significantly focus on the state of charge parameter over other factors, as shown in Figure 6. In a nutshell, the need for more efficient batteries to support. The ongoing boom of the electric transportation industry and the need for more efficient batteries has given much investment in improving battery technology; this is evident in the number of research on improving the state of charge parameter of the Li-ion battery. The state of charge plays a significant role in determining the battery health, charging current, and charging time. As previously reviewed, the topic of the state of charge design within the battery modelling is the focus of almost all research papers. Most of these papers use the mathematical model and focus on the weight factor updating factors obtained from Kalman filter computation.



scope of dual extended Kalman filter for the battery models as it's more complicated for system update even though it can generate a more accurate model. 98% of the papers didn't validate their model with the actual battery model by trying balancing within the physical battery using concepts like hardware in loop system. This research requests further attention to future battery modelling in the direction of the state of health and papers that validate the model with existing battery bank systems.

Figure 5. Methodology overview for parameter update

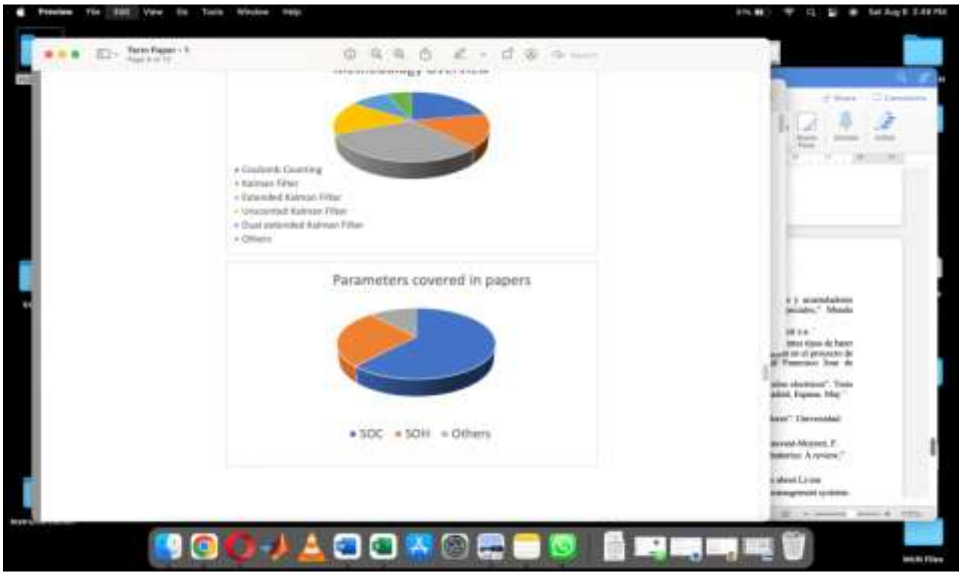


Figure 6. Battery parameters covered as per distribution

Table I. Parameters covered under battery modelling

	Parameters covered			Model aspects			S/W model developed		
	SOC	SOH	Other	Math	GUI	Other	LabVIEW	Matlab	Other
Berecibar et al., 2016 [33]		✓	✓	✓					
Cui et al., 2022 [34]	✓			✓					
Haoran et al., 2018 [35]	✓			✓					
Hossain et al., 2022 [36]	✓				✓				✓
Huang et al., 2021 [37]	✓			✓					
Jokić et al., 2018 [38]	✓			✓					
Khalil et al., 2018 [39]	✓			✓	✓			✓	
Kharisma et al., 2019 [40]	✓	✓	✓	✓	✓			✓	
Li et al., 2011 [41]	✓	✓		✓			✓		
Liu et al., 2018 [42]	✓	✓	✓	✓					
Meng et al., 2017 [43]	✓					✓			
Meng et al., 2018 [44]	✓		✓			✓			
Pebriyanti et al., 2013 [45]	✓	✓		✓	✓		✓	✓	
Shrivastavaa et al., 2019 [46]	✓	✓		✓	✓		✓		
Si et al., 2019 [47]	✓			✓					
Susanna et al., 2019 [48]	✓					✓			✓
Topan et al., 2016 [49]	✓	✓		✓	✓		✓		
Wahyuddin et al., 2018 [50]	✓			✓					
Wang et al., 2020 [51]	✓	✓							
Wang et al., 2021 [52]	✓								
Xuan et al., 2020 [53]	✓			✓				✓	
Yamin et al., 2014 [54]	✓	✓		✓			✓	✓	
Total	21	9	4	16	6	3	5	5	2

Table II. Model update computational methodology used

	Model computational method used						
	CC	KF	EKF	UKF	DEKF	Obs.	Other
Berecibar et al., 2016 [33]		✓	✓			✓	
Cui et al., 2022 [34]		✓					✓
Haoran et al., 2018 [35]			✓				
Hossain et al., 2022 [36]							✓
Huang et al., 2021 [37]				✓			✓

Jokić et al., 2018 [38]			✓	✓			
Khalil et al., 2018 [39]	✓		✓				
Kharisma et al., 2019 [40]	✓						
Li et al., 2011 [41]					✓		
Liu et al., 2018 [42]							✓
Meng et al., 2017 [43]	✓		✓	✓			✓
Meng et al., 2018 [44]							✓
Pebriyanti et al., 2013 [45]							✓
Shrivastavaa et al., 2019 [46]		✓	✓	✓	✓		✓
Si et al., 2019 [47]			✓				
Susanna et al., 2019 [48]	✓						
Topan et al., 2016 [49]		✓					
Wahyuddin et al., 2018 [50]	✓						✓
Wang et al., 2020 [51]	✓	✓	✓	✓	✓		
Wang et al., 2021 [52]			✓				
Xuan et al., 2020 [53]	✓					✓	
Yamin et al., 2014 [54]			✓				✓
Total	7	5	10	5	3	2	10

II. CONCLUSION

In conclusion to the review conducted, it was noticed that most of the research papers were focused on developing a mathematical model for the state of charge of the battery. Other factors like state of health, energy lost at charging and energy loss due to heat were modelled by very few fractions of paper. Similarly, any research doesn't get handy to the public and industrial market unless it's implemented on such a scale that it's easily implementable; this points to the need for graphical user interface models. Few research articles only used the graphical user interface aspect of the model. Similarly, most researchers do not try to see the scope of dual extended Kalman filter for the battery models as it's more complicated for system update even though it can generate a more accurate model. 98% of the papers didn't validate their model with the actual battery model by trying balancing within the physical battery using concepts like hardware in loop system. This research requests further attention to future battery modelling in the direction of the state of health and papers that validate the model with existing battery bank systems.

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