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REVIEW ARTICLE

Battery Models and Estimation Techniques for Energy Storage Systems in Residential Buildings

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Abstract

This paper presents a comprehensive analysis of battery models and estimation techniques, focusing on their applications in residential buildings. The paper begins by exploring various battery models, including electrochemical, electrical equivalent circuit models. Different estimation techniques through various tests are discussed to provide insights into accurate battery parameter estimation. The applications of battery models in residential buildings are then discussed, highlighting energy storage sizing, energy management and optimization, and backup power supply. Additionally, it emphasizes the significance of software tools for battery modelling and simulation. Overall, this paper serves as a valuable resource for researchers, engineers, and decision-makers involved in the design and operation of residential energy systems, enabling them to make informed decisions regarding battery selection, sizing, and control strategies.

Keywords: Battery Models, State of Charge (SOC), Estimation Techniques, Equivalent circuit.

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1. Introduction

With the increasing demand for renewable energy sources and the growing interest in energy storage systems, batteries have become crucial components in various applications, including residential buildings. Efficient management and accurate estimation of battery parameters are essential for optimizing energy utilization, enhancing system performance, and ensuring reliable operation [1], [2]. By understanding and accurately estimating battery parameters, optimal energy management strategies can be developed, resulting in improved efficiency, reliability, and cost-effectiveness [3].

The paper explores different battery models, considering both electrochemical and electrical equivalent circuit models. Kinetic battery model is one of the Electrochemical Model that was discussed to provide a comprehensive understanding of battery behaviour. Furthermore, the review delves into various electrical equivalent circuit models, including the simple Rint model, Thevenin model, and Partnership for a New Generation of Vehicle (PNGV) model among others. These models capture the electrical characteristics of batteries, enabling accurate representation of their behaviour under different operating conditions [4]- [6]. To estimate battery parameters accurately, a range of techniques is utilized. The paper shows the sights of capacity tests, the Hybrid-Pulse-Power-Characterization (HPPC) test, and grey box testing.

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These techniques provide insights into capacity estimation, SOC determination [7]- [9], SOH (State-Of-Health—ability of a battery to provide its nominal capacity over its service lifetime), SOP (State-Of-Power—a quantity describing the battery's power capability), and impedance characterization, contributing to improved battery parameter estimation [10]- [13]. The practical applications of battery models in residential buildings are discussed, highlighting their significance in energy storage sizing, energy management and optimization, backup power supply, and financial analysis. By accurately modelling batteries and estimating their parameters, residential energy systems can be optimized to enhance self-consumption, minimize grid dependence, and reduce energy costs [14], [15].

Finally, the review emphasizes the importance of software tools for battery modelling and simulation. These tools facilitate the implementation and evaluation of various battery models, enabling researchers and practitioners to simulate and analyse battery performance under different scenarios.

2. Type of batteries

Batteries are essential power sources that provide portable and reliable energy for a wide range of applications. They come in various types, each with its unique chemistry and performance characteristics. Understanding the different types of batteries is crucial for choosing the most suitable option for specific applications and optimizing their performance [16]-[18]. Electrochemical batteries generate electrical energy through spontaneous redox reactions and typically involve two metals connected by either a salt bridge or an ion exchange membrane to maintain ionic contact and prevent unwanted side reactions. These batteries operate by facilitating the transfer of electrons from one half-chamber to another, where species in each chamber either gain or lose electrons at their respective electrodes. Some of the widely used battery types include [19]- [22].

(A). Lead-acid battery: These batteries have been in use for decades and are known for their low cost and high reliability. These batteries have a favourable power-to-weight ratio due to their capability to deliver high surge currents. They are commonly found in automotive applications and uninterruptible power supplies (UPS).

(B). Lithium-ion battery: Lithium-ion batteries have gained immense popularity due to their high energy density, lightweight design, long cycle life, enhanced power generation through large surface roughness and porous structure, as well as their mechanical flexibility. They are widely used in renewable energy systems, electric vehicles and portable electronics.

(C). Nickel-cadmium battery: Nickel-cadmium (NiCd) batteries offer good performance in terms of reliability, rechargeability, high discharge rates, high current delivery, and long cycle life. They have a discharge terminal voltage of around 1.2 volts, which remains stable until near the end of discharge, while offering a maximum EMF of 1.3 volts. They were commonly used in applications that require frequent charging and discharging, such as cordless power tools and emergency lighting systems.

(D). Nickel-metal hydride battery: Nickel-metal hydride batteries are an alternative to NiCd batteries, offering higher energy density, rechargeability and being more environmentally friendly. They are commonly used in portable electronic devices and also find applications in hybrid and electric vehicles for energy storage.

(E). Supercapacitors: In recent years, supercapacitors have gained significant interest as energy storage devices based on electrochemical processes. They offer advantages over batteries in terms of charge/discharge rate, power density, environmental impact, and safety.

(F). Biofuel cells: By harnessing biocatalysts, a biofuel cell is a bio-electrochemical device that converts biochemical energy into electrical energy. Unlike electrochemical batteries, biofuel cells utilize renewable enzymes or microorganisms as catalysts instead of expensive metal catalysts, providing a sustainable and environmentally friendly alternative.

3. Battery models

Battery models are essential tools for understanding and analysing the behaviour of batteries in various applications. They can be broadly categorized into electrochemical models and electrical equivalent circuit models, with mathematical models also playing a significant role. They provide insights into the complex behaviour of batteries and serve as essential tools in designing efficient and reliable energy storage solutions for diverse applications [21]–[24].

3.1. Electrochemical model

Electrochemical Battery modelling is a method of representation of the dynamic working of a battery that can be expressed in terms of electrochemical principles that it works on. These models focus on the intricate electrochemical processes occurring within batteries, considering factors such as chemical reactions, ion transport, and electron transfer. These models provide a detailed understanding of battery behaviour at a microscopic level but can be computationally intensive. It describes a system by obtaining suitable and efficient model by involving the combination of electrochemical mechanisms and electrical principles, through the partial differential equations written by considering the effect of various electrochemical reactions takes place in cell on the cell potential [5]. Electrochemical modelling was one of the first uses while dealing with non-linear systems. One of such electrochemical models is Kinetic Battery Model [14].

(a). Kinetic battery models (KiBaM): The KiBaM is a highly instinctive battery model. The reason behind its name "kinetic" is its reliance on a chemical kinetics process as its fundamental principle. Initially, its development focused on capturing the chemical processes of large lead-acid batteries.

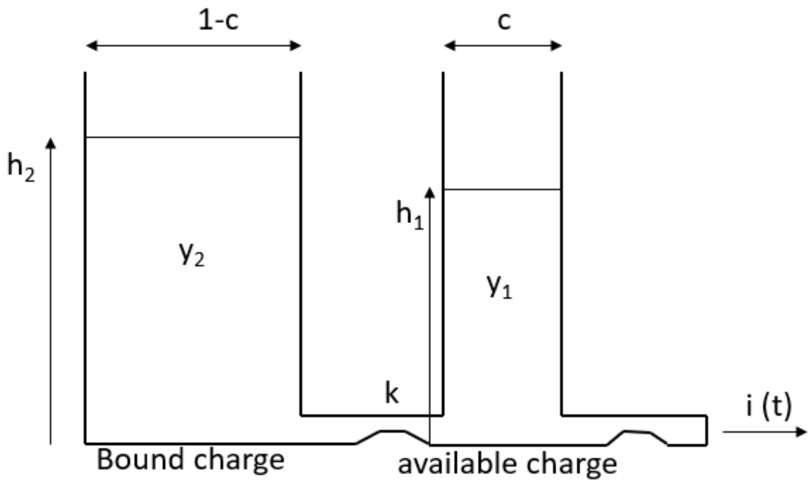

Figure 1: Two-well-model of the kinetic battery model.

The model divides the battery charge between two wells: the available-charge well and the bound-charge well (Figure 1 [12]). A portion of the total capacity, denoted as c, is allocated to the available charge well, while the remaining fraction, $1 - c$, resides in the bound charge well. Electrons are directly provided to the load ($i(t)$) from the available charge well, while the bound-charge well exclusively supplies electrons to the available-charge well. The transfer of charge from the bound charge well to the available charge well occurs through a "valve" characterized by a fixed conductance, k. In addition to this parameter, the rate of charge flow between the wells relies on the disparity in height between the two wells. The heights of the two wells are given by (1).

$$h_1(t) = \frac{y_1(t)}{c}; \qquad h_2(t) = \frac{y_2(t)}{1-c} \tag{1}$$

The two-well model portrays a battery's state through the interplay of available and bound charge wells. A drained available well signifies an empty battery. When a load is connected, it pulls charge from the available well, creating an imbalance between the two wells. Disconnecting the load triggers a transfer of charge from the bound well to the available well until they reach equilibrium. This "resting" period allows for more charge to be available, enhancing battery life. However, there's a trade-off. High discharge currents rapidly deplete the available well, limiting the time for bound charge to transfer. This results in a reduced effective capacity, where some stored charge remains inaccessible, reflecting the rate capacity effect. While the two-well model of the KiBaM accurately captures the rate capacity and recovery effects, it remains suitable for assessing battery lifetime rather than its voltage profile during discharge. Although this model effectively represents the battery's capacity variation resulting from nonlinear capacity effects, it lacks the ability to depict the dynamic behaviour necessary for codesign and co-simulation with other electrical circuits and systems [14].

3.2. Electrical equivalent circuit models

Electrical equivalent circuit models are crucial for understanding battery behaviour in various applications. These models simplify complex electrochemical processes using components like resistors and capacitors. Striking a balance between accuracy and complexity, they range from primitive single resistor to advanced multi-component models. Continuous refinement aims to improve accuracy and capture battery dynamics effectively. Understanding these models is vital for tasks like battery management and performance optimization. They facilitate tasks such as estimating state-of-charge, predicting battery runtime, and developing efficient charging strategies, making them indispensable in energy storage systems and electric vehicles. The following are few widely know electrical equivalent circuit models [1] - [4].

(a). Simple model/Rint battery model: The simplified model consists of an ideal battery with an open-circuit voltage V_0 and a constant internal resistance R_{int} (from Figure 2 [2]), enabling the determination of the terminal voltage V_t through open-circuit measurements and R_{int} estimation via additional measurements with a connected load when the battery is fully charged. This model is also called as Resistive Thevenin Battery model [1].

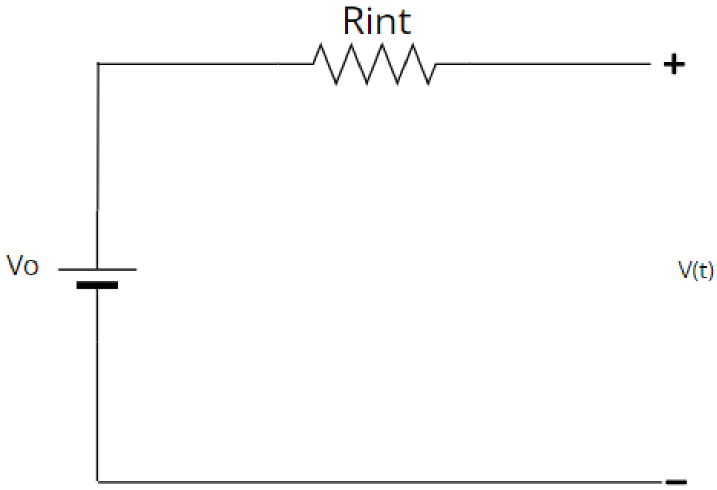

Figure 2: Simple/rint battery model.

While the R_{int} model is straightforward, it fails to account for the dynamic changes in internal resistance caused by temperature, state of charge, and electrolyte concentration. Consequently, this model's limited scope restricts its use to specific circuit simulations and renders it unsuitable for applications in electric vehicles and hybrid electric vehicles.

(b). Thevenin model: The widely employed Thevenin model, illustrated in Figure 3 [4], is a common representation utilized for describing the open circuit voltage (OCV) of a Li-ion battery. This model incorporates an ideal voltage source, a series resistance (R_o), and an RC parallel network (R_P and C_P) to predict the Li-ion battery's response to instantaneous loads at a specific state of charge (SOC). The voltage V_{C_P}, which appears across the ends of the capacitance C_P, serves as the state variable, while the terminal current I_L acts as the input variable and the terminal voltage V_L as the output variable. By applying Kirchhoff's law and formulating Equation (2), the Thevenin model's state-space equation is derived.

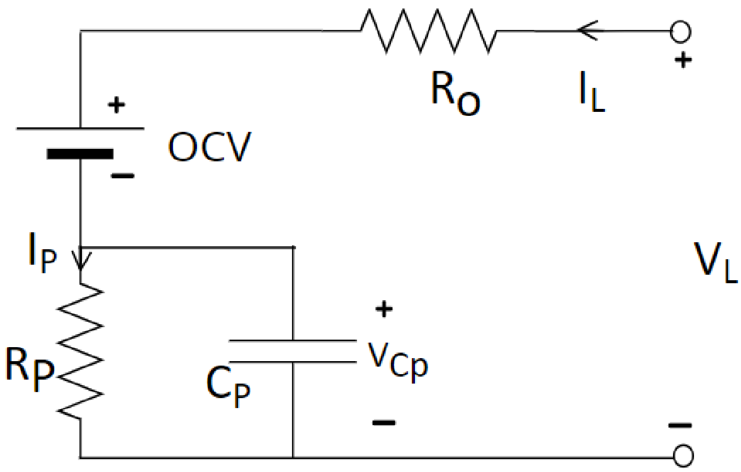

Figure 3: Thevenin model.

$$\dot{V}_{C_P} = -\frac{1}{R_P C_P} V_{C_P} + \frac{1}{C_P} I_L \tag{2}$$

$$V_L = V_{C_P} + R_o I_L + OCV \tag{3}$$

The Thevenin model, favoured for its simplicity in representing Li-ion batteries, faces limitations when the open circuit voltage (OCV) remains constant with state of charge (SOC). This restricts its ability to capture steady voltage variations and predict operation duration. To address this, additional components like capacitors are integrated, enhancing simulation accuracy. Researchers have introduced bipolar and multi-polar models, with the modified Thevenin model being commonly used (Figure 4 [4]). This model includes an ideal voltage source representing OCV, internal resistances, capacitances, and polarization voltages. State variables encompass electrochemical and concentration polarization voltages, while load current serves as the input variable, and terminal voltage as the output. The model's state-space equation is derived through Kirchhoff's law.

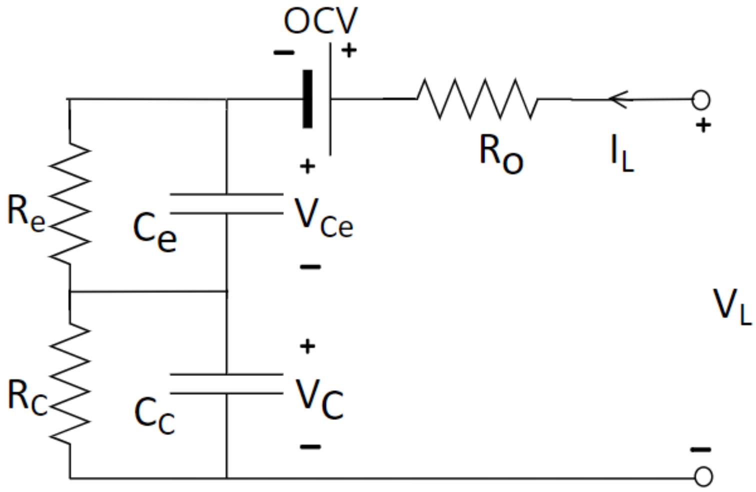

Figure 4: Modified thevenin model.

$$\begin{bmatrix} \dot{V}_{C_e} \\ \dot{V}_{C_c} \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_e C_e} & 0 \\ 0 & -\frac{1}{R_c C_c} \end{bmatrix} \begin{bmatrix} V_{C_e} \\ V_{C_c} \end{bmatrix} + \begin{bmatrix} \frac{1}{C_e} \\ \frac{1}{C_c} \end{bmatrix} I_L \tag{4}$$

$$V_L = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} V_{C_e} \\ V_{C_c} \end{bmatrix} + R_o I_L + OCV \tag{5}$$

Owing to its comparable simplicity and ability to meet the basic requirements for Li-ion battery, the Thevenin model has been extensively used. If the open-circuit voltage (OCV) remains constant with state of charge (SOC), the model is limited to describing only the transient responses of the Li-ion battery at specific SOC levels. Correspondingly, the model can neither be used to describe the steady voltage changes of Li-ion batteries nor to predict their operation duration. The model also fails to describe the relationship between the battery's OCV and SOC as well as to predict its operation duration and the charge and discharge management. By introducing additional components like capacitors into derivative circuits, enhanced simulation effects can be achieved. Despite their limitations, both the Thevenin model and its modified version hold significant practical importance.

(c). Partnership for a New Generation of Vehicle (PNGV) model: Incorporating a capacitor C_o into the Thevenin model, the PNGV model, as depicted in Figure 5 [4], holds significant physical relevance. Here, the ideal voltage source represents the Li-ion battery's open-circuit voltage (OCV), while resistances R_o and R_p respectively account for ohmic and polarization internal resistances. Capacitance C_p captures polarization capacity, I_L denotes load current, I_p signifies polarization current, and V_L corresponds to terminal voltage. Capacitance C_o reflects changes in OCV resulting from integrating load current I_L over time. As the battery charges or discharges, current accumulation alters state of charge (SOC), modifying OCV, evident in voltage variations on capacitor C_o. This model addresses Thevenin's limitations by representing both battery capacity and direct current response through C_o. State variables include voltage V_{C_o} across C_o and voltage V_{C_p} across C_p, with I_L as input and V_L as output. Equation (4) derives from Kirchhoff's law to establish the PNGV model's state-space equation.

The PNGV model is widely adopted due to its systematic parameter identification methods and relatively high model accuracy.

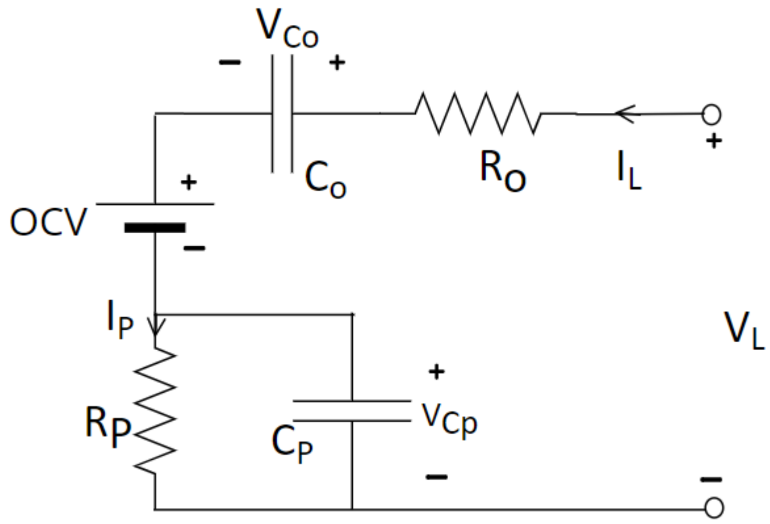

Figure 5: PNGV model.

$$\begin{bmatrix} \dot{V}_{C_o} \\ \dot{V}_{C_p} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & -\dfrac{1}{R_p C_p} \end{bmatrix} \begin{bmatrix} V_{C_o} \\ V_{C_p} \end{bmatrix} + \begin{bmatrix} \dfrac{1}{C_o} \\ \dfrac{1}{C_p} \end{bmatrix} I_L \tag{6}$$

$$V_L = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} V_{C_o} \\ V_{C_p} \end{bmatrix} + R_o I_L + OCV \tag{7}$$

(d). The randle's model: Originally designed for lead-acid batteries, Randle's model has garnered attention for its applicability to lithium-ion battery modelling. Illustrated in Figure 6 [6], the Randle's equivalent circuit for a typical lithium-ion cell includes series resistance (R_s), no-load self-discharge (R_d), bulk charge storage (C_b), double-layer effect of electrodes (C_s), and charge-transfer resistance (R_t). The voltage V_{C_b} across C_b represents the cell's open circuit voltage (OCV).

The utilization of the star-delta transformation on the original Randle's circuit led to the development of a novel battery model, as depicted in Figure 7 [6]. This alternative model maintains the same number of parameters as Randle's model but introduces slight modifications in representing transient states. Previous studies have shown that when combined with real-time state observers like the Utkin and Kalman Filter, the parallel reconfiguration of Randle's model states can enhance state-of-charge (SOC) estimation.

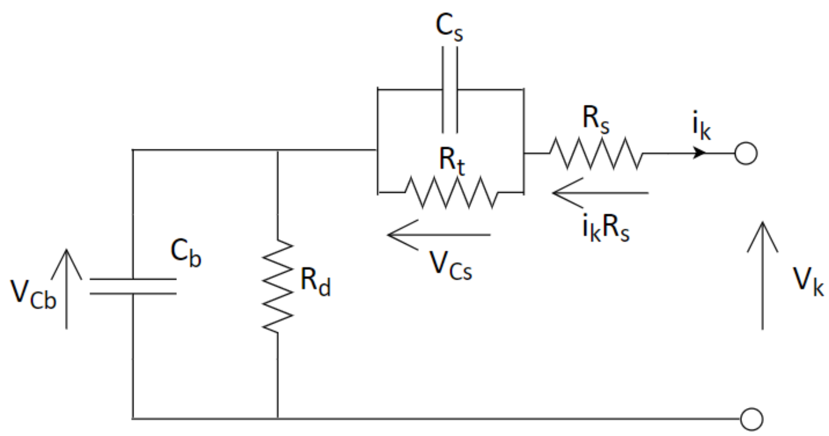

Figure 6: Randle's model.

Thus, in this research, the suitability of this model structure for online SOC and state-of-power (SOP) estimation will be evaluated. By mapping Randle's model parameters as described and discretely solving the output equation, the following outcomes are obtained:

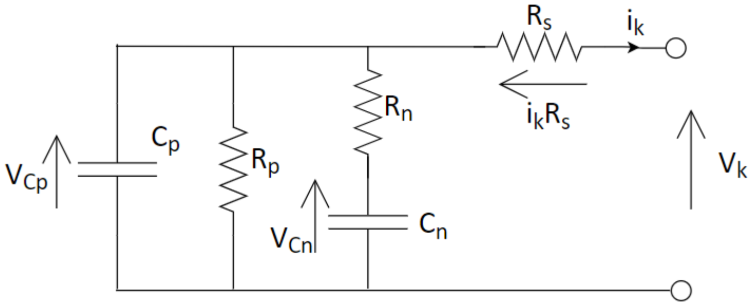

Figure 7: Modified randle's model.

$$C_n = \frac{C_b^2}{C_b + C_s}, \qquad C_p = \frac{C_p C_s}{C_b + C_s}, \qquad R_n = \frac{R_t(C_b + C_s)^2}{C_b^2}, \qquad R_p = R_d + R_t \tag{8}$$

$$\begin{aligned}\begin{bmatrix} V_{C_p,k+1} \\ V_{C_n,k+1} \end{bmatrix} &= \begin{bmatrix} e^{-T_s/\tau_p} & \dfrac{R_t}{R_n}\left(1 - e^{-T_s/\tau_p}\right) \\ 1 - e^{-T_s/\tau_n} & e^{-T_s/\tau_n} \end{bmatrix} \begin{bmatrix} V_{C_p,k} \\ V_{C_n,k} \end{bmatrix} \\ &+ \begin{bmatrix} R_T\left(e^{-T_s/\tau_p} - 1\right) & 0 \\ 0 & 0 \end{bmatrix} i_k, \qquad v_k = V_{C_p,k} - i_k R_s \end{aligned} \tag{9}$$

In (8) and (9), the $R_T = R_p R_n/(R_p + R_n)$, $\tau_n = R_n C_n$ and $\tau_p = R_T C_p$.
(E). Dynamic battery model: A dynamic model of lead-acid traction batteries has been developed to accurately represent their behavior. This model integrates battery terminal voltage (E_{tb}), open-circuit voltage (V_{OC}), battery terminal resistance (R_b), polarization constant (K), and battery discharge current (i_{tb}). Notably, this enhanced model accounts for the non-linearity of both the open-circuit voltage and internal resistance, represented by the K/SOC term [1].

$$E_{tb} = V_{oc} - \left(R_b + \frac{K}{SOC}\right) i_{tb} \tag{10}$$

The fourth-order dynamic model is shown in Figure 8 [1].

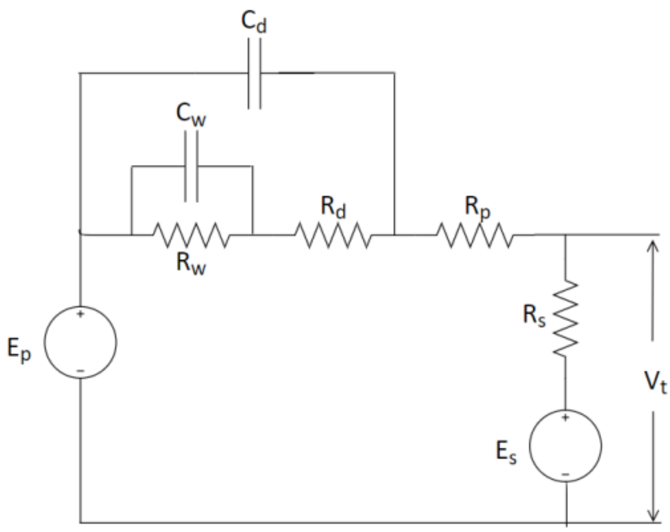

Figure 8: Circuit of fourth-order dynamic model.

The battery model comprises two components: the current I_P, flowing through R_P, R_d, C_d, and R_w, and the current I_s, flowing through R_s, with voltage sources E_p and E_s representing the respective sources. Although generally reliable and precise, this model has limitations: The higher order of the model results in longer computation times. The modelling process becomes complex, necessitating a substantial amount of empirical data. E_p

4. Techniques used for estimation of battery parameters:

4.1. Capacity test:

The capacity measurement cycle begins by discharging each cell at a constant current of 0.5C until reaching the end-of-discharge voltage to eliminate any remaining charge. After a 60-minute rest period, the cell is recharged using the manufacturer's recommended current and voltage levels, following the standard constant-current constant-voltage (CCCV) scheme. Subsequently, after another 60-minute rest, the cell is discharged at a 0.5C current level, and the amount of charge extracted is recorded as the maximum discharge capacity for SOC calculations at the specified temperature [18].

$$V_{OC} = a_8 SOC^8 + \cdots + a_1 SOC + a_0 \tag{11}$$

4.2. The hybrid-pulse-power-characterisation (HPPC) test:

The Hybrid-Pulse-Power-Characterisation (HPPC) test, developed by the Partnership for New Generation Vehicles (PNGV), serves as a standardized procedure for assessing the power and energy capabilities of rechargeable batteries in various discharge and regenerative charging scenarios. In this study, the HPPC test profile is utilized to demonstrate the sensitivity of State of Power (SOP) to variations in State of Charge (SOC) and operating temperature. It is important to note that the test commences with a preliminary discharge and re-charge step to adjust the cell's SOC to 100% prior to conducting the actual testing. Moreover, the HPPC pulses, as depicted in Figure 9 [6], are applied across the SOC range of 10% to 90% in increments of 10% SOC. A discharge current pulse of 0.5C is employed for both cell chemistries to transition the SOC to the subsequent desired level, and a rest period of 60 minutes is allowed between the repetitions of HPPC pulses [6].

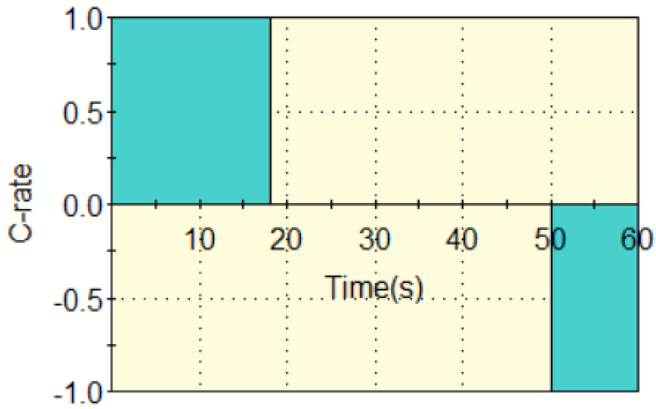

Figure 9: Current profiles for a single repetition of the HPPC.

4.3. Charge/discharge rate and SoC calculations using grey box modelling:

To determine the amount of charge stored or extracted, the charge or discharge rate algorithm is employed, taking into account the present condition of the battery and variables such as C_r and SOC_{cr}. Additionally, the algorithm considers user-defined parameters like the C_r limit (C_{lmt}) and initial battery State of Charge (SOC_{ini}). The battery's charge rate (C_{crtr}) and discharge rate (D_{crtr}) can be mathematically expressed as (12) and (13).

$$V_k = (V_{OC,k} + \nabla V_{OC,k}) - i_k R_s \tag{12}$$

$$\frac{dh(SOC,t)}{dSOC} = \gamma \ \mathrm{sgn}(\dot{SOC}) \left(H(SOC, \dot{SOC}) - h(SOC,t) \right) \tag{13}$$

In order to perform the necessary calculations, the algorithm takes into account the current state of the battery. For regulating the battery's charge current, the algorithm selects the minimum value between the charge rate based on the C_{lmt} (charge rate limit) and the C_{crtr} (charge rate calculated by the algorithm). A similar control algorithm is employed for discharging scenarios. The SOC_{cr} (State of Charge during discharge) and DOD_{cr} (Depth of Discharge during discharge) are computed using Equations (14)–(17) [6].

$$h_{k+1} = \exp\left(-\left|\frac{\eta_i i_k \gamma T_s}{Q_n}\right|\right) h_k + \left(1 - \exp\left(-\left|\frac{\eta_i i_k \gamma T_s}{Q_n}\right|\right)\right) H(SOC, \dot{SOC}) \tag{14}$$

$$V_k = V_{oc,k} - i_k R_s + h_k \tag{15}$$

$$\begin{aligned} \begin{bmatrix} V_{C_b,k+1} \\ V_{C_s,k+1} \end{bmatrix} &= \begin{bmatrix} e^{-T_s/(R_d C_b)} & 0 \\ 0 & e^{-T_s/(R_t C_s)} \end{bmatrix} \begin{bmatrix} V_{C_b,k+1} \\ V_{C_s,k+1} \end{bmatrix} \\ &+ \begin{bmatrix} R_d\left(1 - e^{-T_s/(R_d C_b)}\right) & 0 \\ 0 & R_t\left(1 - e^{-T_s/(R_t C_s)}\right) \end{bmatrix} i_k \end{aligned} \tag{16}$$

$$V_k = V_{C_b,k} - V_{C_s,k} - i_k R_s \tag{17}$$

The initial SOC of the battery, SOC_{ini}, along with the maximum user-defined SOC (SOC_{max}) and DOD (DOD_{max}) limits, are used in Equations (14) and (17). These equations capture the non-linear characteristics of the battery, which are attributed to its unique relationship between charge/discharge voltage and behaviour. By employing this model, the battery's actual performance can be accurately represented, allowing for reliable results. The model also facilitates the detection of parameters and enables comparison with data from various battery manufacturers [6].

5. Applications of battery models in residential building

Battery models play an important role in developing the integration of renewable energy sources and energy storage systems within residential buildings. As the demand for non-renewable and efficient energy solutions continues to grow, battery models provide valuable insights into optimizing energy management and improving overall system performance.

5.1. Energy storage sizing:

Battery models play a major role in correctly sizing and selecting energy storage systems for residential buildings, ensuring efficient storage of surplus renewable energy, and fulfilling the energy requirements of the building as necessary.
(A). Energy consumption patterns: By studying the historical energy consumption patterns of residential buildings, these models evaluate load profiles and find the peak demand periods as well as fluctuations in energy usage, enabling accurate estimation of the battery capacity necessary to meet peak load demands and stabilize energy fluctuations.
(B). Grid interaction data: Battery models analyse grid data to determine the required energy autonomy level for residential buildings, optimizing battery capacity for backup power during outages and maximizing self-consumption of solar energy when grid reliability is high.

5.2. Energy management and optimization:

(A). Real-time and forecasted data: Battery models make informed decisions regarding battery charging and discharging based on real-time data, including solar generation, electricity consumption, and grid electricity prices, while also leveraging forecasted data to optimize battery operation and maximize self-consumption of renewable energy.
(B). Time-of-use tariffs: Battery models optimize the charging and discharging cycles of batteries in residential buildings by considering time-of-use tariffs, enabling them to capitalize on lower electricity prices during off-peak periods and minimize electricity costs by charging the battery when rates are lower and discharging during peak hours when rates are higher.

5.3. Backup power supply:

(A). Critical loads: By evaluating the power requirements of essential items such as medical equipment, refrigeration units, security systems, and communication devices, battery models consider the specific critical loads that must be sustained during an outage, aiding in the determination of the battery system's capacity to support them.
(B). Expected outage durations: Through analysis of historical outage data, weather patterns, and insights from local utility providers, battery models incorporate the expected duration of power outages, enabling accurate sizing of the battery system to meet the required power supply duration.

6. Softwar's used for modeling

Various Software have been used for battery modelling. This software provides power tools that make the work of simulation and predictions of output easy for researchers, students, engineers, and designers. Mostly popularly used software is given below:
(A). XYZ battery simulator: XYZ Battery Simulator is widely used for the simulation of battery performance. This software model permits us to create detailed models by clearly mentioning the parameters of the desired model.
(B). ABC battery designer: ABC Battery Designer allows us to create highly developed models by allowing users to describe the desired battery packs and evaluate their performance based on factors such as cell configuration, load profiles, and environmental conditions.
(C). MATLAB/simulink: This software offers a wide range of tools and functionalities for constructing battery models based on diverse parameters and characteristics, enabling thorough analysis of their behaviour. In MATLAB/Simulink, you have the flexibility to generate battery models by specifying the relevant parameters and characteristics of the battery, encompassing aspects like capacity, discharge profiles, internal resistance, self-discharge rates, and temperature influences.

7. Conclusion

This comprehensive analysis delves into various battery models and estimation techniques, focusing on their applications within residential buildings. By exploring electrochemical and electrical equivalent circuit models, alongside mathematical approaches, the paper provides valuable insights into accurately estimating battery parameters for optimal energy management. Practical applications of these models in residential settings, including energy storage sizing, management, and backup power supply, underscore their significance in enhancing energy efficiency and system reliability. Additionally, the review highlights the importance of software tools for battery modelling and simulation, facilitating the design and operation of residential energy systems. Overall, this research serves as a valuable resource for researchers, engineers, and decision-makers, empowering them to make informed decisions regarding battery selection, sizing, and control strategies for residential energy systems.

Declarations and ethical statements

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Artificial Intelligence usage statement: During the preparation of this manuscript, the authors utilized ChatGPT solely for language refinement and grammatical corrections. The authors carefully reviewed and revised the generated content and take full responsibility for the accuracy, integrity, and originality of the final manuscript.
Availability of data and materials: The data and/or materials that support the findings of this study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

P. V. L. Narasimha Rao: Conceptualization, Methodology, Writing–Original draft, Review & Editing. **K. Balaji**: Writing–Review & Editing. **V. Lavanya**: Data curation, Writing–Review & Editing. **D. Manasa**: Writing–Review & Editing. **Sairam Boggavarapu**: Validation & Formal analysis. **Bhanu Pratap Soni**: Validation & Formal analysis.

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