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Design of a Hardware-Efficient SOC and SOH Estimator for Electric Vehicle Batteries

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Abstract: *The increasing reliance on lithium-ion batteriesin Electric Vehicles (EVs) and energy storage systems demands accurate, real-time estimation of State of Charge (SOC) andState of Health (SOH). Conventional digital estimation methods such as Kalman Filters and machine-learning models provide high accuracy but require complex computation, expensive microcontrollers, and high power consumption. This project presents a hardware-efficient, analog-centric estimation system that performs both SOC and SOH analysis using low-power operational amplifier circuits. A Hybrid Coulomb Counting technique, combined with voltage-based correction, enablesdrift- free SOC tracking, while a pulse-based internal resistance measurement accurately detects battery degradation for SOH estimation. Cadence Virtuoso simulations validate the design's ability to distinguish healthy and degraded batteries through measurable voltage sag characteristics. The proposed approach significantly reduces system complexity, cost, and computational load, making it suitable for compact, real-time Battery Man- agement Systems (BMS) in low-cost EVs and stationary energy storage applications.*

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I. INTRODUCTION

The rapid growth of Electric Vehicles (EVs), renewable- energy storage systems, and portable electronic devices has significantlyincreasedtheneedfor reliablelithium-ionbattery monitoring. As batteries operate under dynamic conditions, ensuring safety, performance, and longevity requires accu-rate estimation of two critical parameters: State of Charge (SOC), which represents the remaining usable energy, and StateofHealth (SOH),whichindicateslong-termdegradation. The Battery Management System (BMS) is responsible for estimating these parameters in real time, and its accuracy directly influences vehicle range prediction, safety decisions, and battery life-cycle cost.

Traditional SOC/SOH estimation techniques rely heavilyon digital computation. Methods such as Extended Kalman Filters (EKF), Dual Fractional-Order EKF, Cubature Kalman Filters,andmachine-learning-basedmodelshavedemonstrated high accuracy but at the cost of increased hardware com- plexity and computational burden [9]. Deep learning ar- chitectures—such as Multi-Branch LSTM and Transformer- based models—further improve prediction capabilities but re- quiresignificant processingpower, largedatasets, andenergy- intensive inference engines [2], [3]. While accurate, these techniquesareunsuitableforlow-costBMSmodulesdeployed in mass-market EVs and stationary battery packs.

Simpler methods, such as Coulomb Counting, offer low computational cost but suffer from drift errors and unreliable long-term performance [6]. Voltage-based methods provide good static accuracy but fail under fluctuating temperatureand load conditions [7]. Moreover,SOH estimation typi-cally requires advanced impedance spectroscopy or adaptive filtering, which is difficult to implement in compact, low- power BMS hardware [14]. These challenges highlight the needforalightweight,hardware-efficient estimationapproach that minimizes microcontroller dependency whilemaintaining accuracy.

To address these limitations, this project proposes a fully analog, hardware-efficient SOC and SOH estimator. The sys- tem uses precision operational amplifier blocks for real-time current integration, voltage scaling, pulse-based internalresis- tance measurement, and analog signal addition. Unlike digital approaches, the analog front-end performs core computations directly, significantly reducing BMS processing requirements and enabling ultra-fast response to changing battery condi- tions. Cadence Virtuoso simulations validate the effective- ness of the hybrid SOC estimation method and the SOHpulse-load diagnostic, demonstrating accurate differentiation between healthy and degraded batteries.

This analog-centric methodology presents a practical alter- nativetocomputation-heavydigitalsystems,makingitsuitable for low-cost EVs, lightweight BMS modules, and compact energystoragedeviceswherepowerefficiency,simplicity,and real-time responsiveness are crucial.

II. RELATED WORK

Accurate estimation of a battery's State of Charge (SOC) and State of Health (SOH) has been an active research areafor more than a decade, with recent advancements acceler- ating due to the widespread adoption of Electric Vehicles (EVs) and large-scale energy storage. Prior research largely focuses on digital, algorithm-centric estimation techniques, which—while highly accurate—introduce significant compu- tational cost, hardware complexity, and power consumption.

Deeplearningapproacheshaverecentlygainedattention for their abilityto map complex nonlinear batterybehaviors. Guo et al. employed Multi-Branch LSTM and Transformer archi- tectures for SOHprediction withadditionalanomalydetection layers,demonstratinghighaccuracyunderdiversecycling

conditions [2]. Similarly, Long et al. incorporated multi- dimensional feature extraction with a Transformer frame- work,usingconstant-currentchargesegmentsandincremental capacity features to improve SOH estimation accuracy [3]. Although these models perform well, they require heavy computationalresources,largedatasets,andhigh-performance embedded processors, making them unsuitable for low-cost Battery Management Systems (BMS).

Another direction in literature focuses on model-based estimation, especially for SOC. Vishnu and Saleem intro- duced an adaptive integral correction mechanism that com- pensates for Coulomb Counting drift using voltage feedback, improving long-term reliability [6]. Qays et al. provided a detailed comparative review of SOC techniques—direct mea- surement, book-keeping (Coulomb Counting), and advanced observers—and concluded that simple methods suffer from noise accumulation while advanced filters increase hardware load [7]. Their analysis highlights a fundamental trade-off between complexity, power consumption, and estimation ac- curacy.

Kalman Filter–based methods remain the dominant ap- proachinindustryandacademia.LingandWeiproposeda Dual Fractional-Order Extended Kalman Filter (FO-EKF) that models electrochemical dynamics more accurately using constant phase elements (CPEs) [10]. Imran et al. enhanced traditional EKF methods by integrating a genetic algorithm that adaptively tunes noise covariance parameters, improv-ing estimation robustness under varying operating conditions [14]. Mannarayana et al. further refined SOC estimation by incorporating state-augmented Cubature Kalman Filtering to addresscolorednoisecommonlyobservedinEVenvironments [13]. These methods show high accuracy but require complex mathematical modeling and high-speed microcontrollers.

For SOH estimation, time-domain and frequency-domain techniqueshavebeen widelystudied. Rahimifardetal.applied an Interacting Multiple Model (IMM) strategy to simulta- neously estimate SOC, SOH, and SOP (State of Power), achieving improved robustness but at the cost of increased computational complexity [9]. Shu et al. developed a col- laborative estimation strategy forlead-carbonbatteries usedin grid frequency regulation, addressing hysteresis effects by adaptively updating battery model parameters [4]. While ef- fective, these techniques depend on heavyonline computation and multi-variable adaptive models.

Across the literature, a major gap identified is the lack of hardware-efficientandanalog-basedestimation systems. Most approachesrequireADCsampling,filtering,matrixoperations, or machine-learning inference, inevitably increasing BMS cost,powerconsumption,andsize.Assummarizedinthe gap analysis ,existing digital solutions suffer fromhigh power draw, microcontroller dependency, firmware complexity, and integration challenges.

The present work addresses this gap by proposing a fully analog, low-complexity SOC and SOH estimator, eliminat-ingtheneedfordigitalcomputation.Unlikepriorefforts, thissystem uses integrator-basedCoulombCounting, voltage- baseddriftcorrection,andpulse-basedinternalresistancemea- surement implemented entirely using operational amplifiers and analog components—offeringreal-time performance with drastically lower hardware overhead.

III. METHODOLOGY

The methodology for this project centers on designing and validating a hardwareefficient, analog-centric estimation sys- tem.Unliketraditionaldigitalapproaches,thecoremathemati- cal operationsfor SOCandSOHareperformedbyspecialized analog circuitry, with the embedded system (ESP32) used ex- clusively for simple output visualization (LEDs/Buzzer). This strategy minimizes computational complexity and maximizes real-timeresponsiveness

A. HardwareRequirements

Tovalidatetheanalog estimation outputsinarealhardware environment,asimplifiedprototypesetupwasdevelopedusing essentialcomponents.AnESP32developmentboardservedas thecentralinterface,responsibleforreadingtheanalogvoltage signals generated by the SOC and SOH estimationcircuitsand driving the corresponding visual and audio indicators. Three LED indicators were employed to represent battery conditions— the red LED signaled an “Unhealthy” SOH or “Critical” SOC state, the green LED indicated a “Healthy” or “Good” condition, and the yellow LED represented interme- diate or warning levels. Additionally, an active buzzer was integrated to provide an audible alert during critically lowSOC conditions. The setup was powered and programmed using a USB cable connected to the Arduino IDE, while a breadboard and connecting wires were used to prototype and interconnect the analog outputs with the ESP32’s input pins efficiently.Thisarrangementenabledeffectivevalidationofthe analog circuit’s behavior and its compatibility with low-cost embedded platforms.

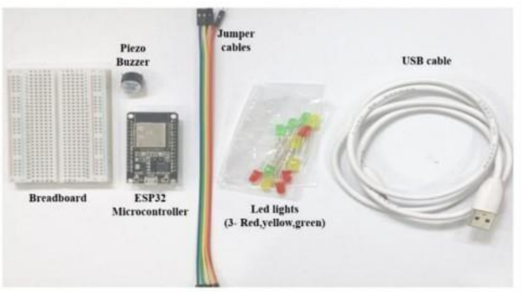

Fig.1.HardwareRequirements

B. SystemDesignArchitecture(Analog-CentricApproach)

The system architecture is partitioned into two dedicated Analog Front-End blocks for SOC and SOH, both drawing data from generalmeasurement circuits and outputting simple analog signal.

- Current Sensing: Current flow is measured across a low- value Shunt Resistor. The resulting voltage drop Vshunt

Fig.2.BuildingblocksofProject

is minute and must be amplified. A highprecision Dif- ferential Amplifier isolates and amplifies this signal intoa clean, usable analog signal proportional to the current Icomp, which is critical for the next stage.

- Voltage Sensing: The terminal battery voltage VBatt is monitored. A Voltage Scaler block scales this voltage down from the high battery operating range to a low- level signal Vref, which is safe for the op-amp circuits and serves as a crucial reference input for the SOC calculation.
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C. StateofCharge(SOC)EstimationCircuit

The SOC circuit is implemented using a Hybrid Coulomb Counting Principle (CCM) executed completely in the ana-log domain, ensuring both high responsiveness and longterm accuracy.

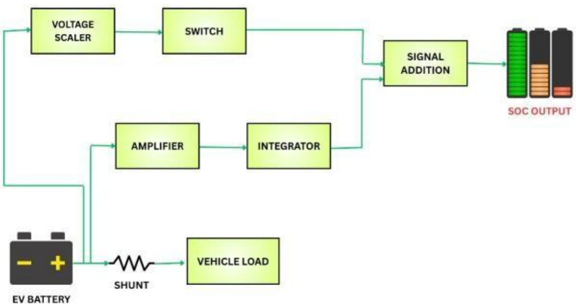

Fig.3.StateofCharge(SOC)estimationcircuitblockdiagram

The principle combines the strengths of two fundamental methods to calculate the remaining battery capacity:

- Coulomb Counting Method (CCM): This serves as the primary real-time tracker. It measures the current (I) flowing in or outof the battery and integrates it overtime(t).Sincecharge(Q)istheintegralofcurrent(Q =I dt), this process provides a continuous, highly responsivemeasureofchargemovement.Thebenefit is high resolution during dynamic loading (driving or charging).
- Voltage-BasedCorrectionMethod:Thisservesasthesec- ondary long-term calibrator. The CCM is susceptible to cumulative drift errors (from sensor noise and efficiency variations). To counter this, the battery’s voltage (which correlates closely with the true SOC in a ”relaxed” state) isusedtoperiodicallycorrecttheCCMoutput,preventing theestimatedSOCfromdivergingfromthetruestateover time.

D. Analog Implementation and WorkingMethodology

The hybrid principle is realized by a sequence of analog blocksthatperformthemathematical operationsofintegration and addition.

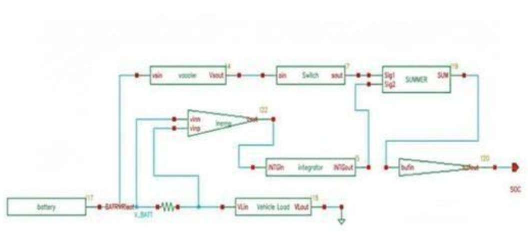

Fig.4.SchematicofSOCestimationcircuit

- **Shunt:**Thiscomponentisplacedinserieswiththebattery path. It generates a small voltage drop Vshunt precisely proportionaltothechargingor dischargingcurrent IBatt, providing the raw signal for current sensing.
- **Integrator:**Thisisanop-ampcircuitconfiguredwitha capacitor in the feedback path. Its output voltage VINTGout is mathematically proportional to the time integral of the input current Icomp. This voltage continuously tracks the accumulated charge (Coulomb Count), representing dynamic changes in SOC.
- **Amplifier:**This is a Differential Amplifier that isolates and significantly amplifies the tiny Vshunt signal. It produces a clean, usable analog signal Icomp that is required by the integrator for accurate current tracking, rejecting common-mode noise.
- **Voltage Scaler:**Takes thehigh batteryvoltage VBatt and scales it down to a reference voltage Vref compatible with the lowvoltage op-amp circuits. This scaled signalis essential because it is used as the voltage-based SOC reference for calibration.
- **Switch:**An Analog Switch used to enable or disable the path of the scaled voltage signal Vref. In a complete BMS, this switch would be digitallycontrolled, allowing the system to set the initial SOC based on voltage(closing the switch at startup) or to periodically enable recalibration when the battery is at rest (low current).
- **Signal Additon:** This Analog Summer circuit performs the crucial final function. It adds the dynamic Integrated Charge Signal VINTGout with the stable Scaled Voltage ReferenceVref.Thiscombinationensuresthecontinuous, real-time tracking from the integrator is periodically constrainedandcorrected bythestablevoltagereference, producing the final robust SOC OUTPUT signal
- **OutputBuffer:**Aunity-gainop-ampbufferplacedatthe output stage.Itspurposeistoprovideisolationandalow- impedance drive, ensuring the final SOC voltage signalis stable and can be connected to the external indicator system (ESP32 input) without loading or distorting the sensitive estimation circuitry.

E. StateofHealth(SOH)EstimationBlock

The SOH circuit is designed to measure the dynamic degradation of the battery, primarily through the increase inits Internal Resistance (IR).

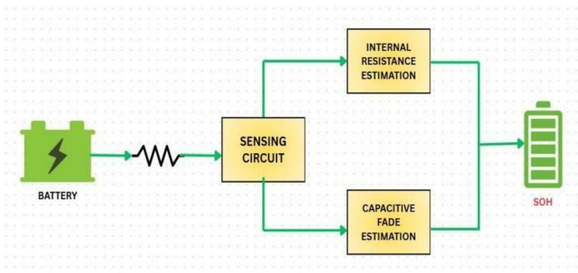

Fig.5.StateofHealth(SOH)Block Diagram

The core principle is founded on the fact that battery degradation (loss of SOH) is accompanied by an irreversible increase in its total internal resistance. When a sudden, con- trolled current pulse (I) is applied to the battery, an instanta- neous voltage drop (V) occurs across the internal impedance, following Ohm's law (V=IR×I).

- Diagnosis:A healthy battery (highSOH)exhibits a smallV,whileadegradedbattery(lowSOH)exhibits a significantly larger V for the same current pulse. The circuit's function is toaccuratelycaptureandanalysethis V.

- CapacityFade:ThisIRincreaseisdirectlycorrelatedwith the reduction in the battery's maximum usable capacity (capacityfade), which is the standard definition of SOH.

F. Schematic of proposed State of Health (SOH) Estimation Circuit

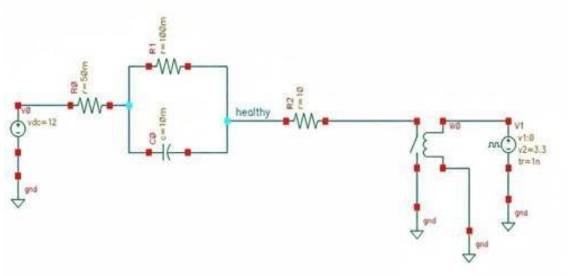

Fig.6.StateofHealth(SOH) Block Diagram

The SOH circuit is implemented in the Cadence environ-mentusinganEquivalentCircuitModel(ECM)tosimulatethe battery's electrical and dynamic characteristics, along with a mechanism to apply a current pulse. The SOH circuit consists of:

- ADCsourcemodelsthebatteryopen-circuitvoltage.
- R0representsinternalresistanceandindicatesSOH degradation.
- R1–C1modelspolarizationandtransientbehaviour.
- Apulsesourceandswitchapplyacontrolledload.
- R2setsthedischargecurrentmagnitude.

G. EmbeddedSystemImplementation

Theembeddedsystemcomponentisminimalist,focusingon visualizationratherthancomputation,adheringtotheproject's goal of hardware efficiency.

- Platform:AnESP32developmentboard,programmedvia the Arduino IDE, is used solely for the output interface.
- Indicator Functionality: The final analog voltages out- puttedby theSOCandSOH circuitsareconnectedto the ESP32's input pins. The programmed logic performs simplethresholddetection(nocomplexADCprocessing) to activate physical indicators: - LEDs: To display the SOC status (e.g., Green LED for Healthy, Red LED for Unhealthy). - Buzzer: To provide an audible warning signal when the SOC analog output voltage drops belowa preset 'low charge' level.

IV. RESULTS AND DISCUSSION

A. SOCCircuitTransientSimulation Results

The State of Charge (SOC) estimation circuit was anal-ysed under transient conditions using Cadence Virtuoso. The analysis focused on two key aspects: the continuous analog tracking ofchargedepletionandthevalidation ofthehardware thresholding mechanism used for the low-battery warning system.

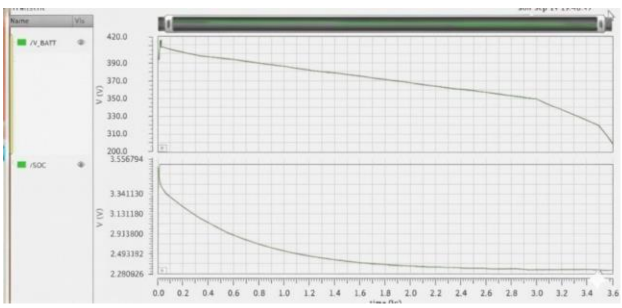

Fig.7.SOCtransientanalysis

The simulation results display the correlation between the battery terminal voltage and the estimated SOC output over a discharge cycle (t=0 s to 3.6 Ks).

- **Battery Voltage (*V*Batt):** Represents the gradual declineofthebatteryterminal voltage from approximately420V down to 310 V, simulating a standard discharge event under load.
- **SOC Output (SOC):** Represents the analog output volt- age generated by the integration and

summing circuits. This voltage exhibits a smooth, monotonic decline that mirrors the discharge profile of the battery.

The final analog voltage outputs from the SOC and SOH circuits aredirectlyinterfaced with the ESP32input pins, where simple threshold detection logic is implemented without complex ADC processing. Based on predefined voltagelevels, the ESP32 activates physical indicators to

TABLEI
SOHCOMPARISONBETWEENHEALTHYANDUNHEALTHYBATTERY

Parameter	**HealthyBattery**	**UnhealthyBattery**
InitialVoltageDrop(1ms)	12V→11.945V	12V→11.477V
DropMagnitude	55mV	523mV
DischargeCurveRange	11.945V→11.878V	11.477V→11.1142V
DischargeCurveMagnitude	67mV	362.8mV
RecoveryJumpVoltage	11.878V→11.9327V	11.1142V→11.624V
RecoveryJumpMagnitude	54.7mV	510mV
RecoveryVoltage(3ms)	11.975V	11.797V
OCVVoltage	12V	12V
Voltage LossfromOCV	0.025V	0.203V
OverallInterpretation	Minimal internal resistance,fast kinetics,opti-mal SOH	Highinternalresistance,slowkinetics,severeSOH degradation

representbatterystatus.LEDsareusedtovisuallydisplay the SOC condition, such as a green LED for healthy operation and a red LED for unhealthy or low-charge states. Additionally, when the SOC analog voltage falls below a preset low-charge threshold, an audible buzzeris triggered to provide an immediate warning, ensuring timely user awareness of critical battery conditions.

B. SOHCircuitSimulation Results

The State of Health (SOH) estimation circuit was validated by performing Transient Analysis in Cadence Virtuoso. The simulation focused on the circuit's ability to differentiate be- tween a "Healthy" and an "Unhealthy" battery by monitoring the instantaneous voltage response to a controlled discharge pulse. Furthermore, a parametric analysis was conducted to observe the effect of temperature on the estimation accuracy.

- **Healthy Battery Response**
- **Waveform Description:** The green trace illustrates the voltage response of a batterywith low internal resistance (simulating a new/healthy cell).
- **Observation:** Upon application of the load pulse (at approx. 1.8 ms), the voltage drops from the nominal 12V.
- **KeyValue:** Theterminalvoltagesettlesatapproximately 11.876 V during the discharge event.
- **Interpretation:** The relatively small voltage drop indi- cates a low internal resistance, characteristic of a healthy battery. The recovery after the pulse is sharp and rapid.
- **Unhealthy Battery Response**
- **Waveform Description:** The red trace illustrates the responseofa batterywheretheinternalresistanceparam- eter (R0) was increased to simulate aging/degradation.
- **Observation:** Under the exact same load pulse condi- tions, the voltage experiences a significantly deeper sag.
- **KeyValue:** Theterminalvoltagedropsto11.412V.
- **Interpretation:** The significantly larger voltage drop (comparedtothehealthystate)confirmsthepresence ofhigher internal impedance. This measurable difference (ΔV) is the analog signal used to identify the "Un- healthy" state.

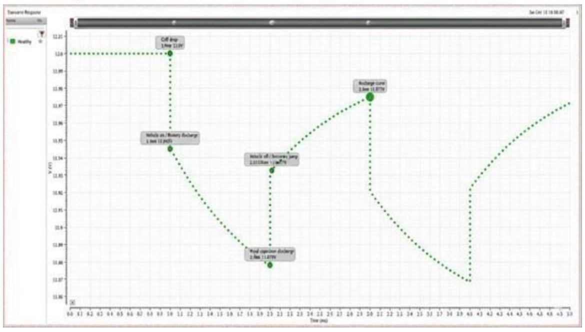

Fig.8.SOHsimulationofahealthybattery

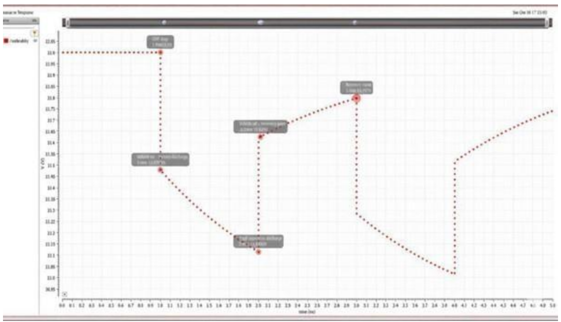

Fig.9.SOHsimulationofanunhealthybattery

C. Parametric Temperature Analysis

Sinceinternalresistanceishighlydependentontemperature, a parametric sweep was performed to simulate the circuit's response under Cold, Normal, and Hot conditions

- **Waveform Description:** The plot displays three distinct voltage curves for the same unhealthy battery model under varying temperatures:
  – **Green Curve (Cold):** Shows the deepest voltage drop (lowest trough at 10.972 V).
  – **YellowCurve (Normal):**Showsamoderatevoltage drop (trough at 11.243 V).

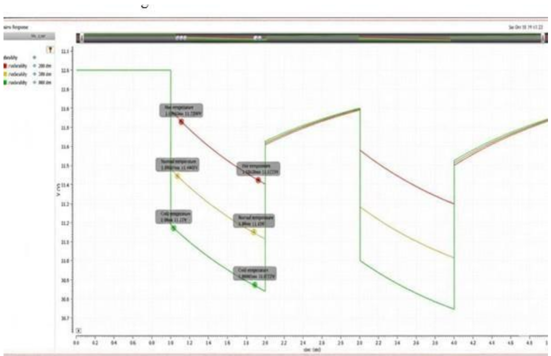

Fig.10.ParametricanalysisofSOHcircuit

  – **Red Curve (Hot):** Shows the least voltage drop (trough at 11.422 V).
- **Interpretation:** The results confirm the electrochemical principle that lower temperatures increase internal re- sistance. The circuit correctly captures this behaviour, showing that a coldbatterymimicsamoredegradedstate (larger voltage drop) than a hot battery.

V. CONCLUSION

This project successfully developed and validated a hardware-efficient, analog-centric solution for real-time State of Charge (SOC) and State of Health (SOH) estimation, significantly reducing the computational burden typical of conventional BMS architectures. By implementing a Hybrid Coulomb Counting method via precision operational ampli- fiers, the system achieved accurate, continuous tracking of chargedepletion withsimultaneousvoltage-baseddriftcorrec- tion.Furthermore,the SOHwaseffectively diagnosedusing a Resistive Pulse Load technique that differentiated between healthy and unhealthy states based on instantaneous voltage drops (V) proportional to internal resistance. Comprehensive simulations in Cadence Virtuoso confirmed the design's ro- bustness, proving that the generated analog signals possesseda sufficient Signal-to-Noise Ratio to reliably drive simple hardware threshold indicators on an ESP32 without the need for complex digital signal processing.

To evolve this prototype into a commercial-grade solution, several key enhancements are proposed. First, temperature compensation can be implemented byintegrating analog ther- mistor circuits, allowing the system to automatically adjust SOHvoltagethresholdsandavoidfalsealarmsincoldenviron- ments. Additionally, transitioning from the current simulation and breadboard setup to a custom Printed Circuit Board(PCB) wouldsignificantlyreducenoise, enhancestability, and minimize parasitic effects. The system can also be expanded withIoTcapabilitiesbyutilizingtheESP32'sbuilt-inWi- Fi module to transmit real-time SOC and SOH data to acloud-based dashboard for remote monitoring and analytics. Furthermore, incorporating lightweight adaptive algorithms into the microcontroller would enable dynamic adjustment of analogthresholds overtime,ensuring long-term accuracy as the battery undergoes natural aging.

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