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A Review of State of Health and State of Charge Estimation Methods

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Abstract: The explosive growth of Electric Vehicles has made developing a robust system for managing batteries that are one of the crucial components of an EV, the need of the hour. Accuracy of the estimation models for determining the State of Charge and State of Health levels of the battery packs plays a key role. There are many sophisticated systems to determine these parameters we have tried to review a few of these systems in this paper. The complete electrification of the automotive industry heavily depends on the energy density and longevity that the battery packs provide and maintaining these packs in a safe operating condition can help achieve these goals.
Keywords: BMS (Battery management system), SoC(state of charge), SoH (State of Health), Battery Thermal Management Systems (BTMS)

I. INTRODUCTION

Awareness regarding Environment change, Global Warming, have drawn peoples' attention towards using eco-friendly products and develop technologies that help preserve our planet. Global Oil and Natural Gas crises have led to the development of Electrical Vehicles over the years. And today we have enough infrastructural and technological capabilities to harness the potential of EV's, changes and development within the EV ecosystem will enable us to innovate and make it more efficient. The main aim of BMS is to improve the lifespan of the batteries used in EV's [5]. As we improve our technologies in this space we should not only think about the efficiency of the product while it is in use but we should also develop it in a way that at the end of the life-cycle the components used in manufacturing should be easily degradable and environment friendly. Degradability of the batteries used in EV's is a challenge for many manufacturers around the world, and currently one of the solutions can be designing the batteries in a way which elongates the life-cycle of the batteries. The BMS module solves major issues due to which batteries become un-useable or which decrease the life cycle of the battery.

The downside of modern battery systems are the complex physical processes occurring inside the battery during operation. Complex monitoring systems do the necessary work of ensuring thesafe and efficient operation of the battery systems. One needs to know how much energy is currently stored inside the battery, the SoC. It is necessary to know the battery system's SoH. Aged batteries can cause unexpected system failures, thus, foreseeing upcoming failures of the battery system is a major task of battery monitoring systems. Failure of foreseeing a battery fault can cause extreme situations, such as, e.g. the lithium-ion battery system of Boeing's new Dreamliner aircraft which caused a fire in the cockpit, resulting in an unacceptable situation in an aircraft [22]. Furthermore, it is necessary to know how much power can be withdrawn from the battery. Another major state of interest, the state of function (SoF), is required to evaluate the battery's power capability for a given operation condition at a given moment, which is necessary to know how much power can be withdrawn from the battery. In conventional vehicles, the state of function is mainly determined by the cranking capability of the battery. However, the power capability of the battery in an electric vehicle needs to be known at every moment of operation. A battery failing to deliver the necessary power during a power consuming maneuver such as, overtaking on the highway, is unacceptable. In this paper we will review the first and the second states and their estimation models.

II. BMS MODEL

A. Design, Scalability

The architecture design of the BMS is chosen by keeping scalability in mind. The BMS uses Slave-Master configuration where the slave micro-controller reports to the master micro-controller which then collects information and processes it to give meaningful insights on the battery health. The number of slave controllers to be used depends on the size and the use case of the battery. For example if the battery is being used in a two wheeler EV then the number of slave controller required would be comparatively less than if the BMS battery was used in a 4 wheeler EV.

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B. Output Integrations

The Master controller of the BMS architecture can be integrated with software graphical UI (user interface) which can help the user get the specifics like State of Health, State of Charge, Range, Life-cycle, etc. on a single dashboard while more complex tasks like cell-balancing are performed by the BMS in the background.

III. BATTERY PACK

Battery pack is the core component in an electric vehicle and a lot of research is being done to improve the specific energy of battery packs. Lithium-ion batteries have high voltage, low self-discharge, high specific energy, portability, and relatively long life compared to other chemistries. Cycle life of Li-ion battery packs can reach 2000 cycles at a rate of 1 C [19]. Since a battery pack consists of individually assembled cells which may have gone through certain variations during the manufacturing process there arises a safety hazard during the operation of the battery pack. Equivalent cell circuit modelling of battery packs help in simulating the battery pack in a variety of operating conditions to study how it reacts and set crucial thresholds for charge/discharge rate and temperature of the operating conditions. Cells inside the battery pack are usually not at the same capacity due to variations in manufacturing processes. Hence an auxiliary circuitry to balance these cells individually to bring them at the same level of capacity is needed. Some voltage balancing algorithms are analysed et al. Duraisamy [1]. However we find that these passive balancing systems take a longer time to balance the cells as opposed to active balancing systems. Active balancing is especially necessary for aged cells to prolong their life [1]. Cell configuration may be PCM or SCM according to the power requirement of the application. Primarily three cell form factors are used, cylindrical which offers very high strength and specific energy at a very low expenses, Prismatic cell configuration provides a very high energy capacity and Pouch cell configuration provides very good heat dissipation however the strength of this configuration is low [20]. The factors that need to be taken care of when designing any battery pack is (1) Energy density, (2) Thermal dissipation, (3) Cost and (4) Weight

Table 1. Comparisons of different battery pack configurations

	Cylindrical	Prismatic	Pouch
Energy density	Medium	High	High
Thermal dissipation	Medium	High	High
Cost	Low	Medium	Medium
Weight	Medium	High	Low

IV. ESTIMATION METHODS

Wide range of stimulation processes will help correctly estimate the values of SoC, SoH, and Range etc. The Controller deals with various interdependent values and generates insights and crucial data which in turn increases the efficiency and performance of the Battery. The BMS makes sure that the battery isn't put through adverse conditions which may deteriorate the health of the battery. Data communication speed and accuracy plays an important role here hence CAN bus is used. Extensive algorithmic computation is required for the estimation of the parameter values. Various Battery monitoring methods are being used in the BMS, because safety, operation and even the life of the passenger is of utmost importance and depends on the BMS. The State of Charge estimation has been implemented using Coulomb Counting method and Open-Circuit Voltage methods, which eliminates the limitation of stand-alone coulomb counting method and further corrected by Kalman filtering method which increases the efficiency [7].Multiphysics model simulation and multifunction integrated BMS technology increases the accuracy [6]. The battery parameters form our experimental results is also included in the model which validates the simulation.

A. SoC

The SoC, that is, state of chargerepresents available capacity, and is one of the most important states to monitor. It also helps increase battery performance. SoC is estimated based on conditions such as operating current, temperature, and voltage [2]. The SoC of the battery is an expression of the current capacity of the battery as a percentage of the maximum capacity. It is generally calculated using current integration to determine the change in battery capacity over time.

If we consider a completely discharged battery with Ib (τ) as the charging current, the charge delivered to the battery is R t t0 Ib (τ) dτ. The SoC of the battery is simply expressed as:

$$SOC\ (t) = Rt\ t0\ Ib\ (\tau)\ d\tau\ Q0 \times 100\% \quad (1)$$

As the charging current, where Q0 is the battery capacity at time t [23]. BMS prevents the battery from discharging below a certain SOC and charging when full.

1) *Open Circuit Voltage (OCV):* There is about a linear dating among the SOC of the lead-acid battery and its open circuit voltage (OCV) given via means of

$$VOC\ (t) = a1 \times \mathrm{SOC}\ (t) + a0 \quad (2)$$

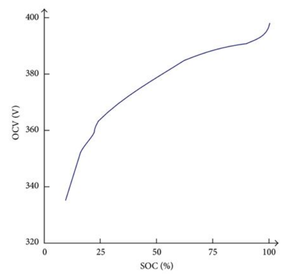

Fig. 1. Typical relationship between SOC and OCV

whereinSoC(t) is the SoC of the battery at t, $a0$ is the battery terminal voltage whilst SoC = 0%, and $a1$ is received from understanding the cost of $a0$ and VOC(t) at SOC = 100%. By (2), the estimation of the SoC is equal to the estimation of its OCV. On the contrary, the lead-acid battery, the Li-ion battery, does now no longer have a linear dating among the OCV and SoC. The OCV dating with SOCturned from making use of a pulse load at the Li-ion battery, then permitting the battery to attain equilibrium. The dating among the OCV and SoC can't be precisely equal for all batteries. Because the traditional OCV-SoC differs amongst batteries, there's a trouble in that the connection of the OCV-SoC ought to be measured to estimate appropriately the SoC. Lee et al. [24] proposed changed OCV-SoC dating primarily based totally at the traditional OCV-SoC.

2) *Electromotive Force (EMF):* The SoC may be measured by the usage of the EMF- electromotive force of the Li-ion battery. The EMF may be decided to be the OCV whilst the battery is in equilibrium. The EMF is associated with the battery SoC. The OCV the usage of EMF changed into modelled the usage of exclusive strategies.A version to expect the EMF voltage for a SoC estimation. The authors divided the battery's voltage curve into parts. The first component consists of the linear region (complete to partial SoC) and the alternative has a hyperbolic region (keen on low SoC) of the curve. In this method, the EMF changed into expected usage of the burden present day and terminal voltage with a few coefficients for the linear region, impedance, and the terminal voltage; the battery present day changed taken into consideration for the hyperbolic region [3]. This version confirmed properly effects for a SoC estimation. The proposed version by Ali et al. [3] has an EMF supply with a parallel resistance and a regular section element.

B. SoH

The battery pack loses some of its capacity over time, this may be caused due to a variety of reasons. The State of Health (SoH) of the battery is a parameter that can help estimate the capacity of the battery pack as a function of depth-of-discharge. It is defined as the ratio of the maximum charge capacity of an aged battery to the maximum charge capacity when the battery was new. This is an indicator to calculate how the battery's capability to store energy is deteriorating, and decreases over the battery's lifetime. The BMS is in charge of making sure that the battery is charged or discharged in proper conditions and there is no significant damage done to the battery pack. SoH is tracked by measuring the internal resistance, since the internal resistance increases as the capacity increases.

The SOH is computed as:

$$SOH = \frac{Qact}{QR} \times 100\%$$

Where QR is the rated capacity and Qact is the actual battery capacity. The industry is yet to come to a consensus on the exact definition of SoH and how to measure it. It is a figure of merit of the present condition of a battery pack, compared to its ideal conditions. The unit of SoH is percent, it is 100% for a new battery and decreases as the battery goes through several charge-discharge cycles. The SoH is usually derived by capacity and the internal resistance, but it can also be derived by other battery parameters like the AC impedance, self-discharge rate, or the power density. If we consider the current capacity as a parameter to determine the SOH we can simply compare the current, current capacity to the current capacity at the beginning.

According to that we can determine the percent of SoH. Generally, if the battery capacity decreases to 80% of the initial value, then the BMS would warn the user to replace the battery pack. The SoH helps in keeping track of battery aging and degradation, and other durability problems. The SoH of the battery pack eventually decreases over its use, slowing this down and extracting maximum possible life out of a battery pack is a field under heavy research. Increasing the durability is the primary goal of this research so that the same pack can be used for a longer life and range, major parameters characterizing the durability of battery packs are capacity and internal resistance hence these are at prime focus. Energy batteries that are primarily used as power source in Electric Vehicles suffer performance degradation due to capacity fade. On the other hand, power batteries that are primarily used in Hybrid Electric Vehicles suffer performance degradation due to the increase of internal resistance. Self-learning of the data to build an adaptive model can help increase the accuracy and reliability of the predicted SoH value [8].

1) *Capacity Fade:* Due to the ageing of the battery pack which is a very complicated process in itself as it depends heavily on environmental factors the capacity of the battery pack gradually reduces. The usage pattern of the battery pack affects the overall life and reliability of the battery pack. Accurate and real time monitoring of the battery packs vital parameters is necessary to take any necessary preventive measures required. The active materials inside the cells reduce the number of charge cycles and this causes reduction of capacity of the cell to hold power. Capacity fade is caused by a loss of active electrode material (loss of storage medium) [9]. Total capacity is the maximum energy (in Ah) that a battery can hold at a given temperature and the residual capacity is defined as the remaining amount of energy the battery can provide before being completely depleted [17]. Metallic lithium is deposited on the surface of the negative electrode which accelerates the capacity fade process due to extremely high voltage or overcharge which leads to composition of the positive electrode which generates a high amount of heat and can also result in short circuits[4]. There is a strong correlation between the SoC and capacity [17]. Durability model-based open-loop SoH estimation method using the external characteristic model uses experimental laws and focuses on the capacity fade and internal resistance increment [4]. Ramadass et al. [18] developed a semi-empirical capacity fade model for Li-ion cells.
2) *Internal Resistance (IR):* There is a linear relationship found between capacity decrement and increase in internal resistance [10][11]. For a Plug-in Hybrid Vehicle both power as well as energy is needed so both the capacity fade as well as internal resistance of the battery pack needs to be monitored. The SOH is predominantly a diagnostics issue [11]. Most of the algorithms and techniques for battery health management have focused on SoC calculation and SoH is usually ignored. The capacity fade may be caused by the decrease in capacity of individual cells in the battery pack, however other variations could also be a possible reason. In case of variation in the capacity of the individual cells, balancing them can help improve the SoH of the battery pack. The internal resistance of Li-ion batteries is a highly important parameter since it is used to determine the batteries' power capability [12]. The accurate information about the degradation due to the rise in internal resistance is necessary to determine the cooling strategy to use. It was observed by Stroe et al. [25] that internal resistance increases nonlinearly during calendar ageing following a power law function but by increasing storage temperature and increasing the storage SOC level the internal resistance accelerates exponentially. Some SOH decrements e.g. a loose screw, are reversible and could be considered as sub-health. Some SOH decrements are however irreversible e.g. battery damage caused by vehicle collision, battery short circuit caused by water, etc. Hence we see that the aging of batteries is just a small part of performance degradation and cannot fully characterize SoH of a battery pack. Most of the current SoH definitions are unfortunately limited to the category of the aging of batteries rather than actually involving the battery SoH parameters. It is more appropriate to call current algorithms as State of Life (SOL). According to Yuana et al. [13] the four major causes for battery degradation mechanisms are the formation of dendrites, distortion in electrode chemical, decomposition of electrolyte and formation of solid electrolyte interphase (SEI) layer. Non-invasive methods to determine the crucial internal parameters of the battery packs need to be developed for an accurate prediction of SoH.
3) *Battery Temperature Management System:* The heating and cooling process is controlled by the BMS based on the overall temperature distribution within the battery pack and the requirements of charge/discharge [2]. Although there may be variations in the manufacturing processes of the cells which may cause significant variations in the crucial thermal and electrical parameters of the cells and eventually affect the battery pack as well. Battery pack must not be subjected to extreme temperature conditions for a prolonged period of time as it may cause serious damage to the battery pack and decrease its SoH value eventually decreasing the RUL as well. Accurate thermal model of a battery pack can help optimize the design of a dedicated battery thermal management system (BTMS) that will be in charge of monitoring the temperature of the battery pack and protecting it. BTMS's can be classified as active or passive [21]. BTMS will be provided with certain threshold values. If the temperature crosses those values the cooling mechanism will be turned on and the cooling process will begin to avoid any

irreversible damage to the battery pack. In cases where the temperature is extremely high the BTMS may even cut off the battery pack from the rest of the vehicle as this may be caused due to a collision and can lead to explosion of the battery pack as Lithium is a very combustible and fairly reactive element. The thermal model of a battery pack combines the battery's phases of heat generation, heat transfer, and heat dissipation to analyze the temperature distributions of battery cells, modules, and stacks in the time and space domains, to optimize the design and safety of the battery thermal management system (BTMS). BTMS must also have a local thermal management system. The conductivity of electrodes and electrolytes is affected by the variation in temperature which is usually related to chemical reactions inside the cells. The relationship between the rate of chemical reactions and reaction temperature follows the Arrhenius equation. As for low temperatures the battery packs will degrade at operating temperatures below 0 °C [14]. Real-time diagnosis of thermal faults is almost unexplored in the existing published literature, despite its critical importance for battery safety and performance. A Partial Differential Equation based model presented by Satadru et al. [15] for the thermal diagnostic scheme of Lithium ion battery packs. This approach helps eliminate control/observation spillover. The combined effect of control and observation spillover is shown to lead to potential instabilities in the closed-loop system [16]. The output of the BTMS block is used to control a fan and/or an electric heater, which attempts to keep the battery temperature within the optimal range. The thermal management block reads ambient and battery temperatures, initiates cooling or heating operation, and sends an emergency signal to ECU in case of abnormal rise in temperature. Therefore, the temperature estimation by using thermal models is a first step and a necessary part to enable precise thermal state monitoring. In addition, predictive thermal management with several advantages, such as the core temperature information, can be utilized.

4) *Remaining Useful Life (RUL):* RUL is the remaining time or the number of charge cycles that the battery has during which it can meet its operational requirements or simply the amount of time from now to the end of its useful life. RUL has placed great emphasis on vehicle BMS research and manufacturing to meet the demand for reduced costs, increased accuracy and reliability, and catastrophic failure prevention. RUL can be calculated as follows:

$$RUL = Tf - Tc \quad (1)$$

whereTf is a random variable of the idle time when degradation is detected and TC is the current time that the predicted signal will most likely pass idle time a uncertainty of. However, the various sources of uncertainty need to be disseminated along with the reliability of the RUL estimate and prediction, as there are inherent uncertainties in the mining process, measurements, environmental / operational conditions, and modeling errors. The RUL parameter is understood to be the remaining time or number of charge cycles until the battery reaches 0% SoH. Basically, there are two concepts for estimating the RUL of the battery that can be found in the literature. The first concept is based on the useful life model used for SoH estimation. Using this life model, it is possible to predict the RUL of the battery using future battery conditions and loads as inputs. To estimate these future conditions, observing the battery usage in the last predefined period can be used. Alternatively, a predefined reference load profile can be used. The downside to this concept is that it relies entirely on the absolute accuracy of the life model and does not include a recalibration mechanism to account for the current SoH of the battery, which is estimated based on measurements. The other concept for estimating the RUL of the battery generally requires two parts. The first part is the estimation of the current characteristics of the battery, which is chosen as the definition of the battery life. It can be the battery capacity, the impedance, and their combination or, in general, the estimated SoH. The second part is the predictive model, which takes these properties as input, analyzes your changes in the past, and predicts your changes in the future. The RUL is the expected time it will take for the characteristic to reach the threshold, which is defined as the end of the battery life. The various prediction methods have their advantages and disadvantages in terms of numerical complexity, precision, and the ability to produce not only the RUL estimate, but also its confidence intervals. The greatest challenge, however, lies in the development and parameterization (training) of the prediction model used, which allows an accurate prediction of the rate of change of the battery properties towards the end of the useful life, taking into account its changes at the beginning. This predictive model can be implemented as a battery life model that can be recalibrated

V. CONCLUSION

Challenges of the oil crisis and environmental pollution have increased the demand for electricity in consumers and industry, which bring opportunities and challenges for energy storage. Two methods of State of Charge estimation were discussed, each with its own properties. It is difficult to evaluate the performance of different processes because existing applications have been in different discharge conditions and different battery sizes. The developments of various SoC estimation methods for battery applications, such as BMS in hybrid electric vehicles, are expected to be valuable. Based on the development history of the SoC estimate, the future development directions of the SoC estimate are proposed at the end.

The SoH of the battery pack depends on many factors and hence it is difficult to standardize the estimation method for calculating SoH. However the importance of the SoH value is very high as even the slightest error in estimating the SoH can lead to irreversible damage to the battery pack. Temperature and over charge/discharge are some of the important factors to take into account while calculating SoH value. Estimating Capacity fade using machine learning techniques seems a promising area. The relation between internal resistance and capacity fade is found out to be almost linear. Calculation of Remaining Useful Life using predictive models is very effective as opposed to calculating its value using standard battery parameters. SoC and SoH estimation methods are present in plenty however no single one can give a complete picture as there are many complex variables that need to be monitored simultaneously. Sensor faults can result in ambiguity in the results even with highly accurate estimation methods so checking the status of these sensors also is necessary. Thermal management is also a crucial function. The reliability of BTMS needs to be checked continuously.

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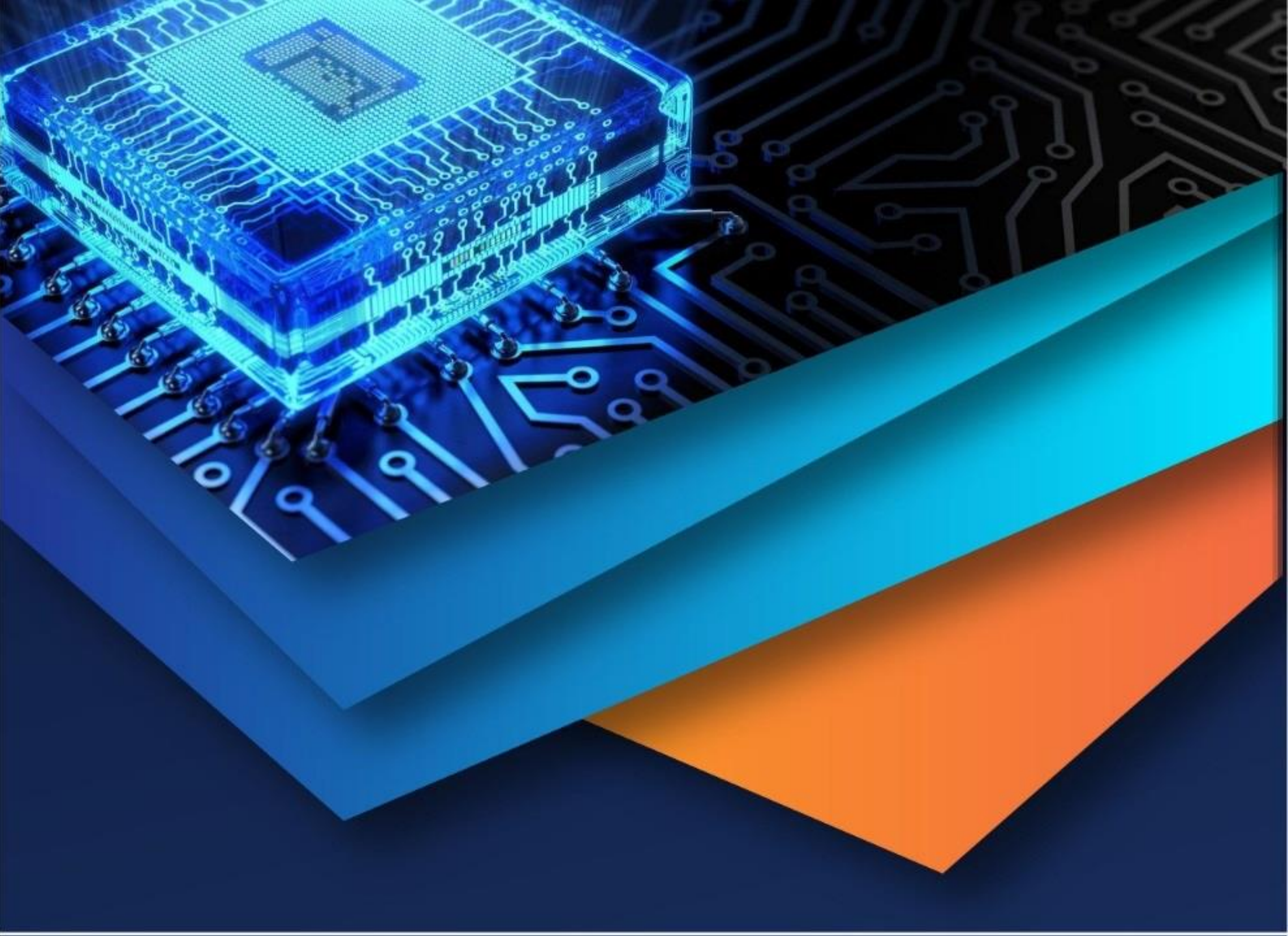

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