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An Assessment of Accurate Range Estimator for Electric Vehicle Applications

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Abstract: The world's primary modes of transportation are facing two major problems: rising oil costs and increasing carbon emissions. As a result, electric vehicles (EVs) are gaining popularity as they are independent of oil and do not produce greenhouse gases. However, despite their benefits, several operational issues still need to be addressed for EV adoption to become widespread. One of the main obstacles for the acceptance of EV's is the driver's fear of being stranded by a depleted battery. In other words, accurate estimation of the remaining SOC is required to provide positive edge towards adoption of EV. In this work, an EV is tested for a drive line cycle of 10 Km for a trip, and key parameters such as elevation, speed, body dynamics, vehicle dimensions, on track speed have been collected. A model of EV power train is developed in MATLAB Simulink from the data logged and a static app is being developed which estimates the vehicle dynamic forces, power consumption, energy utilized for the trip, State of Charge (SOC) and remaining mileage of the vehicle.
Keywords: Electric Vehicles, State of Charge (SOC), EV Range Estimator, Powertrain.

I. INTRODUCTION

Introduction EVs are one of the most promising technologies for providing energy security and pollution reduction. One of the main obstacles for the acceptance of EVs is the range anxiety. Range anxiety is a driver's fear of being stranded by a depleted EV battery. From a buyer's perspective, the uncertainty of the amount of remaining battery capacity to reach the destination remains an uneasy thought. EV architecture is shown in Fig.1. The traction power for a given route needs to be calculated first and it is the sum of the vehicle potential and kinetic energy change, the aerodynamic, and the rolling resistance work. Each of these components is highly dependent on a variety of environmental and behavioural factors. From the traction power, the EV motor output power can be calculated based on the transmission gear ratio and efficiency. Finally the required battery current required by the EV is dependent on the drive system efficiencies, the traffic conditions and the accessory power losses.

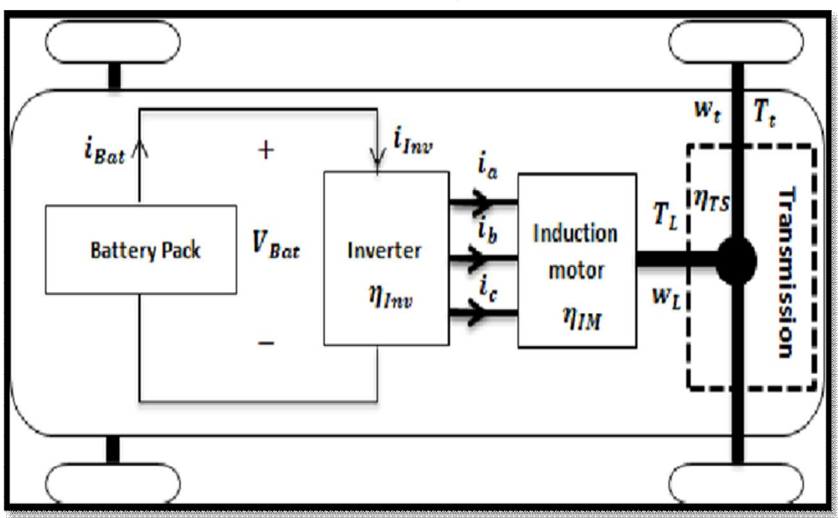

Fig.1 Schematic diagram of EV

The SoC of the EV battery and the vehicle range to destination at each instant of time can be estimated from the battery current required by the EV, the battery voltage, the initial SoC, battery temperature, capacity and efficiency. The proposed SoC estimation takes into account the changes in environmental and the driver's behavioral factors and the dynamic changes of the losses in the EV components.

II. IMPLEMENTATION OF ACCURATE RANGE ESTIMATION SYSTEM

The parameters such as aerodynamic drag, rolling resistance, potential energy and kinetic energy, gear efficiency are mechanical parameters. While the motor and inverter efficiencies correspond to electrical parameters. So, the mechanical parameters are derived from the vehicle specifications and are calculated based on the track route and the velocity of the vehicle. The electrical parameters are evaluated from the data log during the trip course of the vehicle. In order to evaluate the power consumption accurately, the gradient of the track root is evaluated for a distance of 20m at regular intervals of time. The power train architecture of an EV is shown in the Fig.2. The power train consists of four main components 1} Battery pack 2) Battery management system 3) Auxiliary loads, 4) Electric motor and controller 5) Transmission system.

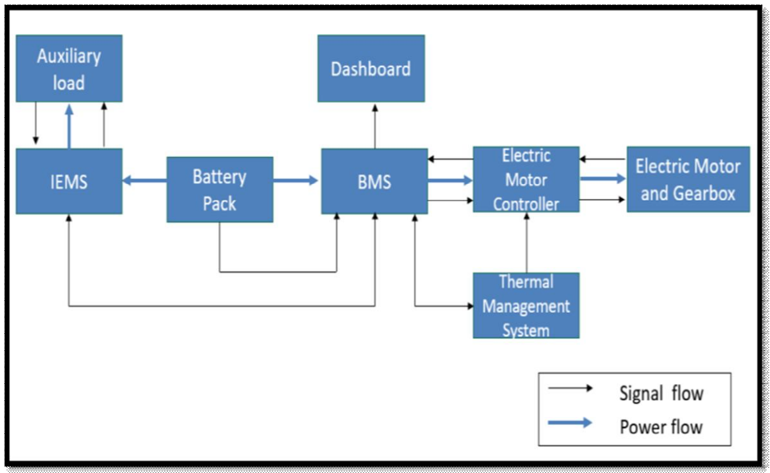

Fig. 2 Typical Powertrain of an Electric Vehicle

The key mechanical parameters are evaluated by testing the EV two wheelers and the data is collected for a round trip of 10Km. The block diagram in the Fig.3 represents the workflow of the problem solution. The inputs and the results are differentiated in orange and green colour simultaneously.

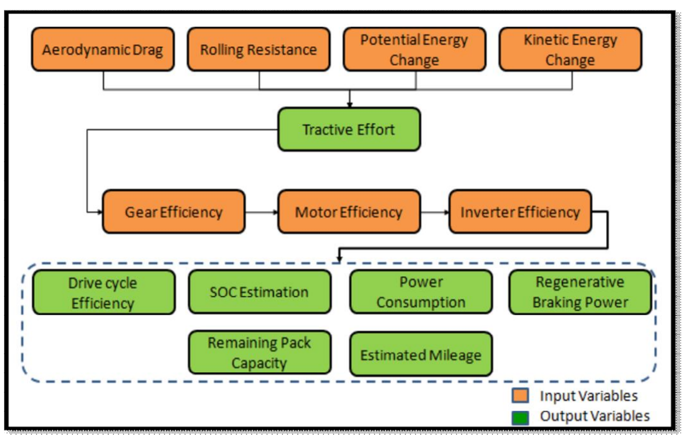

Fig. 3 Block Diagram of Proposed Workflow

To evaluate the accuracy of range estimation algorithm, the validation is conducted on mathematical model-based analysis and testing basis. Initially, a two-wheeler vehicle is procured for testing over a predetermined track route of about 10 km. The trip route originated from SRS ground, Peenya Industrial area, Bengaluru to the sandal soap factor metro station, Bengaluru, and a round trip back to the origin at an elevation of 800m above sea level. The physical parameters such as, vehicle dimensions, drag coefficients and electrical power train parameters are gathered from the vehicle data sheet specifications provided by manufacturers as shown in table I. In the mathematical modelling phase, a graphical user interface otherwise known as a static app is being developed. The app consists of relevant input variables related to the physical parameters of the vehicle and the track route details. The app is developed in such a way that the range estimation is carried out once the parameters of the vehicle are loaded along with the route details. This is developed using GUIDE (Graphical User Interface Development Environment) in MATLAB.

Table I. EV Parameters

S. No	Parameter	Value
1	Model	Ampere Zeal
2	Frontal Area	0.65 sq. m
3	Wheel Radius	0.198 m
4	Aerodynamic drag coefficient	0.33
5	Rolling resistance coefficient	0.0008
6	Rated Motor RPM	1500 RPM
7	Rated Motor Power	500 W
8	Rated Motor Torque	20 Nm
9	Battery Pack Voltage	72 V
10	Battery Pack Capacity	2.2 kWhr
11	Cell Type	Lithium-ion battery
12	Gear Ratio	1
13	Air Density	1.2754$kgm3$
14	Gravity	9.8 $ms2$
15	Mass	230 Kg

III. SIMULATION RESULTS

The EV drive parameters are added to the input panel, and the parameters such as speed, distance travelled, elevation, gradient, aerodynamic power, rolling resistance power, vehicle average speed as per the drive cycle, potential energy change and kinetic energy change are evaluated using the graphical user interface built. The aerodynamic power consumption of the EV using the mathematical model, over the drive cycle given in the Fig. 4. The values are plotted here as per the MKS system. It is observed that the X-axis is given as samples per trip, and y-axis is given as power consumption of the vehicle. The data logged during the drive cycle is at fixed intervals of time considering the variation of gradient for every 20 m. It can be seen that the aerodynamic drag is higher during the acceleration period with increase in velocity. The peak instantaneous power consumed by the vehicle during the drive cycle can be seen at 950 watts. The drag coefficient is considered based on the specification's sheets of the body design.

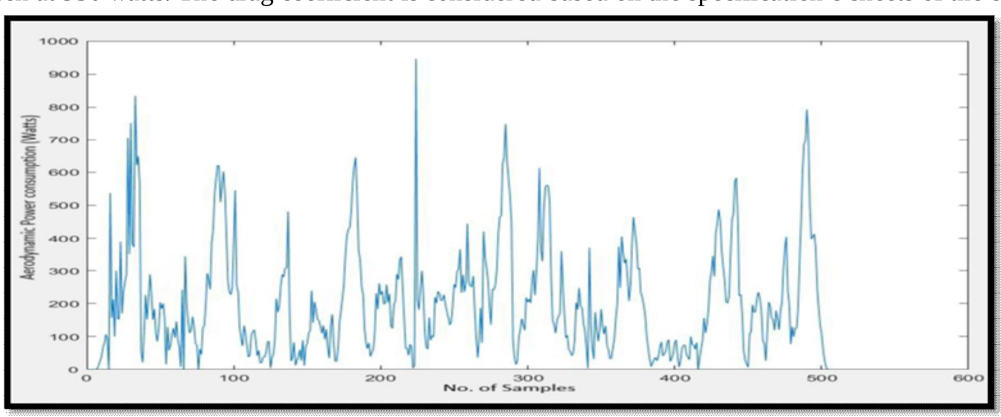

Fig. 4 Aerodynamic Drag Power vs Samples per Trip

The potential energy consumption of the vehicle during the drive cycle is shown in the Fig. 5. The values are plotted here as per the MKS system. It can be observed that the X-axis is given as samples per trip, and y-axis is given as energy consumption of the vehicle. The data logged during the drive cycle is at fixed intervals of time considering the variation of gradient for every 20 m. The graph depicts that the energy utilized by the vehicle to overcome its gravitational forces is about 2.5 KJ. There are also instants where the consumed energy is negative, which depicts that there is a negative gradient in the track route providing a feasibility of regenerative braking during the drive cycle. The energy can be later converted to power based on the duration of the time segment called potential energy change.

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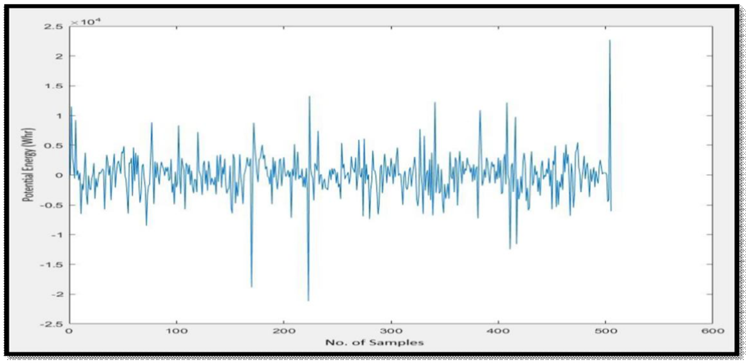

Fig. 5. Potential Energy due to Gravity vs Samples per Trip

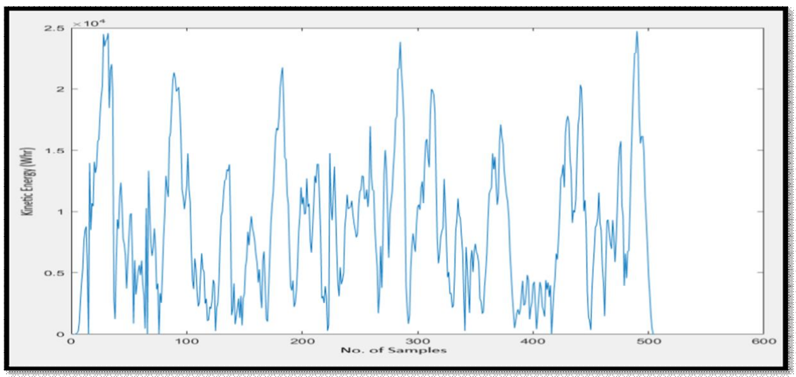

Fig. 6. Kinetic Energy Consumption of Vehicle vs Samples per Trip

The estimated kinetic energy change of the vehicle during the drive cycle is given in the Fig. 6. The values are plotted here as per the MKS system. It can be observed that the X-axis is given as samples per trip, and y-axis is given as kinetic energy consumption of the vehicle. The data logged during the drive cycle is at fixed intervals of time considering the variation of gradient for every 20 m. The kinetic energy change is highly dependent on the mass and the speed of the vehicle.

Assuming the acceleration is linear, the peak kinetic energy change can be as high as 2.5 KJ, with a minimum of 250 J. The energy can be further converted to power consumed by the vehicle based on the duration of energy consumption over the drive cycle.

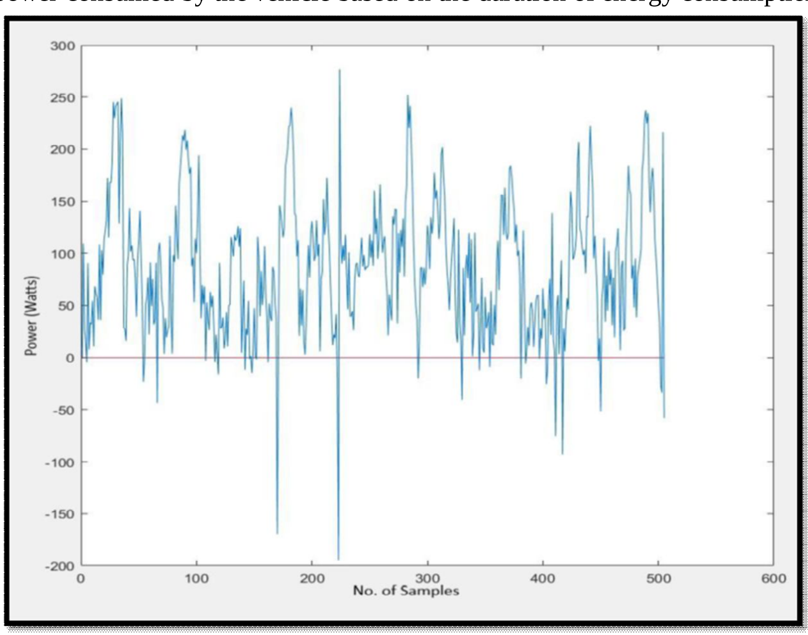

Fig. 7 Tractive Power Consumption of Vehicle on Track Route vs Samples per Trip.

The total power is estimated by adding all the internal and external forces opposing the movement of the vehicle and the additional loads utilized in the system. The total tractive power consumed by the vehicle during the drive cycle is shown in the Fig. 7. The values are plotted here as per the MKS system. It is evident that the X-axis is given as samples per trip, and y-axis is given as tractive power of the vehicle.

The data logged during the drive cycle is at fixed intervals of time considering the variation of gradient for every 20 m. The rated power of the motor is 500 Watts, and it is depicted through the graph that, the peak power consumed by the motor at the instants is 270 watts driving at a top speed of 60 kmph. There are also instants of negative power plots, which are due to the down gradients indicating the regenerated power of the vehicle. The total energy consumed by the vehicle over the trip duration can be estimated by dividing the instantaneous power consumption with the duration of each segment and summing it up to the total energy.

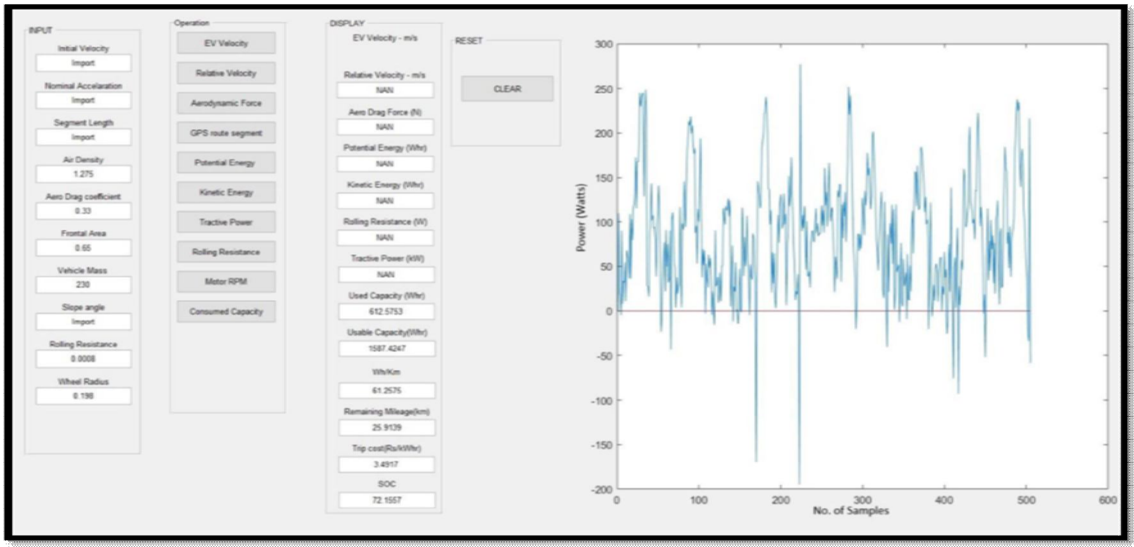

Fig. 8 Overall GUI Outcome of the EV Range Estimator.

The overall architecture of the graphical user interface is represented in the Fig. 8. The values are plotted here as per the MKS system. It can be observed that the X-axis is given as samples per trip, and y-axis is given as tractive of the vehicle. The data logged during the drive cycle is at fixed intervals of time considering the variation of gradient for every 20 m. The graphical user interface thus provides us the values of actual velocity, relative velocity, Aerodynamic drag power, rolling resistance power, potential energy change, kinetic energy change, Used battery pack capacity, Usable battery pack capacity, energy consumption per kilometer, mileage, trip cost and state of charge of the battery. The obtained results are given in the Table II.

Table 5.1: Obtained Results from EV Estimator GUI

S. No	Parameter	Value
1	Tractive Power	36.755 KW
2	Used Pack Energy capacity	600 Whr
3	Remaining Pack Capacity	1587.42 Whr
4	Energy consumption per Km	61.25 Whr/Km
5	Estimated Range	25.9 Km
6	Measured Range	28 Km
7	Average Error	< 8%
6	Trip cost	Rs. 3.4915
7	Remaining Charge	72.15 %

IV. CONCLUSIONS

The Electric Vehicles (EV) is considered to be the best alternatives for the Internal Combustion Engine Vehicles (ICEV's). The current EV's provide about 22% driving range when compared to that of ICEV's. The main drawbacks in EV sector include range anxiety, lack of infrastructure, high initial investments, and inaccurate fuel estimation. Most of the EV drivers reserve 30% of the charge on the dashboard estimation due to the trust issues on the accuracy of the range estimation of production EV's. In this work, the results obtained by simulating the mathematical model developed in the GUI are displayed. Furthermore, the graphs plotted and power consumption of EV due to various parameters are described in this work. Also, the total power consumption of vehicle during the track route is evaluated and compared with practical results obtained during the test cycle of the EV. An accurate range estimation model of EV is presented. The model is developed by extracting the gradient data at regular intervals of distance. The data logged during the drive cycle is at fixed intervals of time considering the variation of gradient for every 20 m. It can be seen that the aerodynamic drag is higher during the acceleration period with increase in velocity. This method reduced the average error of production unit range estimation by 3%. The battery power consumption is estimated considering time domain losses along the specified route along with the gradient at each interval. The drive system efficiency is assumed to be 90% considering practical considerations. The measured range after the trip is found to be 28 km, while the estimated range is 25.9 km. The SOC calculation is found to be accurate with an error less than 8% between measured and estimated values at destination.

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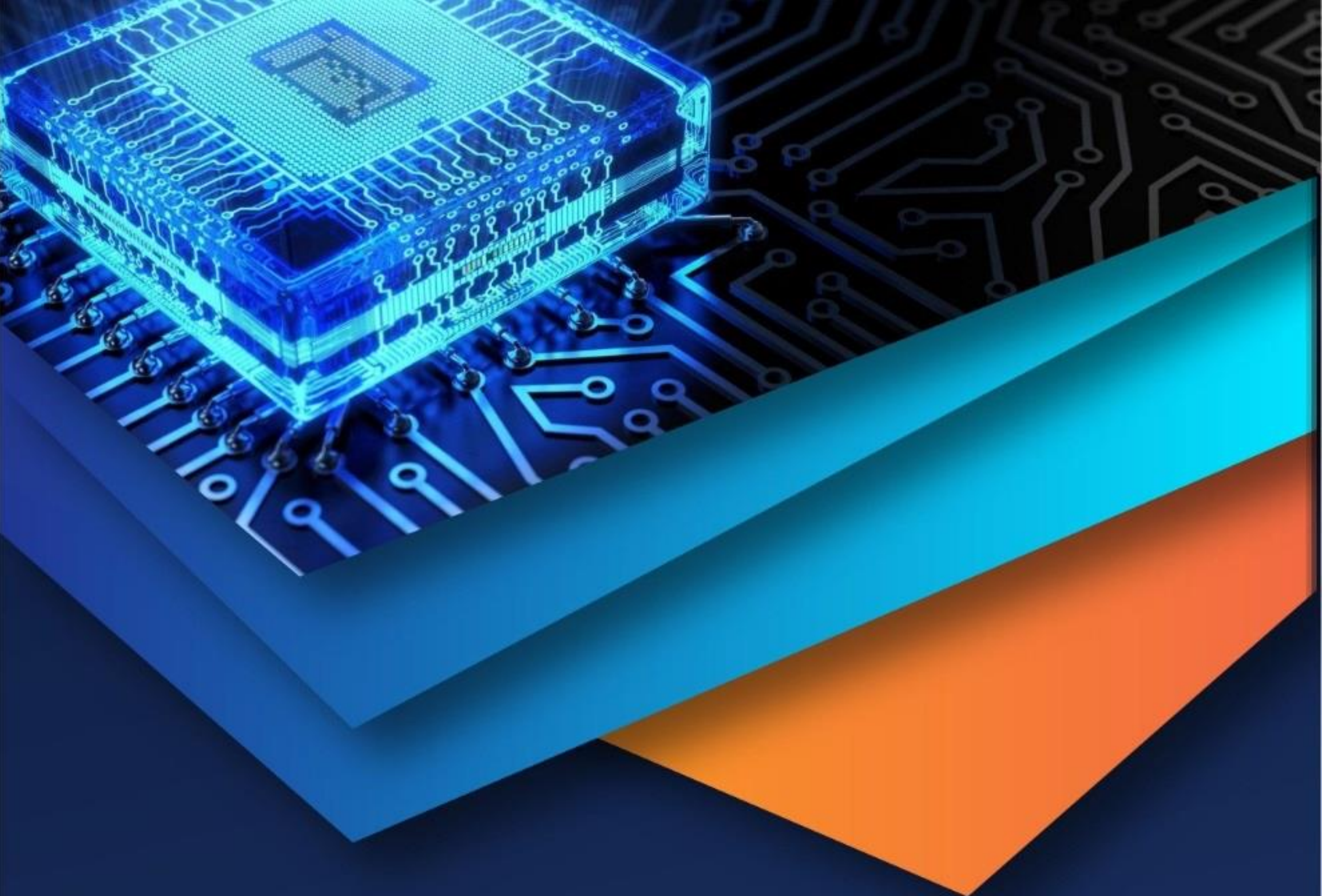

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