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Optimal Driving and Charging Efficiency of a Developed Solar Powered Electric Vehicle

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Abstract: Renewable energy is essential in these modern times for performing certain tasks and operations because the exhaustible energy sources on which we rely, and use will be depleted in the not-too-distant future. The solar powered vehicle is an important initiative in conserving these natural fossil fuel-based energy sources. This study is based on the performance evaluation of a fabricated low-cost Solar Powered Electric Vehicle (SPEV) for developing nations to overcome the effect of air pollution caused by Internal Combustion Engines (ICE). Additionally, the high cost of fuel (both petrol and diesel) consumed by the ICE will be replaced by the solar powered vehicle which in turn will have a long-term economic effect on the users and the nation in general. The solar car's primary operating idea is to utilise the potential power in a deep cycle battery both during and after charging from the solar panel. Energy supplied from the energized battery is transferred to the engine, which in this case is the electric motor. The electric motor is responsible for forward and reverse movement directions, it is an effective replacement to the internal combustion engine present in most vehicles because it has zero emissions, and no fossil fuel is burnt during its operation. The major challenge in fabricating this vehicle is in designing a suitable chassis that will ensure adequate stability and sustainability of the vehicle. The construction of this vehicle is presented in this study and the incorporation of the solar system is simplified. To carry out performance evaluation of the solar powered vehicle, a linear regression algorithm is employed to determine the charging efficiency of this vehicle under different charging scenarios, while the naïve bayes algorithm is employed to determine the driving distance and heterogeneity. The result shows the developed models can successfully predict the maximum and minimum distance the vehicle can attain at different attributes such as the total weight on the vehicle, the terrain, the speed, and the sun-availability. Finally, 66.6% of the variability in the battery state of charge can be predicted by the linear relationship with solar insolation. This means that the developed model accounts for about two-thirds of the observed variation.

Keywords: *Charging efficiency, Driver heterogeneity, Electric Vehicle, Linear regression, Naïve bayes*

1. Introduction

Battery electric vehicles have the outstanding advantages in zero tailpipe emissions, low noise, convenient maintenance, and high energy conversion efficiency. The deployment of electric vehicles helps to reduce oil dependence, improve air quality, and reduce pollutions and greenhouse gas emissions. Promoting the development of electric vehicles is considered as one of the promising solutions for the treatment of severe air pollution in the metropolises[1]. The incentives, such as subsidies and tax credits, have effectively promoted the public acceptance for switching to electric vehicles. For instance, in many mega cities in China, like Beijing, Shanghai, and Hangzhou, the number of vehicle license plates issued per month (car ownership) is under strict control, and the local government has also launched the free licensing policies for electric vehicles [2][3].

However, there have been issues limiting the expansion of EV such as low charging points and the efficiency of the EVs themselves. Also, , due to the limited battery capacity and charging facilities, inconvenient charging is still an important obstacle to the promotion of electric vehicles [4], [5]. Compared to the conventional internal combustion engine vehicles (ICE), electric vehicles have a shorter driving range, generally between 150 km–400 km. Meanwhile, it usually takes hours to charge. Potential customers have repeatedly been found to prefer vehicles with considerably higher available range because of the range anxiety [6]. Although the long driving range design helps to alleviate the user's range anxiety, it results in a higher expenditure on purchase and simultaneously, the affordability and cost-effectiveness is lowered [7]. Optimizing the driving range by incorporating solar panels is one of the feasible ways to solve this problem which is also the direction of breakthrough for this study, in particular the abundance of sunshine in Africa especially. A need for a well-designed/constructed chassis of this vehicle for sustainability and ergonometric of the users is also paramount.

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Cobb W.G. in 1980 developed the first solar model for an automobile, 'SUNMOBILE' was the name that was given to the 15-inch model, he displayed his invention, the solar automobile had a tiny electric motor, as well as 12 selenium photovoltaic solar cells that was portrayed at the Powerama convention held in Chicago as shown in Figure 1 [8]. Ohl (1939) developed the idea of solar cells that is now being utilized by PV production companies in solar panel manufacturing. Alexandre-Edmond Becquerel in 1839, found that certain elements have the ability to develop charged particles when illuminated. At first, photovoltaic cells would be used as a light measuring instrument even though they were inadequate for even modest power appliances [9]. Charles Fritts in 1881, invented the first commercial solar panel. He described it as "continuous, steady, and of substantial force not only through exposure to sunshine but also to faint, dispersed daylight". However, when compared to coal-fired power facilities, these solar panels were extremely inefficient [10].

Fig Error! No text of specified style in document.**:** The Sun-mobile in 1980[11]

A Solar array is a system of photovoltaic modules stacked together. Solar panels create energy employing light from the sun as a fuel source. A Photovoltaic (PV) panel is a series of photovoltaic modules, while an 'array' is a group of PV panels. In this regard, solar power is supplied to the electrical components via photovoltaic arrays. The photovoltaic panel is able to perform this conversion due to the photovoltaic cells which are mostly constructed from semi-conductors like Silicon and Indium, Nitrogen and Gallium alloys that discharges electrical energy when sunlight is radiated on the panel, this excites the electrons which would cause formation of current, that will be sent and utilized by the motor to propel the vehicle forward [12].

Several studies have attempted to carry out performance evaluation on electric vehicles by using various models. Sun et al. (2017) proposed a range prediction model that considers the real-time traffic conditions, vehicle-to-grid (V2G) interactions, and charging patterns of EVs. The authors collected data from a fleet of electric taxis in Beijing, China, and used this information to develop the model, the model achieved a prediction accuracy of 71% [13], [14]. Huang et al. (2020) proposed a range prediction model based on a support vector regression algorithm that takes into account the driving behavior, charging patterns, and weather conditions [15]. Zhang et al. (2019) developed a range prediction model based on a deep neural network that considers the driving behavior and charging patterns of users. They collected data on the driving patterns and charging behavior of over 1000 EV owners and used this information to train the model which achieved 60% accuracy [16]. One of the earliest studies in this area was conducted by Nam et al. (2012). They proposed a method for predicting EV range based on the driving patterns of users. The authors used a data-driven approach to develop a model that takes into account the speed, acceleration, and deceleration of the vehicle, as well as the terrain and weather conditions [17].

This study explores the utilization of two algorithms, which are the Naïve Bayes and Linear Regression algorithm, to carry out the performance evaluation of the fabricated Solar Powered Electric Vehicle (SPEV). Naïve Bayes is a probabilistic classifier that is deployed while the Linear Regression is a versatile algorithm used for predicting continuous outcomes based on linear relationships. The linear regression is a versatile algorithm used for predicting continuous outcomes based on linear relationships, in this case, it is employed to determine the charging efficiency of the SPEV under different charging scenarios, while the Naïve Bayes algorithm which is a probabilistic classifier was employed to predict the driving distance and the heterogeneity of the SPEV. This study is genuine and a significant step towards enhancing users experience of EVs. The design considerations, methodology, and the developed model are presented and discussed extensively.

2. Methodology

The proposed vehicle in this study is based on solar energy, the basic operational flow chart of the electric vehicle is presented in Figure 2. In this instance, the primary source of energy of the vessel is sunshine. The solar panel captures the sun's energy and converts the solar energy into electrical energy. The resulting generated electricity is transferred to the battery, it becomes charged and subsequently utilised to power a DC motor with high torque. This methodology section is divided into two sub sections, which are Vehicle Design and Modelling, and Vehicle Control System and Automation.

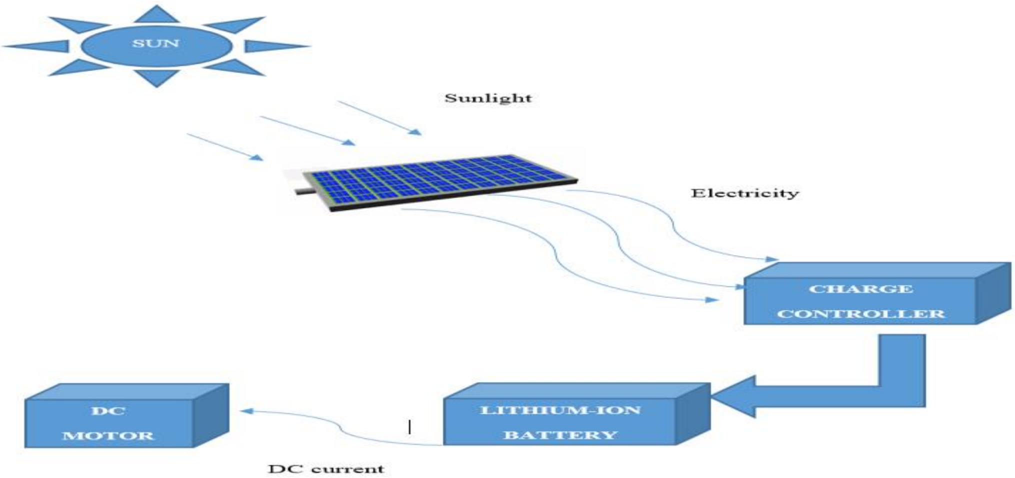


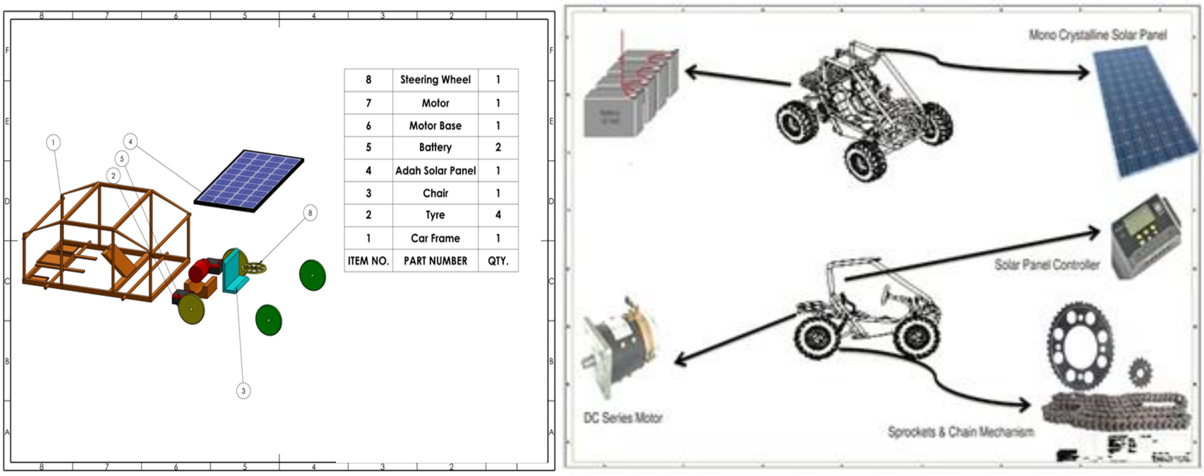
Fig 2: Working Principle of Solar Energy

2.1 Vehicle Design and Modelling

This section involves design specification, CAD modelling, design calculations and components selection of the prototype of the Electric Vehicle.

2.1.1 CAD Design

To consider an automotive vehicle using solar energy, a lot of automation components will be utilized by the vehicle such as, an electric motor, industrial switch, DC contactors, etc. The CAD design is presented in Figure 3. The vehicle features a lithium-ion battery located near the back tire that supplies power to the electric motor. The electric motor is located on a platform that sits at the back of the vehicle; it drives the vehicle forward. A chain and sprocket setup mounted on the rear wheel shaft, translates the electrical energy from the electric motor into rotational energy, which is supplied to the rear wheels, for the vehicle to move.



(a) (b)

Fig 3. (a) CAD Overview of Vehicle, (b) and Location of Components

2.1.2

Design Calculation of Frame and Chasses

The vehicle frame is the most critical component of the vehicle; this is where all the electric components were incorporated, and the comfort of the driver is dependent on the proper fabrication of the frame and chasses. The following materials were used to fabricate the frame of the vehicle.

- Angle bar: An angle bar made of hot rolling carbon steel is the materials used for the side elevations as to give the frame an aesthetic look and primarily to provide support for the weight calculations of the various components and maintain stability.
- Square pipes: the base was fabricated by using square steel tubes of a yield stress of 420 MPa, the tyres, sprockets and the braking system were welded on the base of the vehicle.
- Electrodes: An electric arc welding process was used to weld the metals such as the welding of the steel pipes to create a stable platform for which the solar panel were mounted, and for the fabrication of the elevation of the DC motor.
- Bolts and Nuts: To secure the DC motor on the fabricated elevation as seen in Figure 4, the bolts and nuts were used to fasten the electric motor on the frame of the vehicle.
- Tyres: A bias-ply tire is considered for this study with diameter of 13” on a rim of 6’ like the wheelbarrow tires.

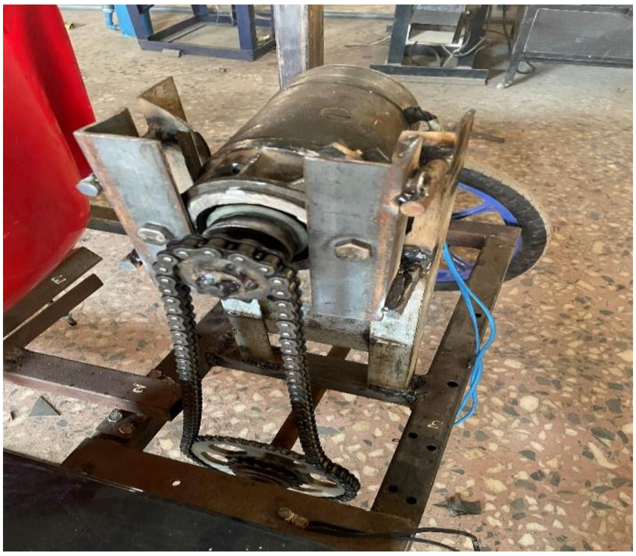


Fig 4. Elevated Platform for the DC Motor

Plate Thickness

$\Upsilon > \sigma$

Where; Υ is the yield stress of Aluminum (N/mm^2), σ is the stress due to application of load (N/mm^2)

$$\sigma = \frac{F}{A}$$

Where; F is the maximum load that would rest on the (N)

The thickness of the plate is expressed as,

$$t = 0.3h\sqrt{\frac{0.036GL}{S}}$$

Where; H is the height of machine (mm), G is the specific gravity of aluminum (kg/m^3), L is the length of the machine (mm), S is the yield stress (N/mm^2)

$$S = 36{,}259\ psi$$

$$t = 0.3\ (1200)\sqrt{(0.36 * 2.7 * 4.5)/36{,}259}$$

t = 4mm

- **Angular Velocity of the Wheel**

Taking the linear velocity to be =50km/h

Speed = 50 x (5/18) m/s

= $\underline{\underline{13.89 m/s}}$

Wheel Diameter =0.58

Therefore, wheel radius becomes; =0.58/2 = 0.29m

Hence, Angular velocity = Linear V/ Radius

= 13.89/0.29

= **47.90 rad/s**

Recall that Angular speed = 2 x π x frequency

Frequency = Angular speed / 2 π

Frequency = 47.90 x 60 / 2 π

= **457.23 rpm**

The following assumptions were considered in the context of the SPEV.

Battery weight = 30kg

Mass of the vehicle = 130kg

Speed = 50km/h

Average speed = 40km/h

Range = 60km/h

Wheel Diameter = 0.58m

Slope% = 0.1

2.1.3 Design Calculations Parameters for the Solar Vehicle

The total weight of the vehicle has been calculated, in order to determine the type of motor needed to move such weight, and the amount of charges required from the solar panel. The sum-up of the calculation is presented in Table 1.

- **Calculation for Peak Torque Required to Move the Vehicle**

Using the formula;

Peak torque = Slope% x Radius of Wheel x (Vehicle Mass + Battery) x Acceleration due to gravity

= 0.1 x 0.29 x (130+ 30) x 9.8

= 45.47 N/m

Peak power required = Angular velocity x Torque

= 47.90 x 45.47

= **2178 Watts**

- **Air Resistance**

Using, Air resistance =Mass of vehicle x (Average Speed)^3 x (5 / 100000)

= 130 x (40)^3 x (5 / 100000)

= **416 Watts**

- **Rolling Resistance**

To attain rolling resistance = 0.092 x mass of vehicle x average speed

= 0.092 x 130 x 40

Rolling resistance = **478.4 Watts**

- **Calculation for Constant Power Required**

Relating Continuous power required,

Constant power required = Rolling Resistance + Air Resistance

= 478.4 W + 416 W

= **894.4 Watts**

- **Continuous Speed Required Calculation**

From the equation;

Constant speed= Average Speed x 60 / (2 x π x Radius of Wheel)

= 40 x (5 / 18) x 60 / (2 x π x 0.29) = **365.73 rpm**

- **Required Calculation for Continuous Torque**

Relating the equation,

Continuous Torque needed = (Rolling + Air Resistance) x 60 / (2 x π x Constant Speed)

= (478.4 + 416) x 60 / (2 x π x 365.73)

= **23.34 N/m**

Table 1. Design Calculation Results

PARAMETER	VALUE
Wheel Angular Velocity	47.90 rad/s
Peak Torque of the Vehicle	45.47 N/m
Air Resistance	416 Watts
Rolling Resistance	478.4 Watts
Constant Power Required	894.4 Watts

Continuous Attainable Speed	365.73 rpm
Constant Torque Required	23.34 N/m
Frequency	457.23 rpm
Peak Power Required	2178 Watts

- Energy Calculation based on the chosen parameters.

Taking time of operation (t) into consideration: t = 6hrs;

➢ used by motor in 2hrs.= Time x Power

➢ Energy generated by panel in 2hrs = Time x Power = 2 x 255 = 510Wh

➢ Energy stored in the battery = Capacity x Voltage = 100 x 12 = 1200W

- Charging of Battery

➢ Time required for battery to charge from 0 to 100% (without considering power loss) = Potential Energy in Battery / Panel Power = 2400/ 12 = 3.3 hrs

➢ Time required for battery to charge from 0 to 100% (considering power loss factor as 2.5) = 4.5hrs

- Discharging of Battery

➢ Discharging time without power loss = Voltage x Capacity / Power of load

= (12 X 100) / 500 = 2.4 hrs

➢ Discharging time with a power loss of about 25% = 2.4 x (75/100) = 1.8hrs

- ***Calculation for the Capability of the Dc Motor***

➢ Specification of Motor (P) = 2.25KW

➢ No. of revolution per min (N) = 2800 rpm

P = (2πrt/60) / 1000

➢ Torque Transmitted (T) = 23.34N/m

➢ Shear stress (τ) $=16T/\pi d^3$

D – Wheel diameter = 58cm = 0.58m

Hence, $\tau = 16 \times 23.40 / \pi (0.58)^3$

$\tau = 610.8\ N/m^2$

➢ Load carried by motor = shear stress x cross sectional area

$P = 610.8 \times 160 \times 100 \times 10^{-4}$

P = 977.28N

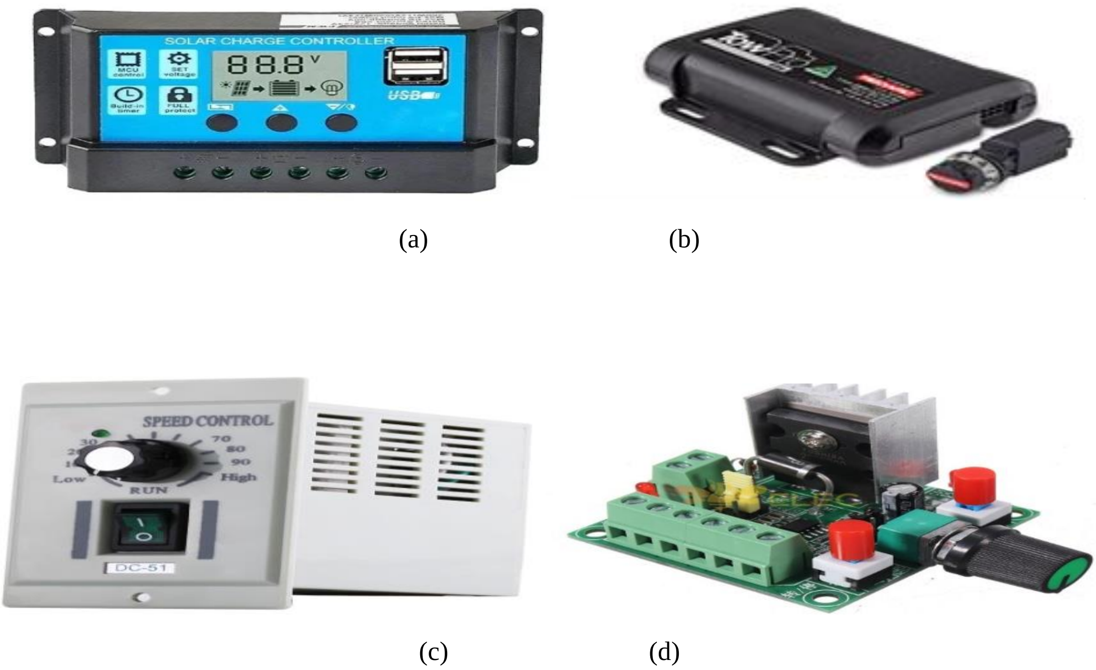
➢ P = **97.7 kg**

2.1.4 Vehicle Control System and Automation

For the control of the vehicle, various components were incorporated as shown in Figure 5, components such as speed controller to control the speed, forward and reverse module for the forward and backward movement of the vehicle, charge controller to control the charges from the solar panel and to avoid overcharging, and braking system to halt the movement of the vehicle were incorporated. The charge controller considered for the study is 12/24v and 40ah rating controller that is connected to the monocrystalline solar panels of 330w as shown in Figure 5a. The speed controller is one between 2000- 3500 rpm with a DC output of 24V-90V as shown in Fig 5b. The forward and reverse relay module chosen for this vehicle is a Pulse Width Modulation (PWM) Stepper Motor Driver of 2D as shown in Fig 5c. The braking system considered for this study is an Electronic Braking System (EBS) that uses Electric sensors to monitor the speed of the wheel as it rotates and detect if it is about to lock up under braking, when this happens, the brakes are automatically released and then rapidly reapplied. A Tow-Pro Elite Electric Brake Controller is chosen for this purpose as shown in Figure 5d.

For the automation of the vehicle, an Arduino microcontroller is chosen. A microcontroller is a compact integrated circuit designed to govern a specific operation in an embedded system. Many components were automated in the SPEV, such as the head lamp which automatically turns on as soon as the sun sets, the vehicle seats which automatically adjusts to the size and comfort of each driver. The prototype SPEV is presented in Figure 6.

Fig 6: The Prototype Solar Powered Electric Vehicle.



(a) (b)

(c) (d)

Fig 5. Control Components , (a) Charge Controller, (b) Speed Controller, (c) Forward & Reverse Module, (d) Electronic Braking System.

3. Result And Discussion

This study explores the utilization of two algorithms, which are the Naïve Bayes and Linear Regression algorithm, to carry out the performance evaluation of the fabricated vehicle.

*3.1 **Evaluating the Driving Range of the SPEV using Naïve Bayes Algorithm***

Evaluating the total distance in which the fabricated SPEV can travel is crucial for determining its efficiency and practicality in real-world scenarios. Several key factors influence the distance an SPEV can cover, such as the total weight, sun availability, driver's speed, and terrain. Understanding the interplay of these factors is essential to optimize SPEV performance and enhance their viability as a sustainable mode of transportation. Naïve Bayes classifier is based on conditional probability and the formula is postulated as Bayes Theorem.

$$Bayes\ Theorem, P(C/A) = [P(A/C)\ P(C)]/P(A).$$

Table 2. Naïve Bayes Classifier

S/N	WEIGHT	SPEED	TERRAIN (Surface)	SUN AVAILABILITY	DISTANCE TRAVELLED (Above 100KM)
1	120kg	40km/h	FLAT	SUNNY	YES
2	120kg	60km/h	HILLY	CLOUDY	NO
3	90kg	30km/h	HILLY	SUNNY	YES

4	90kg	40km/h	SLOPE	CLOUDY	NO
5	120kg	30km/h	SLOPE	SUNNY	NO
6	130kg	30km/h	HILLY	CLOUDY	NO
7	130kg	40km/h	SLOPE	SUNNY	YES
8	90kg	60km/h	FLAT	CLOUDY	YES
9	130kg	60km/h	FLAT	SUNNY	NO
10	120kg	30km/h	SLOPE	CLOUDY	NO

To determine the charging behaviour of the vehicle at different scenarios, Table 2 presents Ten (10) instances with four (4) attributes and two (2) possible outcomes. By applying the Naïve-Bayes model, the probabilities of getting a distance above 100km and a distance below 100km, is evaluated thus:

Outcome

- Above 100KM distance
- Below 100KM distance

Attributes

- Weight
- Speed
- Terrain
- Sun availability

Instances

- 90 – 130kg weight

From Table 3, the probability that the vehicle will go above 100KM distance is;

P(Above 100KM =YES) = 4/10 = 0.4

While the probability that the vehicle will drive below 100KM is;

P(Below 100KM = NO) = 6/10 = 0.6

Table 3. Table of Probabilistic Outcome Based on (a)Weight, (b) Speed, (c) Terrain and (d) Sun Availability

(a)	**WEIGHT(Kg)**	**YES**	**NO**
	120	1/3	3/4
	90	2/3	1/3
	130	1/3	2/3

(c)	**TERRAIN**	**YES**	**NO**
	Flat	2/3	1/3
	Slopy	1/4	3/4
	Hilly	1/3	2/3

(b)	**SPEED (km/hr)**	**YES**	**NO**
	30	1/3	3/4
	40	2/3	1/3
	60	1/3	2/3

(d)	**SUN AVAILABILITY**	**YES**	**NO**
	SUNNY	4/5	1/5
	CLOUDY	1/5	4/5

To evaluate the four attributes, we take each attribute together with their outcomes as shown in Table 3. From this table, we can calculate the conditional probability. For instance in Table 3a, we can determine what will be the driving distance if the total weight on the vehicle is 120kg, which are 0.33 for Yes (above 100KM) and 0.75 for No(below 100KM). Other conditional probabilities can be generated from this table, such as the possible outcome at a various terrain (flat, slopy or hilly), or the speed at various speed of 30,40 and 60, etc.

So at a new instance of {Weight=90kg, Speed= 40km/hr, Terrain=Hilly, Sun availability= Cloudy), the possible driving distance of the SPEV using the developed model becomes;

V_{NB} **= argmax** $P(V_j)\ \Pi_i\ P(a_i|v_j)$

$V_j \epsilon \{yes, no\}$ **= argmax** $P(V_j)\quad P(weight= 90|\ v_j)\ P(Speed=40|\ v_j)$

Vjϵ{yes, no) ***P(Terrain =hilly| v_j) P(Sun availability= cloudy| v_j)***

V_{NB}(yes) = P(yes)* P(Weight|yes)* P(speed|yes)* P(terrain|yes)* P(sun availability|yes)

V_{NB}(no) = P(no)* P(Weight|no)* P(speed|no)* P(terrain|no)* P(sun availability|no)

So the probability that the new instance will drive above 100km distance (yes) is

V_{NB}(yes) = 0.4 x 0.67 x 0.67 x 0.33 x 0.2 = 0.019

While the probability that the new instance will drive below 100km distance (no) is

V_{NB}(no) = 0.6 x 0.33 x 0.33 x 0.67 x 0.8 = 0.035

Therefore

$$V_{NB}(yes) = \frac{V_{NB}(yes)}{V_{NB}(yes)+V_{NB}(no)} = \frac{0.019}{0.019+0.035} = 0.35$$

$$V_{NB}(no) = \frac{V_{NB}(no)}{V_{NB}(yes)+V_{NB}(no)} = \frac{0.035}{0.019+0.035} = 0.65$$

The result shows that the probability that the vehicle will drive below 100km distance (no) is greater than the probability that the vehicle will drive above 100km (yes). So, for this instance (Weight=90kg, Speed= 40km/hr, Terrain=Hilly, Sun availability= Cloudy), the model predicts that the vehicle will drive below 100km distance.

So, at any new instance, the developed model can be used to predict the possible outcome of the driving distance.

3.2 Evaluating the Charging Efficiency by using Linear Regression Model

Linear regression is often used to estimate the relationship between two continuous variables when there is a belief or evidence of a linear association between them. Evaluating the charging conditions of the SPEV is crucial to optimize their performance and efficiency. By considering relevant parameters and employing a linear regression model, we can develop some parameters for evaluation.

Parameters for Evaluation:

- Insolation: The availability of sunlight, measured as insolation, impacts the charging conditions. Higher insolation levels provide more solar energy for charging, resulting in faster charging rates.
- Battery Capacity: The battery capacity determines the amount of energy that can be stored and used for charging. Larger battery capacities enable longer driving range and potentially more efficient solar charging.
- Battery state of charge (SOC): This is the amount of energy stored in a battery as a percentage of its total capacity. It indicates how much energy is currently available for use. A battery with a state of charge of 100% means it is fully charged, while a state of charge of 0% indicates that the battery is completely discharged. Table 4 presents different levels of battery state of charge ranging from 10% to 100%.

Table 4. Charge Level Parameters

S/N	Solar Panel Efficiency (%)	Solar Irradiance (Kw/M^2)	Peak Sun Hours (Hours)	Solar Insolation (Kwh/M^2)	Battery State of Charge (%)
1	18%	0.63	4	2.6	10
2	18%	0.57	5	2.85	20
3	18%	0.6	4.5	2.7	30
4	18%	1	5	5	65
5	18%	0.8	3.5	2.8	56
6	18%	0.746	6	4.476	45
7	18%	0.65	5	3.25	42
8	18%	0.823	5.5	4.526	60
9	18%	0.921	6	5.526	75
10	18%	0.93	5	4.65	80

Based on the data gathered in Table 4 from multiple tests drives performed under various conditions, a linear regression model is done to provide insights into the factors affecting solar-powered vehicle charging.

Linear regression equation is given by;

$$Y = Mx + b$$

Where X is the independent variable, while y is the independent variable.

Y represents the predicted battery state of charge,

X represents the solar insolation,

m is the coefficient of x (slope) = $\frac{(\overline{xy})-(\bar{x})(\bar{y})}{\overline{x^2}-\bar{x}^2}$, and b is the y-intercept = $\bar{y} - a_1 * \bar{x}$

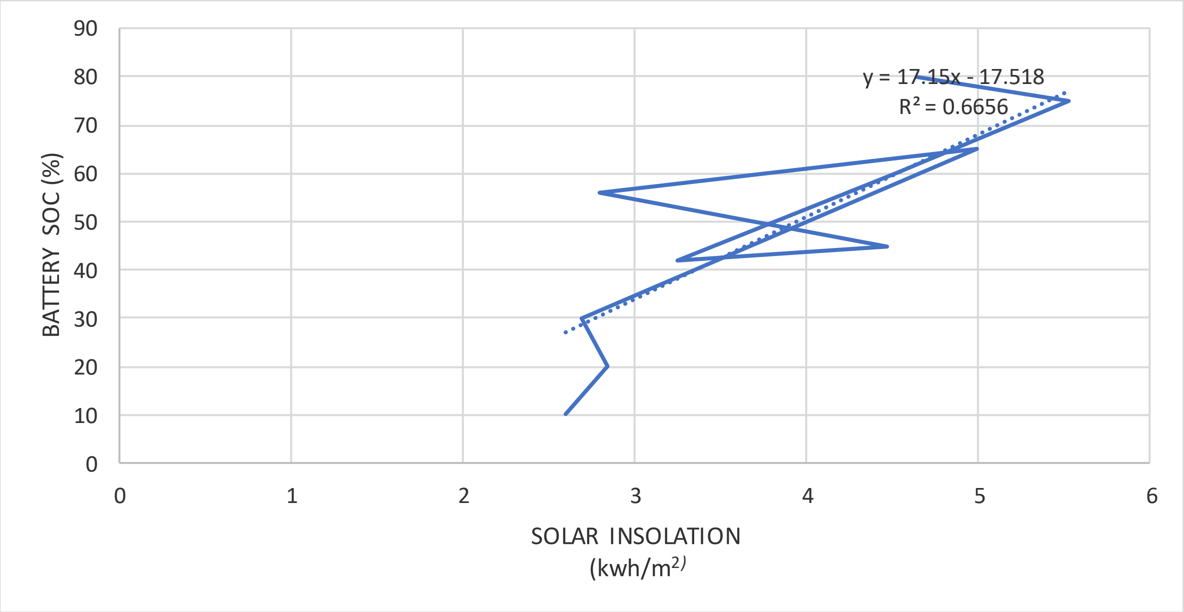


Fig 7. Graph of Battery State of Charge Vs Solar Insolation

The equation in Figure 7 represents the linear regression obtained. In this case, the equation suggests that the battery state of charge (y) can be estimated by multiplying the solar irradiance (x) by 17.15 and then subtracting 17.518. The coefficient in the equation represents the slope of the line. In this case, it indicates that for every unit increase in solar insolation, the battery state of charge is expected to increase by 17.15 % points. The positive coefficient suggests a positive correlation between the solar insolation and the state of charge of the battery, indicating that as the solar insolation increases, the battery state of charge is expected to increase as well.

The y-intercept represents the value of the predicted battery state of charge when the solar irradiance is zero. In this case, it suggests that when there is no solar irradiance (x = 0), the model predicts a battery state of charge of approximately 17.518. The R^2 value, also known as the coefficient of determination, provides an indication of how well the linear regression model fits the data. It ranges from 0 to 1, with 1 indicating a perfect fit. In this case, the R^2 value of 0.6656 suggests that approximately 66.56% of the variability in the battery state of charge can be explained by the linear relationship with the solar insolation. This means that the model accounts for about two-thirds of the observed variation, leaving some unexplained factors influencing the battery state of charge, such as sun intensity, improper battery connections and under-performance of the selected charge controller.

4. Conclusion

This study presents the schematic to develop a solar powered electric vehicle, by considering the weight and design calculations in order to carefully select the appropriate components such as the DC motors, frames, solar panel and the adequate battery size.

To carry out performance evaluation of the SPEV and to meet the goal of the fitness of driving range and charging efficiencies, two algorithms were deployed for this purpose. The results show that the developed models can successfully predict the maximum and the minimum distance the vehicle can attain at different attributes such as the total weight on the vehicle, the terrain, the speed, and the sun-availability. Also, the model predicted that for every unit increase in the solar insolation, the battery state of charge is expected to increase by 17.15 % points. Finally, 66.6% of the variability in the battery state of charge can be predicted by the linear relationship with solar insolation. This means that the developed model accounts for about two-thirds of the observed variation. This design can be improved and developed further in developing countries where transportation is still a challenge.

4.1. Acknowledgment

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References

[1] X. Wang, H. Chen, and C. Lin, "Comparison of Different Battery Types for Electric Vehicles Comparison of Different Battery Types for Electric Vehicles," 2017.

[2] K. Zhong, P. Wang, J. Pei, J. Xu, and Z. Han, "Multiobjective Optimization regarding Vehicles and Power Grids," vol. 2021, 2021.

[3] M. Shahid, S. Zhuang, H. Mudassir, and M. Haris, "An in-depth analysis of electric vehicle charging station infrastructure , policy implications , and future trends," *Energy Reports*, vol. 8, pp. 11504–11529, 2022.

[4] A. Raj *et al.*, "A taxonomy for autonomy in industrial autonomous mobile robots including autonomous merchant ships A taxonomy for autonomy in industrial autonomous mobile robots including autonomous merchant ships," 2011.

[5] J. Du, M. Pei, B. Jia, and P. Wu, "Optimal Deployment of Dynamic Wireless Charging Lanes for Electric Vehicles considering the Battery Charging Rate," vol. 2022, 2022.

[6] Z. Lu, Q. Zhang, Y. Yuan, and W. Tong, "Optimal Driving Range for Battery Electric Vehicles Based on Modeling Users ' Driving and Charging Behavior," vol. 2020, no. 1, 2020.

[7] J. Jayakumar, B. Nagaraj, S. Chacko, and P. Ajay, "Conceptual Implementation of Artificial Intelligent based E-Mobility Controller in smart city Environment," vol. 2021, 2021.

[8] V. Iulia and S. Loránd, "A Brief History of Electric Vehicles," no. September, 2022.

[9] Q. Liu, W. Wang, and X. Hua, "Path Planning Method for Electric Vehicles Based on Freeway Network," vol. 2021, 2021.

[10] P. Daponte *et al.*, "A review on the use of drones for precision agriculture," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 275, no. 1, 2019.

[11] T. Pachal, "Electric Solar Vehicle - RayRacer Dr . Isham Panigrahi," no. April, 2016.

[12] S. Ling, X. Zhu, Q. Wang, and P. Schonfeld, "Prediction of Charging Requirements for Electric Vehicles Based on Multiagent Intelligence," vol. 2022, 2022.

[13] C. R. Forsythe, K. T. Gillingham, J. J. Michalek, and K. S. Whitefoot, "Technology advancement is driving electric vehicle adoption," vol. 120, no. 23, pp. 1–7, 2023.

[14] C. K. H. Lee, "Engineering Applications of Artificial Intelligence A review of applications of genetic algorithms in operations management," *Eng. Appl. Artif. Intell.*, vol. 76, no. May, pp. 1–12, 2018.

[15] N. V Martyushev, B. V Malozyomov, S. N. Sorokova, and E. A. Efremenkov, "Mathematical Modeling the Performance of an Electric Vehicle Considering Various Driving Cycles," 2023.

[16] Y. Jin, B. Yu, M. Seo, and S. Han, "Optimal Aggregation Design for Massive V2G Participation in Energy Market," vol. 8, 2020.

[17] E. Hopkins, D. Potoglou, S. Orford, and L. Cipcigan, "Can the equitable roll out of electric vehicle charging infrastructure be achieved ? Can the equitable roll out of electric vehicle charging infrastructure be achieved ?," *Renew. Sustain. Energy Rev.*, vol. 182, no. May, p. 113398, 2023.