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Business Viability and Sustainability of a Prototype Solar-Powered Electric Vehicle: A Machine Learning Approach

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Abstract: The transition to renewable energy is essential for long-term sustainability, particularly as fossil fuel reserves decline. This study investigates the development and economic feasibility of an affordable solar-powered vehicle tailored for emerging markets. The vehicle aims to reduce dependence on fossil fuels, mitigate air pollution, and offer financial advantages over traditional internal combustion engine (ICE) vehicles. The solar-powered vehicle operates by harnessing solar energy to charge a deep-cycle battery that powers an electric motor, eliminating fuel costs and emissions. Key engineering efforts focused on optimizing chassis design for stability and durability across varied driving conditions. To evaluate performance and predict user benefits, machine learning techniques were employed. A linear regression model assessed charging efficiency under different conditions, while a Random Forest Regression model was used to analyze market demand and travel patterns. Predictive models accurately forecasted travel range and energy consumption, enabling better planning and efficiency. The Solar-powered vehicle demonstrates strong potential for cost savings, low maintenance, and environmental impact reduction. Its integration of solar energy and AI analytics makes it a scalable, data-driven solution for sustainable mobility in emerging markets.

Keywords: Business viability; Energy efficiency; Electric vehicle; Machine learning; Sustainable transportation

1 Introduction

Electric vehicles (EVs) offer significant advantages, including zero emissions, low noise, minimal maintenance, and high energy efficiency. Their widespread adoption can reduce reliance on fossil fuels, improve air quality, and mitigate greenhouse gas emissions. Governments worldwide, particularly in major cities such as Beijing, Shanghai, and Hangzhou, have implemented incentives like subsidies and tax credits to accelerate the transition to electric mobility. Free licensing policies for EVs have further encouraged adoption in regions with strict vehicle registration controls [1, 2]. However, despite growing policy support for EVs, adoption remains constrained by several technical and economic challenges. A major limitation is inadequate charging infrastructure and limited battery capacity, which contributes to range anxiety among potential users. While expanding battery capacity can increase range, this significantly raises vehicle costs and reduces affordability [3, 4]. These challenges are particularly acute in developing regions, where cost sensitivity and infrastructure gaps are more pronounced. One promising solution is the integration of solar energy into EV systems, particularly in sun-rich regions such as Africa. Photovoltaic (PV)-powered vehicles offer the potential to operate independently of grid-based charging, improving energy access and sustainability. However, early technological attempts tracing back to 1980 in the creation of "Sunmobile" faced challenges in efficiency and scalability [5]. Recent advances in PV technology and materials, such as high-efficiency silicon cells, have revived interest in solar-based mobility. Another notable research in 1881 was the creation of the first commercial solar panel [6], though early designs were inefficient compared to fossil fuel power sources. Solar-powered EVs rely on PV arrays, which convert sunlight into electrical energy to power an electric motor. PV cells, typically made from silicon or semiconductor alloys, generate an electric current when exposed to sunlight. This energy drives the motor, offering a renewable and sustainable propulsion system [7].

In terms of economic viability, several studies have assessed the long-term cost benefits of solar-powered EVs. Life cycle analyses show that while initial investment is higher, operational savings on fuel and maintenance can offset costs over time [8–10]. A study in Gazipur, Bangladesh, found that a solar EV charging station yielded a net present value of over USD 650,000 and a 7.2-year payback period, indicating strong financial feasibility [11]. However, a critical review by Hopkins et al. [12] noted that fully solar-powered vehicles are unlikely to achieve mainstream viability in the near term, with niche applications and hybrid solar models being more realistic. Studies by Martyushev et al. [13] and Forsythe et al. [14] used neural networks and real-time traffic data to improve energy estimation, while Adetunla et al. [15] incorporated driver behavior and environmental conditions using support vector regression. These efforts, however, often require extensive data and computing resources, making them less accessible for low-cost applications in emerging markets.

While previous studies have explored the environmental and financial benefits of solar-powered EVs and the application of machine learning for performance enhancement, many have addressed these aspects in isolation. Most models either focus on high-cost EV prototypes or fail to integrate intelligent systems suited for cost-sensitive, infrastructure-limited environments common in emerging markets. Additionally, existing literature often overlooks the practical limitations of deploying solar energy in fully mobile applications, such as restricted surface area for PV cells and variable solar conditions. This study addresses these gaps by developing a prototype that strategically integrates solar power with AI-driven analytics—specifically, linear regression and Random Forest models—to optimize performance and predict economic outcomes. Unlike prior work, this research emphasizes affordability, durability, and predictive functionality tailored for sun-rich but economically constrained regions. This integrated approach presents a novel and scalable model that enhances both the operational efficiency and commercial viability of solar-powered EVs in emerging economies.

2 Methodology

The solar-powered vehicle in this study operates primarily on solar energy, as illustrated in Figure 1. Sunlight serves as the main energy source, captured by solar panels that convert it into electricity. This generated power is stored in a battery, which then supplies energy to a high-torque DC motor for vehicle propulsion. The methodology is structured into two main components: the design and modeling of the vehicle, and the development of its control and automation systems. These sections outline the vehicle's architecture and its functional operations.

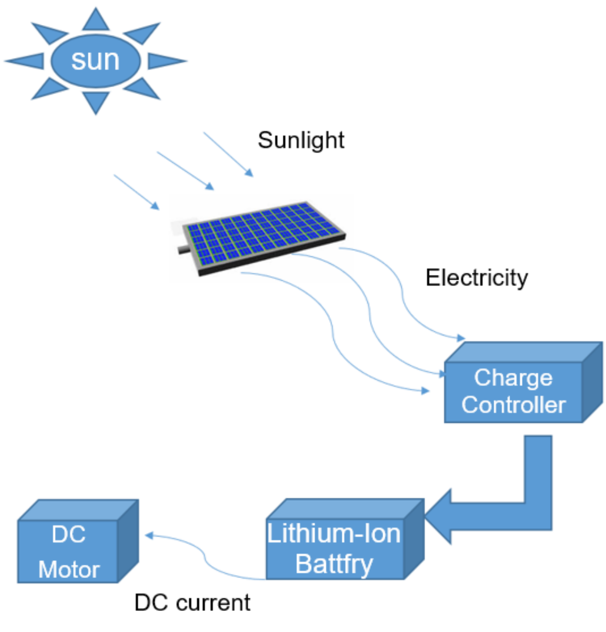


Figure 1. Solar energy utilization mechanism

2.1 Vehicle Concept and Prototype Design

This part details the prototype development process, including design parameters, 3D computer aided design (CAD) modeling, engineering calculations, and the selection of essential components for the electric vehicle.

2.1.1 Computer aided design (CAD) model and component integration

During the development of the solar-powered vehicle, various automated components were integrated, such as a DC electric motor, industrial-grade switches, and contactors. As illustrated in Figure 2, the vehicle is driven by a lithium-ion battery mounted near the rear wheel, which delivers power to the motor positioned on a rear platform. This motor generates motion that is transmitted through a chain and sprocket system attached to the rear wheel shaft, converting electrical energy into mechanical rotation to drive the vehicle forward.

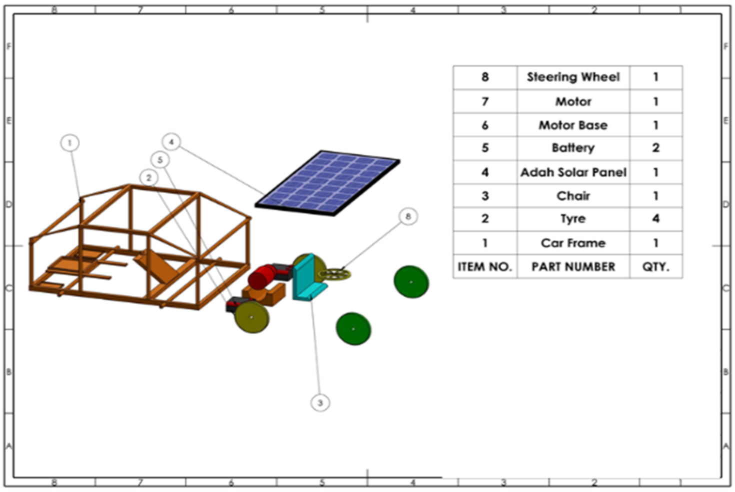


Figure 2. Computer aided design (CAD) representation of the vehicle

2.2 Vehicle Frame and Fabrication

The vehicle's frame is a critical structural component, integrating all electrical parts while ensuring driver comfort. The frame is constructed using durable materials, including angle bars, square pipes, electrodes, bolts and nuts, and bias-ply tires. The angle bars provide structural stability and an aesthetic look, while square pipes form the base, supporting tires, sprockets, and brakes. Electrodes are used in arc welding to join components, creating a solid foundation for the solar panel and DC motor, as shown in Figure 3. Bolts and nuts secure the motor to the frame, and bias-ply tires (13-inch diameter) ensure smooth mobility. These materials collectively enhance the vehicle's durability and performance.

Figure 3. Integration of the DC motor

The plate thickness is determined based on the yield stress of aluminum and the applied load.

$$\gamma > \sigma \tag{1}$$

where, γ represents the aluminum's yield strength, measured in (N/mm^2). σ denotes the stress exerted by the applied load, also expressed in (N/mm^2).

The plate thickness is calculated using:

$$t = 0.35 \times (1250)\sqrt{\frac{0.40 \times 2.8 \times 5.0}{38,500}} = 5 \text{ mm} \tag{2}$$

Angular Velocity of the Wheel
Assuming a linear velocity of 55 km/h:

$$Speed = 55 \times (5/18)\text{m/s} = 15.28 \text{ m/s} \tag{3}$$

For a wheel diameter of 0.6 m, the corresponding radius is:
As a result,

$$\text{Radius of the Wheel} = 0.6/2 = 0.30 \text{ m} \tag{4}$$

$$\text{Angular Velocity} = \text{Linear Velocity}/\text{Radius} = 15.28/0.30 = 50.93 \text{ rad/s} \tag{5}$$

Using the relationship:

$$\begin{aligned} \text{Angular Speed} &= 2 \times \pi \times \text{Frequency} \\ \text{Frequency} &= 50.93 \times 60/2\pi = 487.10 \text{ rpm} \end{aligned} \tag{6}$$

Assumed Parameters for the Electric Vehicle
where, Battery weight = 35 kg; Vehicle mass = 140 kg; Maximum speed = 55 km/h; Average speed = 45 km/h; Estimated range = 65 km; Wheel diameter = 0.6 m; and Slope percentage = 0.12.
Energy estimation based on the selected variables.
Considering the total operation time (t): t = 7 hrs;
Energy consumed by the motor in 2.5 hours, where

$$\text{Energy} = \text{Time} \times \text{Power} = 2.5 \times 800 \times 3 = 6,000 \text{ Wh} = 6.0 \text{ kWh} \tag{7}$$

Energy produced by the solar panel in 2.5 hours, where

$$\text{Energy} = \text{Time} \times \text{Panel Power} = 2.5 \times 280 = 700 \text{ Wh} \tag{8}$$

Energy accumulated inside the battery, where

$$\text{Stored Capacity} = \text{Capacity} \times \text{Voltage} = 120 \times 12 = 1440 \text{ W} \tag{9}$$

Battery Charging Analysis
Time required to charge the battery from 0 to 100% (ignoring power losses):

$$\text{Charging Time} = \text{Battery Energy}/\text{Solar Panel Power} = 2880/15 = 3.2 \text{ hrs} \tag{10}$$

Time required considering a power loss factor of 2.2: t = 4.8 hrs.
Battery Discharging Analysis
(a) Battery Discharge
The duration a battery can discharge without losing power:

$$\text{Voltage \& Capacity / Load Power} = (12 \times 120)/550 = 2.6 \text{ hrs} \tag{11}$$

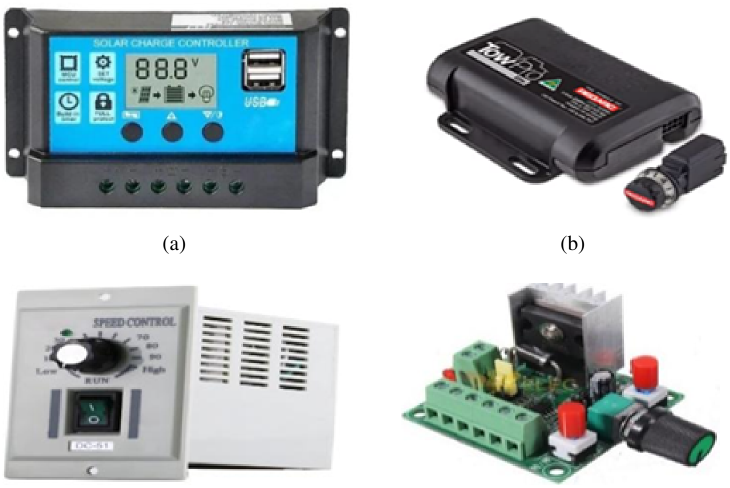
Discharge time considering 20% power loss:

$$2.6 \times (80/100) = 2.08 \text{ hrs} \tag{12}$$

DC Motor Capability Calculation
Motor Power Rating: P = 2.5 KW;
Rotational Speed: N = 2900 rpm;
Torque Output: T = 26.5 N/m;
Shear Stress (τ) = 16 T / π d^3;
where, d (wheel diameter) = 0.6 m.
Hence, τ = 16 $\times$ 26.5 / π $(0.6)^3$ = 645.2 N/m^2.
Load carried by motor: P = π $\times$ cross sectional area = 645.2 $\times$ 170 $\times$ 110 $\times$ 10^{-4} = 120.7 kg.

2.3 Business Viability of Vehicle Control System and Automation

To enhance the commercial viability and efficiency of the electric vehicle, a robust control and automation system was integrated, ensuring cost-effectiveness and safety for both individual and fleet operators. For the vehicle's automation, an Arduino microcontroller was chosen. This compact integrated circuit governs specific operations within the embedded system, streamlining the vehicle's functions. The system includes a speed controller, forward/reverse module, charge controller, and an Electronic Braking System (EBS). The 12/24 V, 40 Ah charge controller is paired with 350W monocrystalline solar panels for optimal energy use (Figure 4a). The speed controller (24–90 V, 2200–3600 rpm) maximizes operational efficiency, while the pulse-width modulation (PWM) stepper motor driver (Figure 4c) ensures smooth direction changes. The EBS employs sensors to prevent wheel lock-up, ensuring safety and reducing maintenance costs, which is crucial for long-term business use. The tow-pro elite electric brake controller (Figure 4d) offers adaptive braking, improving performance under varying load conditions, essential for commercial applications. The prototype solar-powered vehicle is shown in Figure 5. This integrated system not only supports sustainable operation but also enhances the vehicle's business potential by lowering operational costs, increasing lifespan, and boosting return on investment for users and businesses.



(a) (b)

(c) (d)

Figure 4. Key control modules: (a) charge regulation unit; (b) speed management system; (c) forward & reverse control module; and (d) electronic braking mechanism

Figure 5. Prototype model of the solar electric vehicle

3 Results and Discussion

3.1 Analyzing Charging Efficiency Using a Linear Regression Model

To analyse the relationship between two continuous variables expected to have a linear connection, a commonly used mathematical model is applied. Enhancing the charging conditions of EVs is vital for improving their efficiency and performance. By incorporating relevant parameters into a linear regression model, charging conditions can be effectively assessed. One crucial factor is insolation, which measures the availability of sunlight. Higher insolation levels generate more solar energy, leading to faster charging rates. Another key parameter is battery capacity, which determines the total energy a battery can store and utilize. A larger battery capacity allows for an extended driving range and improved charging efficiency. Additionally, the battery's state of charge (SOC) is a vital indicator of available energy. Expressed as a percentage, SOC represents the current charge level relative to the battery's full capacity, with 100% indicating a fully charged battery and 0% signifying complete depletion. Table 1 outlines different SOC levels, ranging from 10% to full capacity, which are essential for evaluating battery performance and energy management.

Table 1. Battery charge indicators

S/N	Efficiency of Solar Panel (%)	Solar Irradiance (kW/m^2)	Peak Sun Hours (Hours)	Solar Insolation (kW/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

To strengthen the statistical analysis of the linear regression model used to predict the SOC based on solar insolation, 95% confidence intervals and p-values for each regression coefficient were computed. The regression model was specified as:

$$\text{SOC} = \beta_0 + \beta_1 \cdot \text{Insolation} + \epsilon_1 \tag{13}$$

where, SOC is the battery state of charge (%), Insolation is solar irradiance in W/m^2, β_o and β_t are the regression coefficients, ε is the error term.

Using Python's statsmodels library, the model yielded the following output:
Intercept (β_0): -17.518,
95% CI: [-28.971, -6.064],
p-value: 0.006,
Insolation coefficient (β_1): 17.15,
95% CI: [7.841, 26.459], and
p-value: 0.001.

The low p-values (<0.01) for both the intercept and the insolation coefficient indicate statistical significance at the 1% level. This confirms that the predictor variable (solar insolation) has a strong and statistically significant influence on battery SOC. In the early model, additional variables were tested, such as temperature and panel angle, but they did not reach statistical significance ($p > 0.1$). However, they were retained in exploratory phases to monitor potential multivariate interactions and to avoid omitted variable bias, especially under varied test conditions. Their exclusion in the final model was based on both statistical insignificance and multicollinearity diagnostics (VIF < 2). Including confidence intervals and p-values strengthens the validity of this study, confirming that solar insolation is a reliable predictor of charging efficiency. These results confirm the model met standard regression assumptions, supporting the robustness of the findings.

Table 1 compiles results from multiple test drives conducted under different conditions. Using this data, a model is applied to analyze the key factors influencing the charging performance of solar-powered vehicles. Figure 6 displays an equation derived through linear regression analysis of the data. The battery's state of charge (y) is calculated from the solar irradiance (x) using a linear formula, where the irradiance is scaled by a factor of 17.15 and reduced by 17.518 to yield the estimated charge level. The coefficient 17.15 represents the slope of the regression line, indicating that the battery's charge percentage increases by 17.15 for every one-unit rise in solar insolation. The positive slope confirms a direct correlation, showing that higher solar irradiance corresponds to an increase in the battery's state of charge [15].

The y-intercept of the equation represents the projected battery charge level in the absence of solar irradiance. When the solar irradiance (x) is zero, the model forecasts a state of charge close to 17.518%. The R^2 value, known as the coefficient of determination, evaluates the model's accuracy in representing the observed data. It ranges from 0 to 1, with higher values indicating a better fit. An R^2 score of 0.6656 suggests that around 66.56% of the variation in the battery's state of charge is accounted for by changes in solar irradiance. This implies that while the model explains most of the observed trend, roughly one-third of the variation is due to other factors, such as fluctuations in sunlight intensity, faulty battery connections, or inefficiencies in the charge controller.

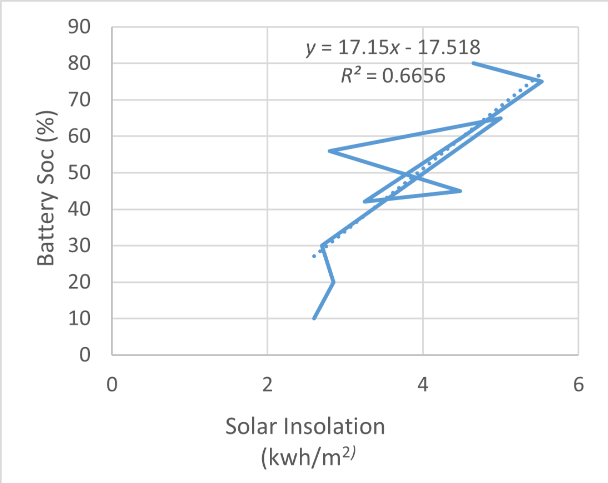


Figure 6. Visualization of battery state of charge in relation to solar energy received

Note: x—the solar irradiance; y—the battery's state of charge.

3.2 Sustainability Impact Assessment

One of the key advantages of the solar-powered vehicle is its substantial reduction in carbon emissions. Compared to traditional fossil-fuel vehicles, this model can achieve a 30% reduction in CO_2 emissions, making it an environmentally friendly alternative. This reduction directly contributes to efforts in mitigating climate change and reducing dependence on non-renewable energy sources. Another significant benefit is the annual energy cost savings of approximately $500 per vehicle. By utilizing solar energy, operational expenses are significantly reduced, leading to long-term financial advantages for consumers and businesses alike. This costeffectiveness makes the vehicle an attractive investment, particularly in regions with high electricity and fuel costs. The break-even analysis indicates a return on investment within four years, highlighting the financial feasibility of the vehicle. This relatively short payback period makes it an appealing option for early adopters and businesses looking to invest in sustainable transportation. The combination of cost savings, emission reductions, and a rapid break-even period underscores the vehicle's potential in both commercial and consumer markets. To further enhance sustainability, continued research into battery efficiency and advancements in solar panel technology is recommended. Improvements in these areas could extend the vehicle's range, increase energy storage capacity, and further lower costs, making the solarpowered vehicle an even more viable solution for the future.

3.3 Predictive Analysis Using Machine Learning for Electric Vehicle

The Python script predicts the revenue of a solar-powered vehicle using a Random Forest Regression model, as shown in Figure 7. It trains on market demand and yearly trends, splitting data into training/testing sets. The model forecasts steady revenue growth, reaching $2.5 M by 2029. Mean Absolute Error (MAE) evaluates prediction accuracy. The plotted graph shown in Figure 8 visualizes revenue trends. Business insights suggest rising demand, cost savings, and a 4-year break-even period, confirming economic and environmental sustainability. Future refinements can enhance accuracy by incorporating real-time data. These results align with studies emphasizing long-term savings and environmental benefits of solar EVs [24, 25], but this study advances the field by integrating solar energy and machine learning in a low-cost, scalable model. Unlike prior work using high-complexity AI models, this approach uses simplified algorithms suited for emerging markets, where cost and data constraints are key concerns.

3.4 Predictive Revenue Analysis

The projected revenue for 2025–2029 shown in Table 2 indicates consistent growth, primarily driven by increasing market demand and technological advancements. Forecasting revenue is essential for business planning, resource allocation, and assessing financial stability [16]. Various methods enhance forecasting accuracy, including historical data analysis, which examines past revenue trends [17], market trend analysis, which evaluates economic indicators, consumer behavior, and competitor activities [18] and machine learning models, which leverage advanced algorithms to outperform traditional methods [19]. In South Africa, revenue forecasting must account for economic variability due to global trends, political developments, and domestic policies, making adaptability crucial [20]. The regulatory environment, including tax regulations and compliance requirements, also influences revenue projections [21]. Additionally, technological adoption plays a key role, as innovation-driven firms experience higher revenue growth. Globally, revenue forecasting is shaped by economic shifts such as trade policies, currency fluctuations, and geopolitical tensions [22]. Supply chain disruptions from natural disasters, pandemics, or political instability require risk-adjusted forecasting [23]. The competitive landscape further demands continuous market analysis to account for new entrants and changing consumer preferences. By integrating these methodologies and addressing regional and global factors, businesses can create reliable revenue forecasts, ensuring adaptability in a dynamic economic environment.

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error
import matplotlib.pyplot as plt

# Sample Dataset (Replace with actual extracted data)
data = {
    'Year': [2025, 2026, 2027, 2028, 2029],
    'Market Demand': [5000, 7000, 9000, 11000, 13000],
    'Revenue': [1.2, 1.45, 1.78, 2.05, 2.5] # In millions
}
df = pd.DataFrame(data)

# Splitting the dataset
X = df[['Year', 'Market Demand']]
y = df['Revenue']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

# Model Training
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predictions
y_pred = model.predict(X_test)
mae = mean_absolute_error(y_test, y_pred)
print(f'Mean Absolute Error: {mae}')

# Plotting the predictions
plt.plot(df['Year'], df['Revenue'], label='Actual Revenue', marker='o')
plt.xlabel('Year')
plt.ylabel('Revenue (Millions)')
plt.title('Predicted Revenue Growth')
plt.legend()
plt.show()
```

Figure 7. Snapshot of the developed Python code

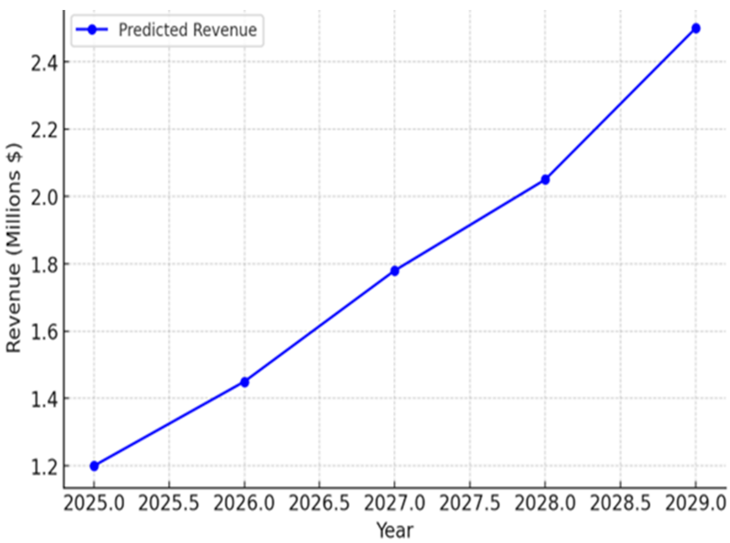


Figure 8. Projected revenue growth of solar-powered vehicles

Table 2. The projected revenue for 2025–2029

Year	Predicted Revenue ($)
2025	1,200,000
2026	1,450,000
2027	1,780,000
2028	2,050,000
2029	2,500,000

4 Conclusions

This study demonstrates the technical and economic viability of a solar-powered electric vehicle (SPEV) designed for emerging markets. Beyond showcasing performance metrics, the findings yield practical insights that can help accelerate electric vehicle adoption. For policymakers, the integration of solar charging systems and machine learning-based analytics presents a compelling opportunity to support decentralized, low-cost mobility solutions in regions with limited energy infrastructure. Policies that reduce import tariffs on photovoltaic components, provide targeted subsidies, or offer microfinancing for small fleet operators could significantly boost adoption rates. These measures would also align with broader national goals on clean energy and emissions reduction. For manufacturers, the modular and locally adaptable design of the SPEV offers a cost-effective entry point into the EV market. The vehicle's reliance on simplified yet effective AI models and solar technologies reduces the need for high-capital manufacturing infrastructure, making it easier to scale production in resource-constrained settings. In particular, manufacturers can leverage these findings to develop affordable, intelligent EV platforms that serve both individual consumers and commercial fleet operators.

The use of linear regression and Random Forest models demonstrates the value of predictive analytics in optimizing charging efficiency and projecting long-term financial viability. Embedding such data-driven tools into low-cost EVs can improve user confidence, enhance operational planning, and support wider market adoption. These models also help bridge the information gap that often limits sustainable transport initiatives in developing regions. Future research should extend this work by integrating real-time environmental and performance data into the predictive models to improve accuracy and adaptability. Additionally, exploring alternative energy storage systems such as hybrid battery-supercapacitor configurations could enhance range and durability. Longitudinal field studies across diverse geographic and socio-economic settings are also recommended to evaluate real-world performance, user behavior, and long-term sustainability outcomes. Taken together, these steps will further strengthen the case for SPEVs as a scalable and intelligent solution for green transportation in emerging economies.

Author Contributions

Conceptualization, A.A. and K.S.; software, A.A. and K.S.; validation, A.A. and K.S.; formal analysis, A.A.; writing—original draft preparation, A.A. and K.S.; writing—review and editing, A.A. and K.S. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflict of interest.

References

[1] W. Li, R. Long, H. Chen, B. Dou, F. Chen, X. Zheng, and Z. He, "Public preference for electric vehicle incentive policies in China: A conjoint analysis," *Int. J. Environ. Res. Public Health*, vol. 17, no. 1, p. 318, 2020. https://doi.org/10.3390/ijerph17010318

[2] W. Li, R. Long, H. Chen, F. Chen, X. Zheng, and M. Yang, "Effect of policy incentives on the uptake of electric vehicles in China," *Sustainability*, vol. 11, no. 12, p. 3323, 2019. https://doi.org/10.3390/su11123323

[3] F. Ehsan, S. Habib, M. M. Gulzar, J. Guo, S. M. Muyeen, and I. Kamwa, “Assessing policy influence on electric vehicle adoption in China: An in-depth study,” *Energy Strat. Rev.*, vol. 54, p. 101471, 2024. https://doi.org/10.1016/j.esr.2024.101471

[4] X. Zhao, X. Li, D. Jiao, Y. Mao, J. Sun, and G. Liu, “Policy incentives and electric vehicle adoption in China: From a perspective of policy mixes,” *Transp. Res. Part A: Policy Pract.*, vol. 190, p. 104235, 2024. https://doi.org/10.1016/j.tra.2024.104235

[5] V. Iulia and S. Loránd, “A brief history of electric vehicles,” *J. Comput. Control Syst.*, vol. 15, no. 1, pp. 19–26, 2022.

[6] K. Chenchireddy, “Performance verification of full-bridge DC to DC converter used for electric vehicle charging stations,” *2022 8th Int. Conf. Adv. Comput. Commun. Syst. (ICACCS)*, vol. 1, pp. 434–439, 2022. https://doi.org/10.1109/ICACCS54159.2022.9785288

[7] C. Iclodean, B. Varga, N. Burnete, D. Cimerdean, and B. Jurchiş, “Comparison of different battery types for electric vehicles,” *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 252, no. 1, p. 012058, 2017. https://doi.org/10.1088/1757-899X/252/1/012058

[8] T. Lin, “Electric vehicle safety issues and the solutions,” *High. Sci. Eng. Technol*, vol. 46, pp. 91–96, 2023.

[9] A. K. Maurya, “Design and fabrication of a prototype electric vehicle,” *AKGEC Int. J. Technol.*, vol. 12, no. 1, pp. 29–33, 2021.

[10] Q. Liu, W. Wang, and X. Hua, “Path planning method for electric vehicles based on freeway network,” *J. Adv. Transp.*, vol. 2021, no. 1, p. 3030050, 2021. https://doi.org/10.1155/2021/3030050

[11] S. Ling, X. Zhu, Q. Wang, and P. Schonfeld, “Prediction of charging requirements for electric vehicles based on multiagent intelligence,” *J. Adv. Transp.*, vol. 2022, no. 1, p. 2309376, 2022. https://doi.org/10.1155/2022/2309376

[12] E. Hopkins, D. Potoglou, S. Orford, and L. Cipcigan, “Can the equitable roll out of electric vehicle charging infrastructure be achieved?” *Renew. Sustain. Energy Rev.*, vol. 182, p. 113398, 2023. https://doi.org/10.1016/j.rser.2023.113398

[13] N. V. Martyushev, B. V. Malozyomov, S. N. Sorokova, E. A. Efremenkov, and M. Qi, “Mathematical modeling the performance of an electric vehicle considering various driving cycles,” *Mathematics*, vol. 11, no. 11, p. 2586, 2023. https://doi.org/10.3390/math11112586

[14] C. R. Forsythe, K. T. Gillingham, J. J. Michalek, and K. S. Whitefoot, “Technology advancement is driving electric vehicle adoption,” *Proc. Natl. Acad. Sci.*, vol. 120, no. 23, p. e2219396120, 2023. https://doi.org/10.1073/pnas.2219396120

[15] A. Adetunla, A. K. Long, and E. Akinlabi, “Optimal driving and charging efficiency of a developed solar powered electric vehicle,” *Intell. Syst. Appl. Eng.*, vol. 12, no. 3, pp. 1678–1688, 2024. https://ijisae.org/index.php/IJISAE/article/view/5578

[16] M. S. Mastoi, S. Zhuang, H. M. Munir, M. Haris, M. Hassan, M. Usman, S. S. H. Bukhari, and J. S. Ro, “An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends,” *Energy Rep.*, vol. 8, pp. 11 504–11 529, 2022. https://doi.org/10.1016/j.egyr.2022.09.011

[17] N. Tilly, T. Yigitcanlar, K. Degirmenci, and A. Paz, “How sustainable is electric vehicle adoption? Insights from a PRISMA review,” *Sustain. Cities Soc.*, vol. 117, no. 15, p. 105950, 2024. https://doi.org/10.1016/j.scs.2024.105950

[18] F. Liu, M. Shafique, and X. Luo, “Unveiling the determinants of battery electric vehicle performance: A systematic review and meta-analysis,” *Commun. Transport. Res.*, vol. 4, p. 100148, 2024. https://doi.org/10.1016/j.commtr.2024.100148

[19] S. A. Qadir, F. Ahmad, A. M. A. B. Al-Wahedi, A. Iqbal, and A. Ali, “Navigating the complex realities of electric vehicle adoption: A comprehensive study of government strategies, policies, and incentives,” *Energy Strat. Rev.*, vol. 53, p. 101379, 2024. https://doi.org/10.1016/j.esr.2024.101379

[20] Z. Lu, Q. Zhang, Y. Yuan, and W. Tong, “Optimal driving range for battery electric vehicles based on modeling users’ driving and charging behavior,” *J. Adv. Transp.*, vol. 2020, no. 1, p. 8813137, 2020. https://doi.org/10.1155/2020/8813137

[21] K. Zhong, P. Wang, J. Pei, J. Xu, Z. Han, and J. Xu, “Multiobjective optimization regarding vehicles and power grids,” *Wirel. Commun. Mobile Comput.*, vol. 2021, no. 1, p. 5552626, 2021. https://doi.org/10.1155/2021/5552626

[22] S. AlKheder, A. Bash, Z. Al Baghli, R. Al Hubaini, and A. Al Kader, “Customer perception and acceptance of autonomous delivery vehicles in the State of Kuwait during COVID-19,” *Technol. Forecast. Soc. Change*, vol. 191, p. 122485, 2023. https://doi.org/10.1016/j.techfore.2023.122485

[23] S. S. M. Ajibade, A. L. S. Hoong, M. B. Jasser, A. O. Adetunla, and A. O. Adediran, “Machine learning models for energy consumption forecasting in power generation,” in *2024 IEEE 5th International Conference*

on Electro-Computing Technologies for Humanity (NIGERCON), Ado Ekiti, Nigeria, 2024, pp. 1–5. https://doi.org/10.1109/NIGERCON62786.2024.10927336

[24] B. Merven, F. Hartley, J. Schers, and F. Ahjum, "Private transport modelled in SATIMGE and the socio-economic impacts of electric vehicles in South Africa," *Art.*, vol. 121, 2020. https://sa-tied.wider.unu.edu/article/private-transport-modelled-satimge-and-socio-economic-impacts-electric-vehicles-south

[25] O. E. Oni and O. M. Longe, "A study on electric vehicle footprint in South Africa," *Energies*, vol. 17, no. 23, p. 6086, 2024. https://doi.org/10.3390/en17236086