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Optimizing energy management in electric vehicle charging using firefly algorithm

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ABSTRACT

The transition to electric vehicles (EVs) poses significant challenges in the management of electric vehicle charging stations (EVCS), especially regarding the integration of renewable energy to ensure efficiency and sustainability. This study aims to optimize the energy management system in EVCS that takes into account technological aspects. The algorithm being proposed is specifically created for a 100 kW EVCS and utilizes the firefly algorithm to maximize renewable energy utilization and minimize charging costs. The research methodology includes the development of an optimization framework that combines solar power generation with the firefly-based optimization algorithm, which considers factors such as power demand, battery capacity, and tariff fluctuations. Simulations show that the algorithm is able to increase solar energy utilization by up to 80%, while reducing charging costs during peak hours. The results also emphasize the importance of real-time energy management to address power demand fluctuations and reduce adverse impacts on the electricity grid. This study concludes that the firefly algorithm is effective in supporting energy management in renewable energy-based EVCS, providing essential knowledge for the development of sustainable charging system within the future.

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1. INTRODUCTION

The move towards electric vehicles (EVs) marks a major change in the automotive sector, propelled by the urgent need to lower greenhouse gas emissions and decrease reliance on fossil fuels. As state authorities worldwide implement policies to promote EV adoption, the infrastructure supporting this transition, particularly electric vehicle charging stations (EVCSs), has become a focal point of research and development. The rising count of electric vehicles on the streets necessitates a corresponding expansion of charging infrastructure to ensure accessibility and convenience for users. This paper aims to explore the current challenges associated with EVCS deployment, particularly in urban environments, and the potential solutions offered by advanced energy management systems that integrate renewable energy options, like solar photovoltaic (PV) systems, into the charging infrastructure [1], [2].

The problem of EVCS deployment is multifaceted, encompassing issues related to site selection, capacity planning, and integration with existing power grids. The rapid growth of EV ownership has led to a surge in charging demand, which can strain local electrical grids if not managed effectively. Research indicates that traditional charging stations can significantly impact grid stability, necessitating innovative solutions that optimize charging station operations and minimize their effects on the grid [3], [4]. Furthermore, the strategic placement of charging stations is crucial to meet user demand while ensuring economic viability for operators. Studies have shown that employing data-driven approaches and optimization algorithms can enhance the efficiency of charging station deployment, ultimately leading to better service for EV users [5]–[7].

Energy management systems (EMS) play a critical role in incorporating renewable energy sources into EVCSs. These systems are capable of optimizing the utilization of solar energy generated by PV installations, thereby reducing reliance on grid electricity and lowering operational costs for charging station operators. Recent advancements in EMS have demonstrated the potential for integrating battery storage systems with PV to build a more durable and eco-friendly charging infrastructure [8]–[13]. By employing algorithms such as the butterfly optimization algorithm, researchers have been able to enhance the performance of EMS in managing the energy flow between the grid, PV systems, and EVCSs, ensuring that charging demands are met efficiently while maximizing the use of renewable energy [10]–[12].

The most advanced developments in EV charging technology optimization have enjoyed significant improvements, especially with the introduction of innovative algorithms and modeling techniques. The butterfly optimization algorithm, for instance, has evolved into a valuable instrument for optimizing various aspects of EVCS operations, including site selection, load forecasting, and energy management [13]–[15]. This algorithm mimics the natural behavior of butterflies in search of food, allowing for effective investigation of the solution domain to find optimal configurations for charging stations. Additionally, the integration of artificial intelligence and artificial intelligence learning methods has further enhanced the capabilities of EMS, facilitating real-time decision-making and adaptive management of charging processes [16]–[18].

This research paper seeks to contribute to the existing compendium of knowledge by addressing the gaps in current literature regarding the optimization of EVCSs through advanced energy management systems. The novelty of this research is found in its comprehensive strategy toward integrating renewable energy sources with cutting-edge optimization algorithms, specifically focusing on the butterfly optimization algorithm. The objectives of this research include developing a framework for optimizing the cost charging and minimizing renewable energy utilization of EVCSs. By achieving these objectives, this research aims to deliver significant insights for policymakers, urban planners, and energy managers in their efforts to develop a sustainable and efficient EV charging infrastructure [19]–[21].

This research explored AI algorithms to evaluate their effectiveness in integrating EVs with solar power. The structuring of the studies is outlined as follows: i) The remainder of this paper consists of arranged as detailed below; ii) In section 2, the method is presented; iii) The results and discussion are discussed in section 3; and iv) Lastly, section 4 contains the concluding remarks.

The current status of EVs in Indonesia is characterized by a gradual increase in adoption, with projections indicating that the quantity of EVs is expected to reach nearly 200,000 units by the end of 2024. This growth is supported by advancements in battery technology, with many EVs now equipped with batteries that have a capacity ranging from 30 to 100 kWh, enabling a driving range of up to 400 kilometers on a single charge [22]. The power supply mode for charging these vehicles predominantly utilizes alternating current (AC) at charging stations, with charger voltages typically ranging from 220 to 480 V, depending on the type of charger used [23]. Charging behavior shows a preference for night-time charging, capitalizing on lower electricity rates and reduced grid demand during off-peak hours. Public charging stations charge an average rate of IDR 1,500 to IDR 2,500/kWh, while residential charging rates are slightly lower, averaging IDR 1,200 to IDR 1,800/kWh [24]. This pricing structure is crucial for incentivizing EV adoption, as it directly impacts the rational costs for consumers.

In parallel, Indonesia's solar energy landscape presents significant potential, with an average insolation of approximately 4.8 kWh/m²/day, which is conducive for solar power generation [25]. The effective duration of solar irradiation in Indonesia typically spans around 5 to 7 hours/day, depending on geographical location and seasonal variations [26]. The prospects for solar energy in Indonesia are promising, with the government aiming to install an overall capacity of 6.5 GW of solar energy facilities by 2025, significantly increasing the current installed capacity, which stands at around 145.81 MWp [27]. Furthermore, the deployment of solar home systems (SHS) has gained traction, with over 300,000 systems installed across the country, particularly in rural areas where access to the grid is limited [28]. This development not only enhances energy access but also contributes to the overall goal of transitioning in support of renewable energy sources, thereby minimizing dependence on fossil fuels and alleviating climate change impacts [29].

2. METHOD

One of the primary functions of an EMS is to handle the intermittency and variability associated with renewable energy sources. As highlighted by Xia *et al.*, [30] the development of EMS has been significantly influenced by advancements in renewable energy technologies and information and communication technology (ICT), which facilitate the creation of net-zero energy ecosystems [30]. Figure 1 shows the system layout of the EVCS. The station is supplied by a 100 kW PV system, has two units' level 3 DC fast charging facilities. The power grid is incorporated into the system through the utilization of a transformer and a DC-DC converter, where the PV system is linked to the bus via a DC-DC converter. The power generated by the PV system is used first to charge the EV. If the power output of the PV system is not sufficient for the EV's needs, then the power supply shall be diverted from the power grid to meet the existing load. The firefly algorithm is used to optimize the charging cost for various EVs at distinct periods. The power availability generated by the output, the EV's power demand, the charging period, and the present charging rate are taken into account as input parameters. The cost of loading and usage of renewable energy are considered as an output parameter.

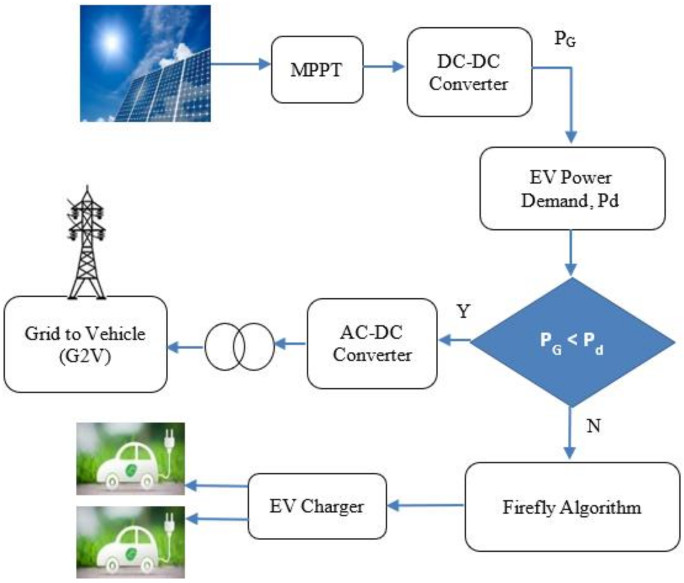

Figure 1. System layout of the proposed EVCS

2.1. Firefly optimization algorithm-based energy management systems

The energy management algorithm aims to achieve two goals: reducing the rate of charging and maximizing the use of renewable resources [31]. These objectives could be represented in detail as shown in (1).

$$Min\ (C_{Charging})\ \text{and}\ Max\ (Ren_{Utilization}) \tag{1}$$

This objective function operates within these constraints:

$$SOC_{max} \geq SOC_i \geq SOC_{min}$$

$$T_D = \frac{SOC_{max} - SOC_{min}\ x\ C_{batt}}{\eta\ X\ L_{ch}}; \tag{2}$$

$$0 \leq T_D \leq 2\ and\ L_{Ch} = 3$$
$$P_{Gen} \geq P_{EVCS} \tag{3}$$

where T_D denotes the duration of charging expressed in hours, and ranges from 0 to 2. L_{Ch} indicates the level of charging. Within this research, we use a level 3 charger (22-50 kW). The produced power, denoted as PGen, is contingent upon the accessibility of renewable resources. Additionally, it is influenced by fluctuations in electricity prices within the suggested EVCS.

In this paper, the state of charge (SOC) constraint is applied to prevent degradation of the quality of the EV battery. In addition, the battery also has an important role in meeting the fast or slow charging rate, which is generally in line with the SOC constraint for further efficient EV charging. The energy requirements of the EV are influenced by both the SOC and the capacity of the battery. In the model put forward, the minimum and maximum SOC are set at 20% and 80%, respectively. The battery capacities for the EVs in question are 17.3 kWh and 26.7 kWh. Next, the electricity power produced by the EVCS on its own needs to be at least equivalent to the power requirement of the EVCS. In this case, the utilization of renewable energy is maximized. Duration of charging, T_D is the time needed to fully recharge the battery. The duration of EV charging is stated as detailed:

$$T_D = T_{stop} - T_{start} - T_w \tag{4}$$

T_{start} indicates the charging start time, T_{stop} indicates the departure time, and T_w signifies the waiting time.

The duration of charging falls within the range of the charging start time and the charging termination time. The charging period, T_C, is categorized into peak hours (5 PM - 11 PM) and off-peak hours (11 PM - 5 AM). The total real-time cost of charging depends on four input parameters: the availability of power, the power demand of the EV, the duration of the charging period, and the current tariff.

Real-time cost of charging for EVs, expressed as fc, is influenced by several factors, including the present rate of charging rate, r(t), SOC, capacity of battery (C_{Batt}), and duration of charging (T_D). EVs at low SOC levels tend to increase power demand, which in turn will contribute to the increase in total power demand at EVCS. Charging cost variations occur at different periods, both on-peak and off-peak, which are determined based on specific off-peak and peak times in the context of the region analyzed in this study. To calculate fc, a certain integration is performed in the time span between Tstart and Tstop, as explained below:

$$f_c = \int_{T_{start}}^{T_{stop}} \frac{(SOC_{max} - SOC_i)\ X\ C_{batt}}{T_D}\ X\ r(t)dt \tag{5}$$

2.2. Firefly optimization model

The firefly algorithm is a method inspired by natural phenomena, which is centered on the intensity of light that is emitted by fireflies when they flash. This flashing light usually functions to attract the attention of ideal mating partners. The pattern of light flashes is influenced by the frequency and intensity of the light pulses produced. In its operation, the firefly algorithm is based on three fundamental principles [32]:

- In the context of interactions between fireflies, all individuals of this species show interest in each other regardless of gender.
- This interest is influenced by the intensity of the light emitted. Fireflies that emit light with lower intensity tend to be attracted to fireflies that emit brighter light. If the brightness of light produced by fireflies is at the same level, they will move in a random pattern. In addition, this attraction also increases between the individuals.
- The intensity of light emitted is also affected using the value of the relevant objective function.

To develop the formulation, certain flashing traits of the fireflies are idealized. The firefly algorithm as shown in Algorithm 1.

Algorithm 1. Base firefly algorithm pseudo-code

```
1: t = 0; s* = ∅; γ = 1.0; // setup: generation counter, optimal solution, attractiveness
2: P(0) = InitializeFA();      // setup a population
3: while (t < MAX_FES) do
4: α(t) = AlphaNew();// evaluate a  new value for α
5: EvaluateFA(P (t), f(s)); // assess s based on f(s)
6: OrderFA(P (t), f(s)); // sort s based on f(s)
7: s* = FindTheBestFA(P (t), f(s)); // identify the optimal solution
8: P (t+1) = Move FA (P (t));     //adjust the attractiveness as needed
9: t = t + 1;
10:end while
```

The defining features of the firefly algorithm:

$$\beta = \beta_0 e^{-\gamma r^2} \tag{6}$$

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \tag{7}$$

$$x_{i\_new}^k = x_{i\_old}^k + \beta_0 e^{-\gamma r^2}(x_{j\_old}^k - x_{i\_old}^k) + \alpha(rand - \tfrac{1}{2})) \tag{8}$$

Since the firefly attractiveness directly depends on the brightness perceived by the surrounding fireflies, the attractiveness β at a distance r can be formulated using (6). $\beta 0$ is the attractiveness when $r = 0$, and γ is the light absorption coefficient that manages the decline in illumination strength. Based on the perception, the interval separating fireflies i and j, denoted by xi and xj, is formulated in (7). Xi,k represents the k-th element of the spatial coordinate xi. belonging to firefly i, and d the dimensional quantity. The motion of firefly i drawn to the more luminous firefly j is formulated in (8).

The firefly optimization framework is employed in the development of EVCS to derive an optimized charging rate for the integration of renewable energy under diverse input conditions. The parameters input to the firefly model include the availability of output power, the demand for power from electric vehicles, the duration of the charging interval, and the prevailing tariff structure. Conversely, the parameters that are evaluated as outputs comprise the charging costs and the use of renewable energy resources.

The availability of electricity from EVCS is contingent upon renewable energy input sources, like solar energy. The capacity for the generation of power may be enhanced in case the solar energy input is adequate. Conversely, when solar energy is unavailable, electricity generation is markedly diminished.

The energy demands of an EV are affected by both the capacity of the battery and the SOC. Variations in power demand arise from the fact that EVs at charging facilities exhibit differences in both battery capacity and SOC. Thus, the power requirements fluctuate due to the heterogeneity in battery and SOC configurations among electric vehicles at charging stations.

The time required to charge electric vehicles utilizing charging level 3, commonly referred to as DC Fast Charging, in Indonesia is contingent upon various elements, such as the battery capacity of the vehicle, the power output regarding the charging infrastructure, as well as the state of the battery at the time of initiation of charging. Typically, the utilization of DC Fast Charging enables the replenishment of electric vehicle batteries to approximately 80% within a timeframe ranging from 30 minutes to 2 hours.

3. RESULTS AND DISCUSSION

The proposed optimization process utilizes the firefly algorithm. The outcome parameters depend on the energy generated from renewable resources, charging duration or time, power demand from EVs, and the existing tariff. These tariffs are divided into two, namely, based on peak and off-peak hours. Nevertheless, applying this rule regulator shows that the charging tariff fluctuates according to varied intervals.

Figure 2 is a three-dimensional graph depicting the relationship between existing electricity tariffs, power demand, and charging costs, showing that charging costs vary significantly based on changes in tariffs and power demand. Cost variations are seen to be higher at higher power demands, with charging costs reaching up to IDR 12,000 at 12 kW demand. This graph indicates that tariffs determined by time periods (peak and off-peak hours) and fluctuations in power demand greatly affect charging costs. This knowledge is important for optimizing energy use and managing charging costs, so that it can be applied in more efficient tariff settings and more effective energy management strategies.

Figure 3 shows that increasing renewable energy production can directly meet the power demand of electric vehicles, reduce dependence on fossil fuels, and enhance overall energy efficiency. Furthermore, solar-powered EVCS that supply electricity during the day can motivate EV owners to charge during off-peak hours at a lower cost, increasing efficiency and cost savings. This analysis supports more effective energy resource planning and management, as well as optimization of strategies for sustainable energy infrastructure.

Figure 4(a) explains the change in charging cost against power generation. Charging cost increases along with the increase in power generation consumed by EVs. In this condition, power generation from solar energy becomes a priority compared to grid production. This is intended to reduce the negative impact on the distribution grid. In reality, the rise in power generation is triggered by the increase in EV consumption and this condition usually occurs during peak hours. Charging EVs during peak hours becomes more expensive than during off-peak hours. Therefore, this condition triggers owners of EV to charge their EVs wile off-peak hours.

Figure 4(b) shows the change of charging cost against power demand. Charging cost increases with increasing power demand. The smaller the SOC of every EV battery, the greater the power demand and the larger the SOC of the EV battery, the smaller the power demand. The charging pattern of EV batteries is influenced by SOC, where charging at low SOC can cause a significant spike in power demand. Therefore, an effective energy management system is needed to optimize charging and reduce costs, especially in limited charging infrastructure and fluctuating electricity prices.

Figure 4(c) shows the change in Renewable utilization towards power generation. Changes in the utilization of renewable energy, especially solar resources, significantly affect the power generation process in this EVCS. This EVCS system is designed to rely on solar resources as the main component in generating electricity. However, the availability of electricity generated is highly determined by the intensity and consistency of solar resources. When the availability of power is insufficient, it indicates that the utilization of solar resources is not optimal, which can be caused by weather fluctuations or limitations of solar energy processing technology. Since the proposed EVCS relies mainly on renewable energy, increasing the incorporation of renewable energy technologies and resources can directly increase the power generation capacity. This will ultimately support the greater power requirements for the EV charging process, thus ensuring the sustainability of an environmentally friendly energy system.

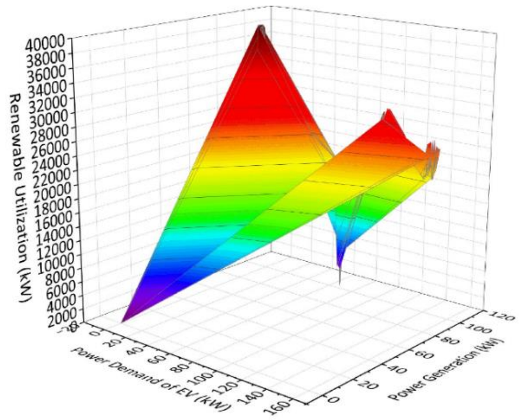

Figure 2. Surface view power demand of EV, existing tariff, and charging cost

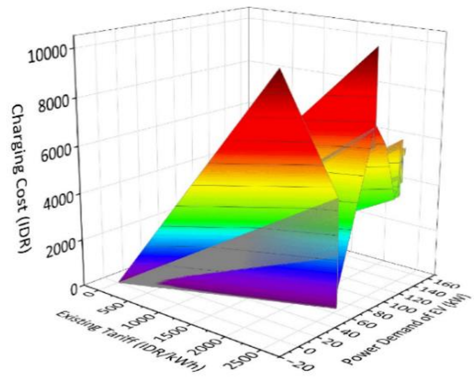

Figure 3. Surface view power generation, power demand of EV, and renewable utilization

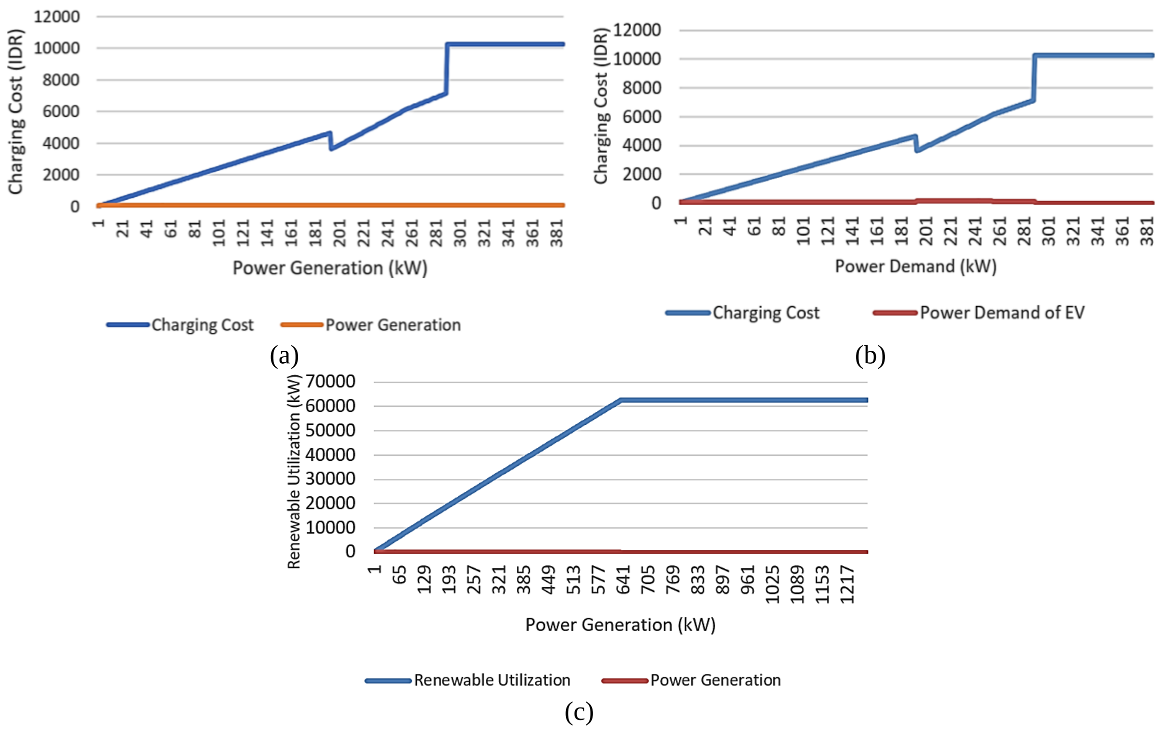

Figure 4. Changes in the input-output variable values of the EV charging system: (a) changes in charging costs vs power generation, (b) changes in charging costs vs power demand, and (c) changes in renewable energy vs power generation

Figure 5 shows the comparison of EV charging cost using the firefly algorithm and without the firefly algorithm. Applying of firefly algorithm in the charging process shows significant cost efficiency compared to conventional methods. At the 381st second, the EV charging cost with the firefly algorithm is around 7,500 IDR, while without the firefly algorithm, it reaches around IDR 10,500, showing a saving of around IDR 3,000. The increase in cost with the firefly algorithm tends to be linear and stable, increasing by around IDR 4,500 from the 1st second to the 381st second, while the increase in cost without the firefly algorithm is steeper, reaching a total of IDR 5,500 in the same period. At each time point, the charging cost without the firefly algorithm is always higher than using the firefly algorithm, for example, at the 1st second with costs of around IDR 3,000 and IDR 5,000, respectively. Thus, firefly not only reduces charging costs but also offers a more economical and efficient solution, making it a leading alternative in EV charging technology.

For EV charging in Indonesia, PT. PLN as the electricity provider, offers a 30% discount on charging costs outside of Peak Load Hours from 11 PM to 05 PM. Regarding tariffs, based on the Minister of Energy and Mineral Resources Regulation Number 1 of 2023 on the Provision of Electric Charging Infrastructure for Battery-Based Electric Motor Vehicles, the electricity charging tariff at public electric vehicle charging stations (SPKLU) is set at IDR 2,466/kWh. However, by using the firefly algorithm, the optimization of EVCS with renewable energy sources results in dynamic rates for EV charging.

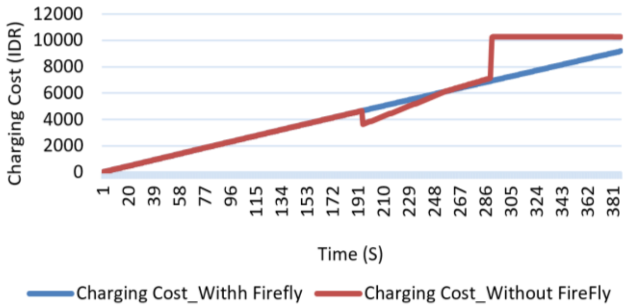

Figure 5. Charging cost with and without firefly algorithm

4. CONCLUSION

The application of the firefly algorithm in the energy management system of renewable energy-based EVCS has demonstrated significant improvements in operational efficiency and sustainability. Simulations have shown that solar energy utilization can be increased by up to 80%, leading to a substantial reduction in charging costs, particularly during peak hours. The real-time energy management system optimizes power demand, balances resources, and minimizes adverse impacts on the power grid. Additionally, by accounting for variations in battery SOC and capacity, the system ensures optimal use of available resources, thereby enhancing the overall performance of the EVCS. However, challenges remain, particularly in the integration of solar power with battery storage systems, due to fluctuations in sunlight intensity and limitations in energy storage technology. To address these issues, further research is needed to enhance the integration of solar power generation with energy storage solutions. Recommendations include developing more efficient energy storage technologies, utilizing artificial intelligence to improve system adaptability, and trialing large-scale implementations in urban areas. Additionally, energy policies supporting renewable energy use and the expansion of EVCS infrastructure in high solar potential areas are essential for a sustainable transition to electric vehicles. Implementing these strategies will help optimize energy management in EVCS, ensuring both operational efficiency and environmental sustainability.

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AUTHOR CONTRIBUTIONS STATEMENT

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Syafii	✓	✓					✓	✓		✓		✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [S], upon reasonable request.

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