This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Date of publication xxxx 00, 2024, date of current version xxxx 00, 2024.

Digital Object Identifier xxx/ACCESS.2024.DOI

Can electric vehicle charging stations be carbon neutral with solar renewables?

ALPASLAN DEMIRCI[1], ZAFER OZTURK[2], MUSA TERKES[1], SAID MIRZA TERCAN[1], RECEP YUMURTACI[1] and UMIT CALI[3,4] (Senior Member, IEEE)

[1]Department of Electrical Engineering, Yildiz Technical University, Istanbul, Türkiye
[2]Department of Electrical and Electronic Engineering, Düzce University, Düzce, Türkiye
[3]Department of Electric Energy, Norwegian University of Science and Technology, Trondheim, Norway
[4]School of Physics, Engineering and Technology, University of York, York, United Kingdom

Corresponding author: Umit Cali (e-mail: umit.cali@ntnu.no).

ABSTRACT In line with sustainable energy and environmental targets, the share of electric vehicles in the automobile market is expected to reach 80%. On the other hand, unplanned electric vehicle charging station installation for EV charging demands and high dependency rates on the distribution grid may adversely affect grid reliability, energy costs, and environmental targets. This article investigates whether electric vehicle charging stations can achieve carbon neutrality through strategic techno-economic integration with solar renewables. Furthermore, an exhaustive analysis investigated achieving carbon neutrality via integrating energy storage systems with photovoltaics, factoring in investment costs and carbon taxes. The findings revealed a substantial potential to reduce grid energy dependency by up to 54.3%. Implementing a more stringent carbon tax has facilitated a notable enhancement in energy storage system capacity, elevating the self-consumption rate by 72% and declining carbon emissions by 25.55%. Self-consumption decreases by 30% during high charging demand in the morning and evening hours, leading to increased dependency on the grid and highlighting the pressing need for improved strategies to reduce carbon emissions. Notwithstanding the significant investment required for energy storage systems, a levelised increase in carbon taxes has effectively curtailed grid energy demands by up to 34.7%. Moreover, decreases in storage costs can increase the decline in grid dependency by an additional 18%. Despite the integration of energy storage systems, the ambitious zero carbon target remains unattainable due to the existing installation area constraints of EV charging stations. This study can help policies that align with global efforts to mitigate climate change, enhance energy security, optimize costs, drive technological innovation, and meet increasing demands for sustainable policies.

INDEX TERMS Carbon tax, Electric vehicle, Energy storage systems, Hybrid power system, Investment cost, Self-consumption

I. INTRODUCTION

Global temperature concerns have made alternative energy supply increasingly critical. Moreover, the increasing trend of the electric vehicle (EV) population in transportation has given hope to climate policies. Are EVs and renewable energy sufficient for net zero targets under climate agreements? Although consumers are satisfied with the investments made in EV charging infrastructure and sales figures, the increasing EV charging load has a negative impact on grid operation in terms of power quality [1, 2]. The energy required by optimally located EV charging stations (EVCS) can be met via renewable energy integration, while intermittent power generation profiles make reliable energy supply margins a significant challenge. Energy storage systems (ESS) are an essential building block of hybridization to improve the supply-demand balance and smooth generation. When ESS alternatives are evaluated, lithium-ion battery technology superior to its counterpart stands out, and its market is predicted to reach 832 billion dollars [3]. With the intensification of prosumers, such as the hybrid power system (HPS), these emission commitments will be achieved in a shorter time [4]. Wind turbines (WT) are being pushed to the background in EVCS investments in regions with low wind speed due to high investment costs and inefficient land use. Although EVCSs do not currently represent rural areas, their use in urban areas is widespread. HPSs provide many advantages

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

in line with climate-based economic development goals by simplifying grid operation and increasing prosumer adoption. For instance, up to 90% of the EV charging demand of consumers living near Supercenters can be met with solar energy [5]. Using the demand side in capacity optimization or forecasting can reduce the cost of energy (COE) of HPSs to 0.046 $/kWh and the related CO_2 to 472.4 g [6]. Moreover, such hybrid systems with battery storage increase the reliability of energy supply to 80.8% and the power sizing sufficiency of the system to 91.3% [7] and can reduce the grid's energy supply by 8.33% [8]. Two-level optimization of energy management in hybridization can increase the share of clean energy in EV charging demand to 93% [9]. In addition, the socio-economic standards of EV users can be maximized with monthly savings of around 12-18 $ [10]. Optimal photovoltaic panel (PV) installations with a high benefit margin cover an economic area of only 2 to 6 m^2 [11]. Although PV array sizes of 1-1.5 kWp can provide 75% of EV charging during working hours in commercial or office parking lots, the rising investment costs of the desired zero-carbon target could shake hybrid EVCS dreams [12].

Each region has different demands, the number of parked cars, and building structures. This leads to continuous uncertainty about which region will consume, generate or store PV electricity. Underestimating the uncertainties in EV charging could lead investors to make mistakes of up to 10% in their economic business plans [27]. The potential increase in EVs and uncertainty in EV charging demand could reduce reliability due to capacity shortages. Keeping the capacity shortage below a specific limit can make the optimal number of EVs and charging stations more economical and reliable [28]. The lack of a one-size-fits-all EV distribution scale brings together synergies in EV adoption and penetration of PV arrays as collaborators in electricity sector planning. However, the temporal coupling of EV charging and PV generation leads to an unrealistic matching of grid stability and peak load management [29]. Although the SolarEV smart city concept is critical to the potential of energy decarbonization, it requires serious action from policymakers, industries, and communities [30]. EV penetration in the 10-20% range can economically manage small-scale deployment in highly urbanized environments, although high PV investment costs can disrupt this synergy [31]. Could free green charging to be beneficial by shifting EV charging to times of high renewable energy production? CO_2 can be reduced by more than 50% despite a significant increase in charging load, especially on weekends [32]. It is also estimated that increasing PV penetration above 50% could meet the variable EV charging demand [33]. In addition, shifting supply to periods in line with demand could increase electricity bill savings and electricity sales revenues by 74.2% and 19.86% [34]. Moreover, reducing EV demand variability by 30% via batteries and electricity sales of residual energy could reduce the cost of HPS by 11.2% at different levels of energy supply reliability [13]. Also, the simultaneous increase of EV active loads and battery storage capacity could reduce the annual cost of electricity by 21.2% in a distribution retailer's trading plans [35]. Smart inverter control methods considering curtailed PV energy, net power flows and voltage profiles, and renewable penetration in the match can balance daily daytime EV charging peak loads. Accordingly, peak load shifting, minimizing peak period impact, capping demand at a fixed level, and attempting to capture all PV generation controls may be sufficient for a single system [36]. Moreover, curtailment rates above 10% and non-exportable solar PV penetrations above 35% can be reduced by shifting flexible loads, such as EV charging, to periods of high renewable energy generation [37]. Using EV charging stochastics and sensitive loads on the demand side of energy management can meet economic operating targets and reduce CO_2 [38]. Even rapid PV generation fluctuations at distribution network busbars can be alleviated by a variable EV charging process, but the cost of charging for EV owners increases [39]. Integrating EV charging as a load rather than a capability to offer flexibility does not reduce operating costs enough to reduce the benefit margin. However, the question of achieving the 100% renewable energy target with an effective supply-demand match has always been confusing [40].

Increasing charging density in EV fleets will make significant HPS installation capacities critical in the future. However, the high investment costs of batteries hinder investors' investment plans in many application areas, such as self-consumption, and complicate governments' actions in the pursuit of clean energy for climate goals. Every measure against non-competitive batteries is essential in investment plans [41]. Optimal storage size selection and dynamic electricity tariffs are key to maximizing PV-ESS profitability, but high discounting and low inflation rates can negatively impact the effective system cost [42, 43]. Time-varying retail tariffs combining prosumer and grid operator benefits and managed appropriately can provide plausible incentives for HPS installation and operation and shorten the payback period by up to 5.17 years [14]. A modest investment reduction of 20% in ESS cost could increase HPS revenues by 3.2% and RF by up to 6.2% [44]. Although battery investment costs can be considered very expensive in peak demand reduction and load shifting applications, the current service and 25% incentive policy in the US has been able to reduce the payback period to less than ten years [45]. However, introducing investment tax credits and government capacity payment restrictions (energy self-supply) significantly hinder HPS deployment and reduce net revenues by 50% [46]. In addition, citizens wanting to maximize the benefits of renewable energy may be reluctant to install new renewable energy sources (RESs). Therefore, uniform development may not guarantee the desired infrastructure for self-consumption [47]. Moreover, ESS investment costs of 50-300 $/kWh for a PV-ESS-powered EVCS cannot effectively reduce COE and do not allow for an economical design [48]. Accordingly, the 110% subsidized tax reduction introduced by the Italian government for PV and ESS has significantly reduced the negative impact of batteries on system cost [49]. Moreover,

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

TABLE 1. Comparison of related studies regarding motivation

Ref.	Planning & Method	Sensitivity Criteria							Finding & Results
		IDR	CPV	S-SR /WS	CT	SR /IP	RP	DV	
[13]	Impact of stochastic renewable energy potential and EV charging on the optimal sizing of HPS considering different reliability levels.		✓	✓				✓	A 30% variation in EV charging demand changes WT and ESS capacity by 30.8% and 62.5%, and costs by 31.22%. A 5% increase in reliability concerns reduces costs by 13.1%, but using ESS is not economically assessed.
[14]	Impacts of reducing construction cost and subsidies on EVCS feasibility considering different peak demand times and policy recommendations to address the issue.			✓		✓		✓	EVCS has an excellent economic performance, while the station's grid co-benefits and social benefits are at a superior margin beyond the financial performance.
[15]	Development of integrated electric bus charging coordination to solve the charging control problem caused by the mismatch between supply and demand.		✓	✓			✓	✓	The renewable energy on-site consumption ratio increased by 77.9%, and grid dependency was reduced by 44.25%.
[16]	Cost-optimal assessment of the impact of EV charging strategies (immediate, controlled, bi-directional) on ESS sizing in charging hub microgrids.		✓	✓		✓	✓	✓	Economic stationary ESS capacity can be obtained if more than 65% of EVs start charging immediately and ESS costs fall below 150 €/kWh.
[17]	Determination of the most economical component sizes to meet fast EVCS demand for different service vehicles.		✓	✓		✓	✓	✓	The energy from the grid was reduced by 11%, waste energy was reduced by 35%, PV power increased by 34%, and the self-consumption ratio (SCR) improved by 3.7%.
[18]	Development of an optimal PV-EV sizing framework with smart EV charging through self-consumption-sufficiency balance scores considering load-matching performances.		✓	✓			✓	✓	SCR and self-supply rate (SSR) have increased by 44.5% and 43.6%.
[19]	Hourly analysis of multi-smart EV effect in the energy system with gradual increase of uncontrollable and distributed RES capacity.		✓	✓			✓	✓	There was a 17.6% reduction of CO_2 by doubling PV capacity at 30% EV penetration and a 0.47 kt reduction per internal combustion engine (ICE) removed.
[20]	Comparison of HPS capacity optimization, self-consumption, and environmental, real data with simulation environment for light passenger vehicles.		✓	✓		✓	✓		After designing an AC-connected campus PV EVCS, the CO_2 and carbon tax savings reached 3635.78 kg/kWh and 73 €/tonne thanks to the annual unsubsidized excess of PV yield.
[21]	Spatial (residential, shopping mall, office building) EV charging demand scheduling problem and testing the strategy developed for supply-demand matching in a 33-bus urban distribution system.		✓	✓	✓			✓	A 10 $/t carbon tax and optimal capacity allocation increased the socio-economic benefit by 14.8%.
[22]	Analysis of the relationship between optimum component capacity and energy flow in the light of EV peak demand and time-of-use (TOU) change.		✓	✓	✓			✓	When the load and generation are matched, the LCOE is reduced by 12.3% due to increasing the PV and battery capacity to 68.3 kW and 263 kWh.
[23]	Design and optimization of grid-connected hybrid renewable energy systems for supermarkets with EV charging platforms.		✓	✓	✓		✓	✓	If the daily EV charging session increases by 50, PV capacity grows by 1.55. Moreover, a carbon tax increase of 60 $/ton raises the RF by 3.7% and 7.7% at low and high grid emission factors.
[24]	Evaluation of EV charging schemes on power system expansion planning and operation in the future projection of massive electrification.		✓	✓	✓			✓	The massive penetration of EVs into the electricity generation system can heavily incentivize investments in solar capacity.
[25]	Improvement of system output by increasing battery and PV usage when energy consumption and production are matched in the gym.			✓		✓	✓	✓	The charging strategy reduced nominal and peak load by 51.7%.
[26]	Optimum sizing of the facility with fast, medium, and slow chargers, variable charging demand, economical operation of the planning.			✓		✓		✓	Reducing total planning cost by 944.5 $/year, energy 70%, line reinforcement 17%, charge facility 12%.
Our study	Feasibility of an optimal PV-ESS-based EVCS considering EV charging demand uncertainties, the integration potential of ESS with PV, investment subsidy, and carbon tax.	✓	✓	✓	✓	✓	✓	✓	The network peak demand is reduced by 54.3% with the proposed method, and COE is reduced by up to 78% due to the increase in solar irradiance, regardless of the peak time.

IDR: Inflation and discount rate; **CPV:** Capacity of PV; **S-SR/WS:** Stochastic solar radiation or wind speed; **CT:** Carbon tax; **SR-IP:** Subsidy rate or incentive policy; **RP:** Renewable potential (SCR, SSR, RF, E_{PV}/E_{load} and so on); **DV:** EV charging variability

the subsidization of 30% of the initial costs of RESs added to the Chinese central government's 0.42 yuan/kWh subsidy policy has been able to shift the general public incentives in favor of PV [50]. Several proposals in the relevant policies, such as removing the PV generation tariff in favor of self-consumption and storage tariffs, can perfectly match batteries with solar PV. On the other hand, rewarding PV self-consumption is the most effective policy to incentives resilience solutions such as batteries [42]. Although subsidy expenditures on resilience can effectively reduce CO_2 by increasing PV capacity, subsidy above the optimum threshold point has little impact on the optimal design and operation of the system [51]. Moreover, the gradual government incentives for low-capacity PV investments may only be necessary if the individual characteristics of residential users are considered [52]. Also, the willingness of users to pay for renewable energy may not require subsidy proposals in the transition to a low-carbon society [53].

Carbon tax policies, similar to investment subsidies but with a lower contribution, would increase battery use and

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

provide a better solution to the cost of clean energy production than conventional sources. A 1 /ton increase in carbon tax could avoid 11.58 kg/yr of CO_2 per capita [54], and even a low carbon tax policy of 0.015 $/kg could reduce the levelized cost of energy (LCOE) of HPSs to 0.24 $/kWh [55]. A possible 50% increase in the tax could enhance total renewable energy penetration by up to 14% [56]. Increasing the tax rate to 100% could save 10.1% on electricity bills [57]. However, unsuitable carbon tax policies can leave governments facing fiscal deficits [58]. If the carbon tax is kept below 83 $/tonne CO_2-eq and more than 7500 $ new jobs can be created each, policies could favor HPS [59]. Rewarding prosumers making financial altruism in CO_2 reductions with various carbon reduction subsidies could bring the prosumer trend to a critical role in climate goals [60, 61].

In the literature, there are several sensitivity studies for optimal EVCSs minimizing prosumer cost and maximizing government benefit, categorized as inflation and discount rate, PV capacity [13, 15–24] stochastic solar radiation or wind speed [13–26], carbon tax [21–24], investment subsidies [14, 16, 17, 20, 25, 26], renewable potential [15–20, 23, 25], and EV charging demand [13–19, 21–26] presented in Table 1. Most of these studies have not evaluated the economic decision criteria for optimal EVCS from a simultaneous sensitivity criteria perspective toward zero carbon emission. This article investigates whether electric vehicle charging stations can achieve carbon neutrality through strategic techno-economic integration with solar renewables. Moreover, a comprehensive analysis deeply evaluated the potential for a zero-carbon target by integrating energy storage systems with photovoltaics, considering investment costs and carbon taxes.

The original contributions of this paper are as follows:

- A new proposed model explores the potential for achieving carbon neutrality in electric vehicle charging stations through strategic integration of solar renewables with energy storage systems from a techno-economic perspective.
- Self-consumption is dramatically reduced by 30% due to the high charging demand during morning and evening hours, which simultaneously increases dependency on the grid. This highlights the pressing necessity for enhanced strategies to mitigate carbon emissions.
- Carbon emissions are significantly affected by the timing of charging demand, demonstrating that even with the use of PV systems alone, a reduction of up to 30% in emissions can be achieved. This highlights the importance of energy management and demand management strategies.
- Energy storage systems have significantly mitigated carbon penalties, driving an impressive 21.1% increase in renewable energy usage compared to PV-grid scenarios. This advancement has played a crucial role in achieving a substantial 70% reduction in carbon emissions, underscoring the transformative potential of energy storage in sustainable energy systems.
- Despite the integration of energy storage systems, the ambitious zero carbon target remains unattainable due to significant constraints in the available installation area.

This article is organized as follows. Section I introduces the literature review and contributions. Section II describes the methodology, mathematical modeling, and assumptions. Section III compares and evaluates the results. Finally, Section IV concludes and provides recommendations for future work.

II. MATERIAL AND METHODOLOGY

A. SYSTEM MODELING

Solar PV module is the main component of HPS with EVCS. The performance of the PV array varies depending on the solar incident radiation, the panel temperature, the PV panel efficiency, and the derivative factor (DF). The amount of power produced by the PV array at time t is given in Equation (1) [62], the maximum efficiency formula of PV panels under normal conditions (STC) is shown in Equation (2) [63], and the cell temperature formula of the PV array under operating condition is given in Equation (3) [64].

$$P_{\text{PV}}^{t} = P_{\text{PV}}^{stc} \cdot f_{\text{PV}} \cdot \frac{IR_T^t}{IR_T^{\text{stc}}} \left[1 + \alpha_P (T_C^t - T_C^{\text{stc}})\right], \quad \forall t \tag{1}$$

$$\eta_{\text{mp}}^{\text{stc}} = \frac{P_{\text{PV}}^{stc}}{A_{\text{PV}} \cdot IR_T^{\text{stc}}}, \quad \forall t \tag{2}$$

$$T_C^t = \frac{T_a^t + \left(T_c^{\text{NOCT}} - T_a^{\text{NOCT}}\right) \frac{G_T^t}{G_T^{\text{NOCT}}} \left[1 - \frac{\eta_{\text{mp}}^{\text{stc}} (1 - \alpha_P T_C^{\text{stc}})}{\tau\alpha}\right]}{1 + \left(T_c^{\text{NOCT}} - T_a^{\text{NOCT}}\right) \frac{G_T^t}{G_T^{\text{NOCT}}} \frac{\alpha_P \eta_{\text{mp}}^{\text{stc}}}{\tau\alpha}} \tag{3}$$

Here, the actual PV output power (P_{PV}^t) is determined by the nominal PV panel capacity under standard conditions (P_{PV}^{stc}), PV panel derating factor (f_{PV}), incident radiation and PV cell temperature under standard and normal conditions (IR_T^t, IR_T^{stc}, T_C^t, and T_C^{stc}), and temperature coefficient of the power (α_P). The maximum PV panel efficiency under standard conditions ($\eta_{\text{mp}}^{\text{stc}}$) is calculated based on the nominal PV panel capacity under standard conditions, PV panel area (A_{PV}), and incident radiation under standard conditions. PV cell temperature considers various parameters. These can be listed as follows: the solar radiation striking the PV array (G_T^t), the solar transmittance of any cover over the PV array (τ), the solar absorptance of the PV array (α), the nominal operating cell temperature (NOCT) (T_c^{NOCT}), the ambient temperature at which the NOCT is defined (20°C, T_a^{NOCT}), the solar radiation at which the NOCT is defined (0.8 kW/m^2, G_T^{NOCT}).

The ESS allocation is essential for the efficient operation of HPS and for storing clipped energy (CE). The output energy of the ESS varies according to the charge and discharge status based on state of energy (SoE_t^{ESS}). Equation (4) calculates the BESS's energy state using the charging and discharging efficiency (η_{chr} and η_{disch}) and power ($P_t^{ESS_{chr}}$

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

and $P_t^{ESS_{disch}}$), considering its value in the previous time step (SoE_{t-1}^{ESS}) [65]. Equation (5) shows that the aging BESS capacity limits the energy state between 20% and 90% [66].

$$SoE_t^{ESS} = SoE_{t-1}^{ESS} + P_t^{ESS_{chr}} \cdot \eta_{chr} - \frac{P_t^{ESS_{disch}}}{\eta_{disch}}, \quad \forall t \tag{4}$$

$$SoE_{\max}^{ESS} \geq SoE_t^{ESS} \geq SoE_{\min}^{ESS}, \quad \forall t \tag{5}$$

Fresh battery energy storage is modeled using a Modified Lithium Battery (ASM) model. Four Arrhenius-based sub-models were developed: functional, temperature & relative capacity, depth of discharge (DoD)-dependent cycle lifetime and temperature-dependent shelf life. The power loss and the theoretical capacity are determined by Equations (6) and (7) [67].

$$P_{\text{out}}^{ESS} = V_0 I - R_0 I^2 \tag{6}$$

$$I_{P_{\text{out}}}^{\max} = \frac{V_0}{2R_0} \tag{7}$$

Here, P_{out}^{ESS} is the output power of the ESS, V_0, R_0 and I are the nominal voltage, series resistance, and current of the ESS. $I_{P_{\text{out}}}^{\max}$ is the current of the maximum ESS output power.

The temperature-dependent capacity can be calculated by using the temperature and battery characteristics (d_0, d_1, d_2 constant values) with Equation (8) [68]. The cycle degradation curves for each DoD can be obtained from the battery manufacturer or can be calculated with Equations (9) and (10) [69]. Even if the battery energy storage is not used, the loss of capacity can be expressed as temperature-related calendar degradation. The aging by Arrhenius equation is shown by Equation (11) [70].

$$C_{T_{\text{avail}}}^{\text{ESS}} = C_{T_{\text{nom}}}^{\text{ESS}} \cdot (d_0 + d_1 T + d_2 T^2) \tag{8}$$

$$\frac{1}{N} = A \cdot \text{DoD}^{\beta} \tag{9}$$

$$D = \sum_{i=0}^{N} (A \cdot D_i^{\beta}) \tag{10}$$

$$k_t = B \cdot e^{-\frac{d}{T}} \tag{11}$$

Here, the ESS capacity based on the available temperature is represented by $C_{T_{\text{avail}}}^{\text{ESS}}$. On the contrary, considering nominal temperatures, the ESS capacity is indicated by $C_{T_{\text{nom}}}^{\text{ESS}}$. The curve parameters are denoted by d_0, d_1 and d_2 respectively, where T is the available ESS temperature. A is the DoD coefficient, DoD^{β} is the DoD exponent fit and N is the project year. D is the exponential coefficient, k_t is the time and temperature degradation constant and k is the storage rate constant (h^{-1}).

Maximum charge and discharge power of the ESS are calculated at each time step. The charging power determines whether surplus renewable electricity can be absorbed. The maximum charging and discharging powers vary from one time step to the next, according to the state of charge (SoC). Three different limitations are imposed on the maximum charging power of ESS. The first limitation comes from the kinetic battery model for determining the maximum discharge power in Equation (12). The second limitation, the maximum charge C-rate, can be calculated by Equation (13). The third limitation concerns the maximum charging current of ESS as determined by Equation (14). Finally, the maximum charging power is determined by Equation (15), minimizing the three limits. The maximum discharge power during a specific operating period is calculated by Equation (16). The maximum useful discharge power is determined by Equation (17) [71].

$$P_{c_{\text{max, kbm}}}^{\text{ESS}} = \frac{kQ_{\text{avail}}^{\text{ESS}} e^{-k\Delta t} + Q_{\text{init}}^{\text{ESS}} kc(1 - e^{-k\Delta t})}{1 - e^{-k\Delta t} + c(k\Delta t - 1 + e^{-k\Delta t})} \tag{12}$$

$$P_{c_{\text{max, mcr}}}^{\text{ESS}} = \frac{(1 - e^{-\alpha_c \Delta t})(Q_{\max}^{\text{ESS}} - Q_{\text{init}}^{\text{ESS}})}{\Delta t} \tag{13}$$

$$P_{c_{\text{max, mcc}}}^{\text{ESS}} = \frac{N_{\text{bat}} \cdot I_{\max} \cdot V_0}{1000} \tag{14}$$

$$P_{c_{\max}}^{\text{ESS}} = \frac{\min\left(P_{c_{\text{max, kbm}}}^{\text{ESS}}, P_{c_{\text{max, mcr}}}^{\text{ESS}}, P_{c_{\text{max, mcc}}}^{\text{ESS}}\right)}{\sqrt{\eta_{\text{rt}}^{\text{ESS}}}} \tag{15}$$

$$P_{d_{\text{max, kbm}}}^{\text{ESS}} = \frac{-kcQ_{\max}^{\text{ESS}} + kQ_{\text{avail}}^{\text{ESS}} e^{-k\Delta t} + Q_{\text{init}}^{\text{ESS}} kc(1 - e^{-k\Delta t})}{1 - e^{-k\Delta t} + c(k\Delta t - 1 + e^{-k\Delta t})} \tag{16}$$

$$P_{d_{\max}}^{ESS} = \sqrt{\eta_{rt}^{ESS}} \cdot P_{d_{max,kbm}}^{ESS} \tag{17}$$

Here c is the storage capacity ratio, Δt is the length of the time step (hrs), $Q_{\max}$ is the total capacity of the storage bank (kWh) and α_c is the maximum charge rate of the storage (A/Ah). N_{bat} is the number of batteries in the storage bank, $I_{\max}$ is the maximum charging current of the storage (A), V_0 is the nominal voltage of the storage and η_{rt}^{ESS} is the battery round-trip efficiency (%).

Finally, Table 2 explains the technical parameters and aging curve coefficients used in the mathematical model of ESS [71].

In contrast, converters are required for energy flow between DC and AC systems in HPS. It consists of a converter, a rectifier, and an inverter. Choosing the appropriate size of converter power is very important in sizing the HPS model correctly. A small converter can waste a certain amount of energy. The power output formula of the inverter is shown in Equation (18), and the power output formula of the rectifier is seen in Equation (19) [72].

$$P_{\text{inv}}^t = \eta_{\text{inv}} \cdot P_{\text{DC}}^t, \quad \forall t \tag{18}$$

$$P_{\text{rec}}^t = \eta_{\text{rec}} \cdot P_{\text{AC}}^t, \quad \forall t \tag{19}$$

Here, the powers to be provided by the converter in the inverter (P_{inv}^t) and rectifier (P_{rec}^t) modes are determined. The efficiency (η_{inv} and η_{rec}), AC, and DC output power (P_{AC}^t and P_{DC}^t) are used for inverter and rectifier modes.

The time required to charge EV is given in Equation (20), the charge power in Equation (21), and the total EV power at time t is given in Equation (22) [73].

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

TABLE 2. Technical parameters for fresh battery pack

Parameters	Fresh Battery (FB)
Useful Capacity [kWh]	1
SOH [%]	100
Nominal Voltage [V]	3.7
Max. Charge Current [A]	270
Max. Discharge Current [A]	810
Max. Capacity [Ah]	270.27
Rate Constant [1/hr]	79.288
Capacity Ratio	1
Effective Series Resistance [mΩ]	0.36049
Max. Operating Temperature [°C]	50
Min. Operating Temperature [°C]	0
Other Round-trip Losses [%]	8
Initial SoC [%]	100
Min. SoC [%]	20
Degradation Limit [%]	50
End of Life (EOL)	
Calculate EOL by	Calendar or cycling degradation, whichever is greater
Cycling degradation uses DoD based on	Degraded battery capacity
CURVE PARAMETERS	
Relative Capacity vs. Temperature	d_0: 0.923 d_1: 0.00345 d_2: -0.0000375
DoD vs. Cycles to Failure	A: 0.00014423 β: 1.7945
Shelf-Life vs. Temperature	B: 1.267 d: 3826.70644

$$\tau_{e,j} = st_{e,j} + \frac{E_{\text{avg}}^{\text{EV}_{\text{chr}}}}{P_{\text{EV}}^{\max}} \tag{20}$$

$$P_{\text{EV}_j}^{t} = \begin{cases} P_{\text{EV}}^{\max} & \text{if } t \in \tau_{e,j} \\ 0 & \text{if } t \notin \tau_{e,j} \end{cases} \tag{21}$$

$$P_{\text{EV}}^{tot} = \sum_{j} P_{\text{EV}_j}^{tot} = P_{\text{EV}_1}^{tot} + P_{\text{EV}_2}^{tot} + \cdots + P_{\text{EV}_9}^{tot} + P_{\text{EV}_{10}}^{tot}, \quad \forall t \tag{22}$$

Here, $\tau_{e,j}$ is the time horizon for the charging of j EV of type e [hr], $st_{e,j}$ is starting charge time of j EV of type e [hr], $E_{\text{avg}}^{\text{EV}_{\text{chr}}}$ is average required energy for EV type e [kWh], $P_{\text{EV}}^{\max}$ is maximum charging power in the slow mode for EV type e [kWh], $P_{\text{EV}_j}^{t}$ is charging power of j EV of type e at time t [kW], P_{EV}^{tot} is total EV load at time t [kW], j is EV user index, t is the time index, and e is EV type (cars).

$\tau_{e,j}$ is determined by $E_{\text{avg}}^{\text{EV}_{\text{chr}}}$, $st_{e,j}$, and $P_{\text{EV}}^{\max}$ depending on the EV type. $P_{\text{EV}_j}^{t}$ is assessed based on whether the relevant time (t) is included in $\tau_{e,j}$. If so, $P_{\text{EV}_j}^{t}$ is set to $P_{\text{EV}}^{\max}$. P_{EV}^{tot} is calculated from the cumulative sum of the charging power by EV type, considering the number of EV types (N_{EV}).

EVCS demand profiles with three different peak periods are between 07:00-09:00, 11:00-13:00, and 17:00-19:00 in the morning, noon, and night when the demand for EV charging is highest. Accordingly, the energy demand needs of each of them are 2479, 2505, and 2496 kWh/day. These variations in peak load, and therefore in the profile, significantly impact the cost of electricity purchased from the grid. Accordingly, peak times' technical, economic, and environmental effects on the HPS demand profile will be discussed, and the impact on the grid will be evaluated. Table 3 shows grid price tariffs [74].

TABLE 3. Grid price tariffs

Grid Type	Tariff Type	Hours	Price
Grid Purchases TOU)	*Flat Tariff*	06.00-17.00	0.100 $/kWh
	Peak Tariff	17.00-22.00	0.160 $/kWh
	Valley Tariff	22.00-06.00	0.056 $/kWh
Grid Sales		24 hours	0.510 $/kWh

Figure 1 shows the HPS model design with EVCS. A PV capacity range between 120 kW and 900 kW is considered depending on the PV installation area constraint, and HPS modeling is analyzed in line with this range. Advanced Storage Model Lithium-Ion (ASM) ESSs with 1 kWh capacity are preferred in HPS. As shown in Figure 2, the details of the block diagram created for modeling the HPS, including the optimization process of the control structure and comprehensive analysis, are presented. Annual solar radiation and temperature data of the Antalya region were used. The data is obtained from the National Aeronautics and Space Administration (NASA) using the hybrid optimization of multiple energy resources database [75]. Antalya's average daily radiation and temperature is 4.5 kWh/m^2/day and 18.23 °C [76]. Capital, replacement, and operation & maintenance (O&M) costs of HPS components are given in Table 4 [77]. The project lifetime of the HPS is 20 years.

Prosumers often generate an inconsistent daily load profile, resulting in peak load points at different times. The peak

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

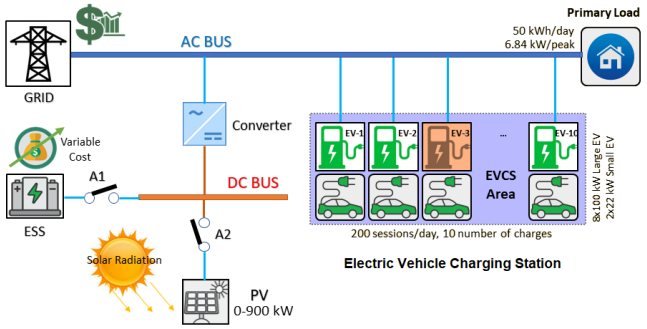


FIGURE 1. Proposed hybrid power system model for electric vehicle charging station

TABLE 4. Cost price of HPS components

Specification	Solar PV	ESS	Converter
Capital cost	1000 $/kW	300 $/kWh	300 $/kW
Replacement cost	900 $/kW	250 $/kWh	300 $/kW
O&M cost	10 $/kW/yr	2 $/kWh/yr	0.02 $/kW/yr

demands at busbars, which consume electricity frequently, can increase the electricity bill and cause power quality concerns on the network feeder. Two alternatives to alleviate these problems are using ESS or shifting the load's power to another time. The pre-stored energy in the ESS is discharged at the relevant times, and this peak value is decreased by reducing the purchasing of electricity from the grid. However, this may result in more ESS use in the system. Shifting excess load demand to another time can provide a sufficiently balanced peak shaving without the need for excess ESS. Therefore, the "Peak Shaving (PS)" control method was used at optimization analysis. This control method limits the peak power purchased from the grid to a certain level. It also tries to reduce demand charges and optimize the lowest cost HPS adjusting energy arbitrage.

B. OBJECTIVE AND DECISION CRITERIA

To calculate the net present cost (NPC), the costs related to the HPS need to be detailed. The discount rate and capital recovery factor (CRF) used in the calculations is calculated as in Equation (23) and (24) [74]. According to this, initial investment is calculated by Equation (25) and maintenance by Equation (26). The steps in Equations (27), (28) and (29) need to be followed to calculate the replacement cost [63]. The sinking fund factor can scale the future value of a series of equal annual cash flows with Equation (27) [63]. The scale factor and remaining service life required for the economic analysis are calculated by Equations (28) and (29) [64]. In this way, replacement Equations (30), penalty from carbon tax Equations (31), electricity purchase cost Equation (32), and revenue from sales can be calculated by Equations (33) [63]. The system's cumulative financial sum at the year's end is expressed by Equation (34) [78].

$$i = \frac{i' - f}{1 + f} \tag{23}$$

$$CRF\,(i, N) = \frac{i.\,(1+i)^n}{i.\,(1+i) - 1} \tag{24}$$

$$C_{\text{inv}} = \text{CRF}(i, N) \cdot \sum_l \left(IC^l \cdot C^l_{\text{cap}} \right) = \text{CRF}(i, N) \cdot C^{\text{tot}}_{\text{cap}} \tag{25}$$

$$C_{\text{main}} = \epsilon \cdot \sum_l \left(IC^l \cdot C^l_{\text{cap}} \right) = C^{\text{tot}}_{\text{cap}} \cdot (1+i)^N \tag{26}$$

$$\text{SSF}(i, N) = \frac{i}{(1+i)^N - 1}\ ;\ \text{SSF}(i, N_{\text{comp}}) = \frac{i}{(1+i)^{N_{\text{comp}}} - 1} \tag{27}$$

$$f_{\text{RC}} = \begin{cases} 0 & \text{if } N_{\text{RC}} = 0 \\ \frac{\text{CRF}(i,N)}{\text{CRF}(i,N_{\text{RC}})} & \text{if } N_{\text{RC}} > 0 \end{cases} \tag{28}$$

$$\begin{aligned} N_{\text{rem}} =& N_{\text{comp}} + N_{\text{rep}} - N \\ =& N_{\text{comp}} + \left(N_{\text{comp}} \cdot \text{INT} \left(\frac{N}{N_{\text{comp}}} \right) \right) - N \end{aligned} \tag{29}$$

$$C_{\text{rep}} = C_{\text{RC}} \cdot f_{\text{RC}} \cdot \text{SSF}(i, N_{\text{comp}}) - C_{\text{RC}} \cdot \frac{N}{N_{\text{comp}}} \cdot \text{SSF}(i, N) \tag{30}$$

$$C_{\text{tax}} = CO^{\text{tax}}_2 \cdot \lambda \cdot \sum_t E^t_{\text{GP}} = CO^{\text{tax}}_2 \cdot TCO_2 \tag{31}$$

$$C_{\text{GP}} = \sum_t E^t_{\text{GP}} \cdot C^t_{\text{purch}} \tag{32}$$

$$C_{\text{GS}} = \sum_t E^t_{\text{GS}} \cdot C^t_{\text{sell}} \tag{33}$$

$$C^{tot}_{\text{ann}} = C_{\text{inv}} + C_{\text{main}} + C_{\text{rep}} + C_{\text{tax}} + C_{\text{GP}} - C_{\text{GS}} \tag{34}$$

Here, C_{inv} is initial investment cost ($/yr), C_{main} is total maintenance cost ($/yr), C_{rep} is average annual replacement cost ($/yr), C_{tax} is total carbon tax ($/yr), C_{GP} is total cost of purchasing electricity ($/yr), C_{GS} is revenue from selling electricity ($/yr), IC^l is capacity of HPS's components (kWh), C^l_{cap} is capital cost of HPS's components ($), $C^{\text{tot}}_{\text{cap}}$ is the capital cost of the current system ($), ϵ is the maintenance factor of the HPS, C_{RC} is every component's replacement cost the end of the component's service life ($), f_{RC} is scale factors, $\text{SSF}(i, N)$ is sinking fund coefficients (%), N_{comp} is service life (yr), CO^{tax}_2 is carbon tax ($/t), λ is CO_2 coefficient of electricity purchase (g/kWh), E^t_{GP} is the electricity purchased from the grid (kWh), E^t_{GS} is the electricity sold to the grid (kWh), TCO_2 is annual CO_2 (g/yr), C^t_{purch} is cost of electricity purchased ($/yr), C^t_{sell} is the revenue from selling electricity ($/yr), N_{rem} is remaining service life (yr), and N_{rep} is replacement service life (yr).

$$\text{Minimize } NPC = \frac{C^{\text{tot}}_{\text{ann}}}{CRF(i, N)} \tag{35}$$

The system's NPC is obtained by subtracting the current value of all costs over the project's life from the present value of all income earned during the project's lifespan. It includes capital cost, replacement cost, operation and maintenance (O&M) cost, fuel cost, grid purchases, and emission cost penalties. The optimization model calculates the NPC value by summing the discounted cash flows at the end of each year. The annual cost is multiplied by the NPC value by

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

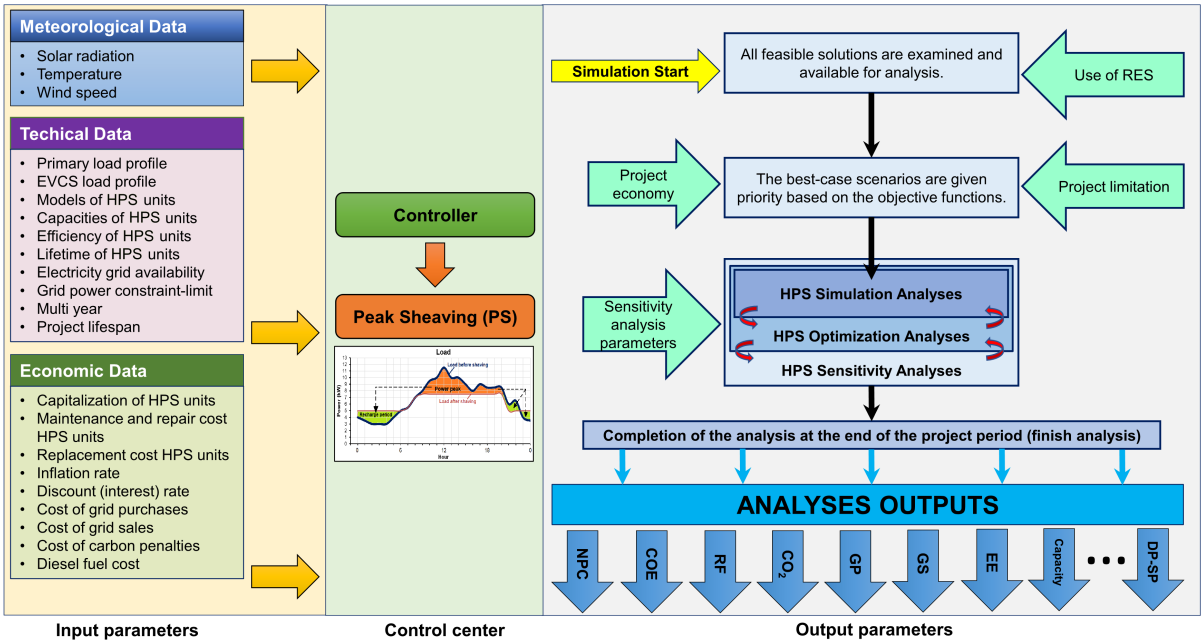


FIGURE 2. Overall Framework for Energy Management System of the Hybrid Power System

the CRF. NPC at the end of the project lifespan is given in Equation (35) [79]. Equation (35) shows the objective function of minimizing the NPC is determined from the ratio of the total annual cost to the capital recovery factor. The capital recovery factor depends on the annual real interest rate (i) and the project horizon (n). The annual real interest rate is calculated using the nominal interest rate (i') and the expected inflation rate (f).

On the other hand, Table II-B explains the decision criteria and equations considered in assessing the optimization and feasibility results. The average cost per kWh of useful energy produced by the HPS represents the cost of energy (COE). Renewable fraction (RF) is a fraction display that shows the rate at which the total annual energy power generation from RES is transferred to the load. The ratio of RES to the loads in the system is handled in this fraction notation. CE must be discharged or cut off because it is not used to service a load or charge ESS. If RES generates power greater than load demand and ESS is full, or the grid sale is restricted [80]. In contrast, P_F represents the difference between the photovoltaic power output (P_{PV}) and the combined demand of battery power and load power at time t when the photovoltaic output exceeds the load demand (P_L). Also, P_G represents the difference between the load power demand and the combined output of photovoltaic power and battery power at time t when the load demand exceeds the photovoltaic output. The sum of the PV generation power is calculated using the integral, subtracted from the total feed-in power (P_F), and then divided by the total PV generation power representing the SCR [81]. In contrast, SSR is calculated by subtracting the total electrical load from the total grid supply power (P_G) and dividing it by the total electrical load. Overall, the ratio of the power fed from the PV to the load to the total PV production power determines the SCR [79], and the share of the supply power to the total load determines the SSR. P_{GP} and P_{GS} refer to the power purchased from and sold to the grid, while P_{load} indicates the served load. $E^{with\ HPS}$ represents the total electricity purchased from the grid if HPS is used for the served load, while $E^{only\ grid}$ corresponds to the total electricity purchased in a system where the load is met from the only-grid. $P_{curtailment}$ is the wasted electricity that exceeds demand and cannot be sold due to grid sales constraints. Also dt denotes time steps of one hour. Another metric is the energy exchange ratio (EXR), which expresses the ratio between the energy provided by the HPS ($E^{with\ HPS}$) and the energy provided by the grid only ($E^{only\ grid}$) [82]. EV vehicles have near-zero CO_2 emissions compared to petrol-powered vehicles. However, due to the electrical energy consumed in the charging phase of the EV, it creates a certain amount of CO_2 emission to the environment on thermal power plants. For this reason, meeting the charge state with sources with excess RES will reduce this emission to a certain extent [83]. The objective function for minimizing CO_2 emissions while charging the EV at a charging station [84]. Lower CO_2 is essential for HPSs. Several restriction actions are taken to ensure without high carbon values. Foremost among these is the CO_2 penalty.

III. OPTIMIZATION RESULTS

The technical, economic, and environmental evaluation of the increase in installed capacities of hybrid power systems for load profiles with different peak demand times is shown in Table 6 and Table 7. It should be noted that in Table 7, by prioritizing consumer benefits, changes in desired feasibility

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

TABLE 5. Decision Criteria

Metric	Formula	Metric	Formula
CO_2	$0.4261 \sum P_{GP}$	SCR	$\frac{\int P_{PV}\,dt - \int P_F\,dt}{\int P_{PV}\,dt}$
RF	$1 - \frac{\sum (P_{GP})}{\sum (P_{load})}$	SSR	$\frac{\int P_L\,dt - \int P_G\,dt}{\int P_L\,dt}$
EXR	$1 - \frac{\sum E^{\text{with HPS}}}{\sum E^{\text{only grid}}}$	CE	$\sum P_{curtailment}$

outcomes are highlighted in green, while changes in undesirable outcomes are emphasized in red. A neutral approach is taken for more specific aspects, such as converter capacity usage, as there are no significant differences (or highlighted in black). Overall, changes in decision criteria are expressed as percentages, with a "-" sign included in the numerical representation for decreases in feasibility outputs categorized as increases. The same applies to increases.

The analyses have shown that, even though the demand periods in the load profile may vary, only carbon emissions decrease with the inclusion of ESS. Integrating ESS for consumers with peak demands in the evening, combined with increased PV installation capacities, can reduce carbon emissions concerns by up to 25.54%. The mismatch between peak demand periods and production periods allows for the utilization of excess electricity in charging the ESS, resulting in a 5.5% increase in the beneficial use of renewable energy.

ESS integration can also raise the potential benefits from PV in terms of SCR criteria that measure wasted electricity production by up to 10.93%, thereby generating public support in favor of consumers. Such demand profiles, particularly during evening peak loads, highlight the viability of the ESS charging schedule. Consequently, the SSR criteria measuring the beneficial use of electricity provided by PV can increase by up to 15.54%. However, the investment and additional operating and maintenance costs associated with ESS have resulted in expected increases in indicators such as NPC. As a result of ESS integration and the increase in PV installed capacity, a desired reduction in the CE criterion has not been achieved. While there is a trade-off between wasted energy and optimal sizing, the CE not increasing significantly does not lead to mismatched installed capacities according to demand. Moreover, due to the peak load present during midday, load needs are primarily met, which reduces the interaction between ESS and PV charging. This situation may not guarantee the desired carbon emissions benefits for consumers with high installed PV capacities during peak demand in midday, as those achieve the least benefit from ESS integration across various decision criteria.

The carbon tax is also essential while determining the optimal HPS configuration, apart from selecting the capacity according to the ESS unit price. It has been determined that the PV benefit in almost every capacity is relatively high. In an environment where electricity is sold to the grid, it is more reasonable not to use costly ESS. ESS sizing primarily aims to compensate for excess or missing energy when the PV and demand do not match. Peak load is more likely to be met, especially at noon when PV is plentiful. If PV is insufficient, low-capacity ESS is preferred over other peak times. Accordingly, the PV/Grid usage share is higher than at other peak times. Since the midday peak in Figure 3 is more likely to be met by PV, the initial cost of ESS started at a lower level. That is, the initial cost of ESS should be low for optimization to facilitate the choice of ESS. Due to daytime solar energy, the initial cost is relatively low compared to daytime peaks. However, this level rises at the evening peak. In this structure, which works in coordination with the demand profile, the energy needed for the rest of the day is as vital as the peak power in using ESS. In short, a temporal evaluation of the load profile is also required. The slight variation in the carbon tax affected the configuration selection of the evening peak profile. The daytime and midday peaks, respectively, followed it. As a result, as the carbon tax increased, the preference for ESS increased to 40% for daytime, 50.4% for noon, and 84% for evening.

As the carbon tax increases with low ESS capacity or high unit cost (Case 1), EXR is reduced by 23.7% at the daytime peak, 18.2% at the midday peak, and 34.7% at the evening peak. SCR was increased by up to 22.7% under noon peak time. Similar to Figure 5, with reduced solar utilization, ESS and, thus, the sensitivity of RF are pretty different. The essential load peak is when the sun is absent in the evening. Due to the daytime solar energy, the daytime load peak remains in the second order. Regarding ESS usage, the noon peak, where PV and demand match, is at the third important point. Regardless of the peak profile, SCR did not change much when the carbon tax was low, ESS capacity increased, or the initial cost decreased by up to 80%. The carbon tax is more decisive for the relevant parameters. Also, as the maximization of ESS capacity is approached, the beneficial effects of the relevant parameters decrease. In other words, the beneficial effect of reducing the financial value from 1 to 0.81 and reducing the cost from 0.27 to 0.20 does not affect the result the same. The benefits are more pronounced at each parameter's low ESS capacity or high prices. In case 2, where the initial cost of ESS is reduced, and its capacity is increased to 2300-2500 kWh with the most significant carbon tax (100 $/t), the EXR is improved by 17.9% in the daytime peak, 13.4% in the noon peak and 14.7% in the evening peak compared to the first case. Thus, RF by up to 13.5% was achieved compared to the first case. Also, COE increased by 72.8% at the daytime peak, 76.6% at the midday peak, and 83.3% at the evening peak due to increased carbon tax and lower ESS cost. While ESS costs are decreasing, operating costs are rising due to increased battery usage and a carbon tax. Considering that the benefit is high and the harm is low, it can be stated that relevant increases are expected. Payback

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

TABLE 6. Optimal system results considering the peak load times

Peak Load Time	PV (kW)	ESS (kWh)	DC/AC ratio	SCR (%)	SSR (%)	CE (%)	COE ($/kWh)	NPC (M$)	RF (%)	CO_2 (kg/yr)
Morning	300	11	1.26	73.10	34.60	0.29	0.076	4.04	40.9	392,74
	600	90	1.28	49.82	47.17	0.55	0.049	3.36	62.3	327,28
	900	573	1.24	43.91	62.37	0.42	0.032	2.68	76.8	243,79
Midday	300	6	1.21	88.24	41.78	0.17	0.072	3.58	43.8	349,79
	600	45	1.28	58.54	55.44	0.59	0.045	2.96	66.0	278,71
	900	207	1.28	46.28	65.74	0.69	0.029	2.43	78.1	226,33
Night	300	11	1.26	62.86	29.79	0.28	0.081	4.46	39.1	421,81
	600	202	1.25	46.25	43.79	0.37	0.054	3.84	60.9	346,47
	900	810	1.24	41.70	59.24	0.42	0.031	2.63	75.3	263,11
Morning	300	Without ESS	1.23	72.50	34.35	0.23	0.076	4.03	40.8	393,81
	600		1.24	47.75	45.21	0.34	0.047	3.29	61.7	336,89
	900		1.24	36.07	51.25	0.40	0.030	2.73	72.6	308,43
Midday	300		1.20	87.98	41.65	0.14	0.072	3.57	43.8	350,28
	600		1.24	57.38	54.34	0.36	0.044	2.92	65.7	283,26
	900		1.24	42.23	59.99	0.42	0.028	2.37	76.0	257,06
Night	300		1.23	62.29	29.49	0.22	0.080	4.45	39.1	422,47
	600		1.25	40.83	38.66	0.36	0.051	3.75	59.1	376,31
	900		1.24	30.77	43.70	0.38	0.034	3.20	69.8	353,37

TABLE 7. The effects of ESS integration on the optimal feasibility results

PV	Peak Load Time	Increase/decrease trend in feasibility results with ESS								
		Installation	Decrease	Increase						
		ESS (kWh)	CO_2 (%)	RF (%)	SCR (%)	SSR (%)	DC/AC ratio	CE (%)	NPC (%)	COE (%)
300 kW	Morning	11	0.27	0.1	0.6	0.25	2.44	0.06	0.25	0.39
	Midday	6	0.142	0	0.24	0.13	0.83	0.03	0.28	0.28
	Night	11	0.16	0	0.57	0.3	2.44	0.06	0.23	0.5
600 kW	Morning	90	2.85	0.6	2.07	1.96	3.23	0.21	2.13	3.63
	Midday	45	1.61	0.3	1.16	1.1	3.23	0.23	1.37	2.03
	Night	202	7.93	1.8	5.42	5.13	0	0.01	2.4	6.26
900 kW	Morning	573	20.96	4.2	7.84	11.12	0	0.02	-1.83	5.26
	Midday	207	11.96	2.1	4.05	5.75	3.23	0.27	2.53	6.14
	Night	810	25.54	5.5	10.93	15.54	0	0.04	-17.81	-9.91

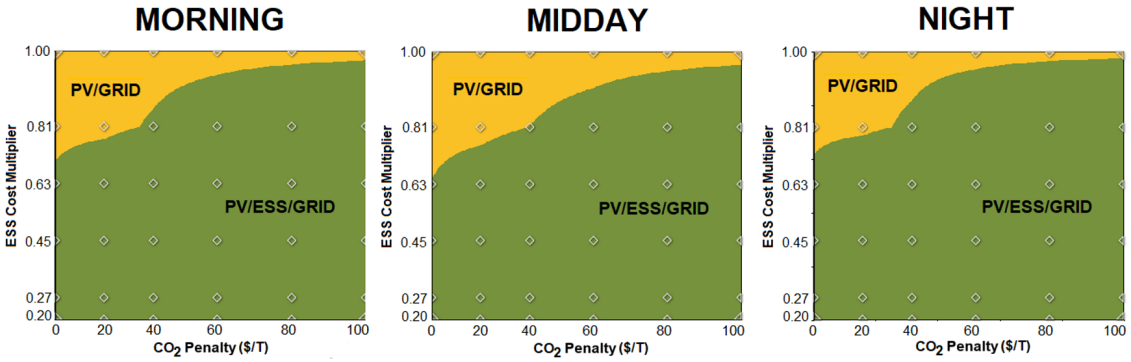


FIGURE 3. Effects of the carbon tax and ESS cost change on optimal HPS

periods have been shortened. With increasing carbon taxes and keeping ESS costs high, NPC will increase by 75% to 85%; note that 2300-2500 kWh ESS capacity can be achieved and CO_2 can be reduced by 55-70% with decreasing ESS costs. Moreover, in case 3, based on carbon tax and ESS cost, EXR is reduced to 41.6% at the daytime peak, 31.6% at the

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

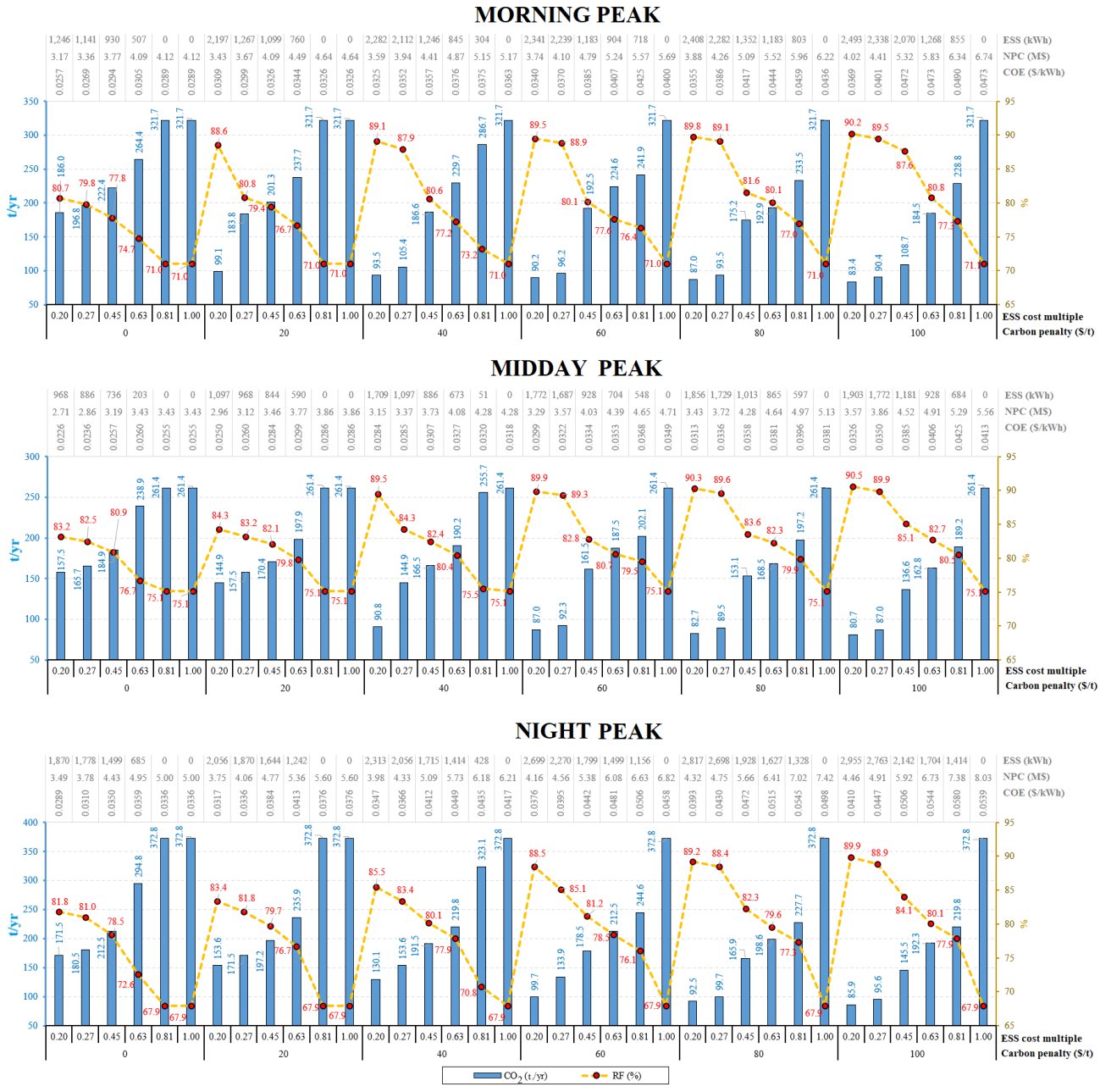


FIGURE 4. ESS capacity, cost and carbon tax impacts on carbon emissions

midday peak, and 49.4% at the evening peak.

The cost of ESS and the carbon tax are highly effective in maximizing and minimizing benefits as seen Figure 4. The average beneficial effect of ESS cost and carbon tax on the respective parameters is as follows, in descending order: EXR (15.33%), SSR (14.13%), SCR (9.8%), RF (8.26%). The carbon tax and the ESS cost multiplier affect the EXR the most. Since the main point of change of RF depends on PV capacity, it is natural that RF is least affected by sensitivity analysis.

Battery energy storage systems play a critical role in enhancing energy efficiency and reducing CO_2. Data indicates that the emission reduction rates achieved with high ESS capacities are noteworthy. However, to meet zero carbon emission targets, a transition to clean energy sources across the entire energy system is necessary. When examining the installation processes of EVCS, it has been observed that existing stations occupy areas of up to 5000 m², with the PV installed capacity (requiring approximately 6.6 m² for 1 kW of installed power) potentially being around or below 900

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

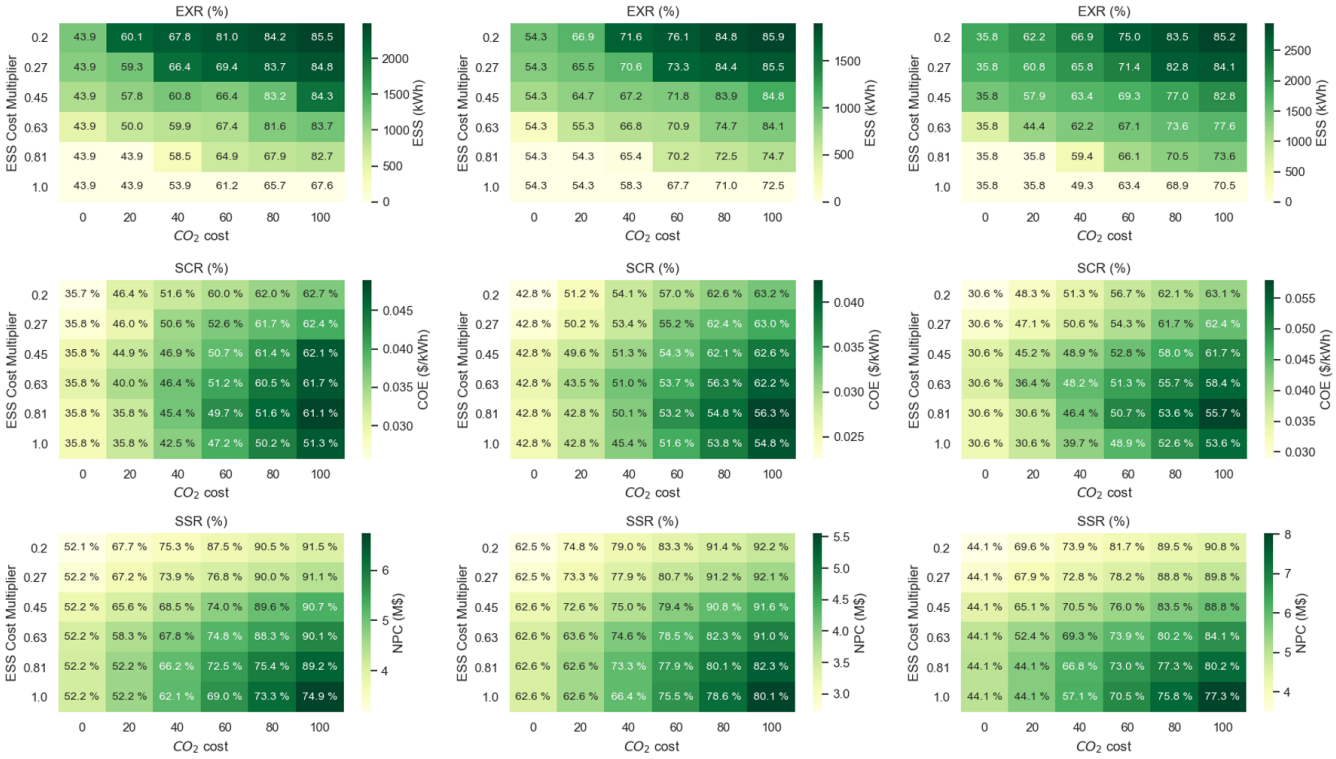


FIGURE 5. The effects of ESS initial cost and carbon tax on EVCS performance

kW. This area limitation, depending on charging demand, increases both clean energy usage and reliance on the grid for high-demand load profiles. For instance, in the model shown in Figure 4, the maximum installed capacity for RF (Renewable Factor) could rise to 71% without the use of ESS, with carbon emissions recorded at 321.7 tons/year. In scenarios where the installation costs of ESS decrease and carbon taxes are incorporated into the system, RF can increase to as much as 90.5%, while carbon emissions can drop to 80.7 t/yr. However, this increase has not provided a linear growth in clean energy usage. Due to constraints in clean energy production, as high ESS capacities approach 2500 kWh, the useful capacity utilization rate decreases, slowing the RF growth rate. This situation complicates independent energy management for stations with high charging demands. Another critical point is that in optimal scenarios without a carbon tax when ESS costs exceed 250 $/kWh, PV-grid power systems emerge as the most feasible model. Depending on the changes in peak demand times, RF varies by up to 7.2% in scenarios with only PV. This indicates that the timing of charging demand is critical, and even without the use of ESS, carbon emissions can be reduced by up to 30% based on load demand times. However, when ESS costs fall below 250 $/kWh, PV-ESS-grid scenarios become more viable. The inclusion of carbon taxes in the optimization process has led to an increase of over 100% in ESS installed capacities. As a result, with the increase in carbon taxes and the decrease in ESS installation costs, RF has increased by up to 20% compared to scenarios with only PV, while carbon emissions have been reduced by 55%. On the other hand, in scenarios with ESS, the maximum RF level has been found to reach up to 90% across three different demand times with similar carbon emissions. Notably, in scenarios with intense evening peaks, the ESS installed capacity is found to be 35% higher compared to other scenarios. This increase has raised NPC by up to 20%. Ultimately, while zero carbon targets may not be entirely achievable due to area constraints, clean energy usage can be increased by up to 90% through ESS integration. Beyond this, the addition of a complementary renewable energy plant to a hybrid power system is necessary for the desired increases. Additionally, demand management for charging and the configuration of hybrid energy storage systems emerge as alternative solutions. Another solution is to redirect users to the nearest clean energy charging stations through load shifting or temporary service outages, aligning with the goal of achieving zero carbon emissions.

IV. CONCLUSIONS

In this article, a method that maximizes energy management with clean energy sources is developed for EVCS, considering the variability in peak energy demand times. Technical, economic, and environmental effects were analyzed in depth, with sensitivity analyses made by considering ESS and PV integration potential, investment cost, and carbon penalties.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

Optimization results showed that the grid peak energy demand could be reduced by up to 54.3%. Moreover, it was determined that the SCR decreased by 30% in the morning and evening when the energy demands of EVCS were high, compared to the afternoon, and the grid dependence increased by up to 30%. Sensitivity analyses have proven that COEs can be reduced by up to 78% due to increased solar radiation potential, regardless of peak time. ESS integration increased SCR by up to 10%. On the other hand, the optimal ESS capacities are up to 3 and 4 times higher, respectively, in the scenarios of the morning and evening peaks compared to the EVCS with intense midday peaks. Due to the carbon tax, ESS capacities increased by up to 84%, grid energy demands decreased by up to 34.7%, and RF increased by 21.1%, especially in high ESS investment cost scenarios. In addition, in these scenarios, CO_2 could be reduced by up to 70%. ESS scenarios have achieved a maximum RF of up to 90% during three different demand periods. Particularly in scenarios with high evening peaks, it has been determined that the installed capacity of ESS is 35% higher compared to other scenarios, resulting in an increase in NPC by up to 20%. However, due to PV area constraints, the zero carbon target cannot be fully achieved despite the integration of ESS. Future goals of this study include investigating the integration of a complementary renewable energy plant alongside the hybrid power system. Additionally, developing alternative solutions for demand management and the configuration of hybrid energy storage systems is planned. To achieve the zero carbon emissions target, strategies such as load shifting and temporary service interruptions to direct users to the nearest clean energy charging stations will also be explored. These efforts aim to contribute to a more comprehensive understanding of sustainable energy solutions.

REFERENCES

[1] A. Demirci, "Optimal sizing and techno-economic evaluation of microgrids based on 100% renewable energy powered by second-life battery," *IEEE Access*, vol. 11, pp. 113 291–113 306, 2023.

[2] S. Adak, H. Cangi, R. Kaya, and A. S. Yılmaz, "Effects of electric vehicles and charging stations on microgrid power quality," *Gazi University Journal of Science Part A: Engineering and Innovation*, vol. 9, no. 3, p. 276–286, 2022.

[3] IEA, "Net Zero by 2050: A Roadmap for the Global Energy Sector," Tech. Rep., 2021. [Online]. Available: https://www.iea.org/reports/net-zero-by-2050

[4] C. Filote, R. A. Felseghi, M. S. Raboaca, and I. Aşchilean, "Environmental impact assessment of green energy systems for power supply of electric vehicle charging station," *International Journal of Energy Research*, vol. 44, no. 13, pp. 10 471–10 494, 2020.

[5] S. S. Deshmukh and J. M. Pearce, "Electric vehicle charging potential from retail parking lot solar photovoltaic awnings," *Renewable Energy*, vol. 169, pp. 608–617, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148121000756

[6] B. Sun, "A multi-objective optimization model for fast electric vehicle charging stations with wind, PV power and energy storage," *Journal of Cleaner Production*, vol. 288, p. 125564, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652620356109

[7] P. Bastida-Molina, E. Hurtado-Pérez, M. C. Moros Gómez, and C. Vargas-Salgado, "Multicriteria power generation planning and experimental verification of hybrid renewable energy systems for fast electric vehicle charging stations," *Renewable Energy*, vol. 179, pp. 737–755, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148121010077

[8] S. Kumar and S. Koteswara Rao, "Optimum capacity of hybrid renewable energy system suitable for fulfilling yearly load demand for a community building located at Vaddeswaram, Andhra Pradesh," *Energy and Buildings*, vol. 277, p. 112570, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378778822007411

[9] L. Bartolucci, S. Cordiner, V. Mulone, M. Santarelli, F. Ortenzi, and M. Pasquali, "PV assisted electric vehicle charging station considering the integration of stationary first- or second-life battery storage," *Journal of Cleaner Production*, vol. 383, p. 135426, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652622050004

[10] A. K. Karmaker, M. R. Ahmed, M. A. Hossain, and M. M. Sikder, "Feasibility assessment design of hybrid renewable energy based electric vehicle charging station in Bangladesh," *Sustainable Cities and Society*, vol. 39, no. January, pp. 189–202, 2018. [Online]. Available: https://doi.org/10.1016/j.scs.2018.02.035

[11] R. Yin and J. He, "Design of a photovoltaic electric bike battery-sharing system in public transit stations," *Applied Energy*, vol. 332, p. 120505, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261922017627

[12] A. Sierra, C. Gercek, K. Geurs, and A. Reinders, "Technical, financial, and environmental feasibility analysis of photovoltaic ev charging stations with energy storage in china and the united states," *IEEE Journal of Photovoltaics*, vol. 10, no. 6, pp. 1892–1899, 2020.

[13] D. Sadeghi, A. Hesami, and S. Bahramara, "Optimal sizing of hybrid renewable energy systems in presence of electric vehicles using multi-objective particle swarm optimization," *Energy*, vol. 209, p. 118471, 2020. [Online]. Available: https://doi.org/10.1016/j.energy.2020.118471

[14] M. Yang, L. Zhang, Z. Zhao, and L. Wang, "Comprehensive benefits analysis of electric vehicle charging station integrated photovoltaic and energy storage," *Journal of Cleaner Production*, vol.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

302, p. 126967, 2021. [Online]. Available: https://doi.org/10.1016/j.jclepro.2021.126967

[15] H. Ren, Z. Ma, C. Fai Norman Tse, and Y. Sun, "Optimal control of solar-powered electric bus networks with improved renewable energy on-site consumption and reduced grid dependence," *Applied Energy*, vol. 323, no. July, p. 119643, 2022. [Online]. Available: https://doi.org/10.1016/j.apenergy.2022.119643

[16] L. Haupt, M. Schöpf, L. Wederhake, and M. Weibelzahl, "The influence of electric vehicle charging strategies on the sizing of electrical energy storage systems in charging hub microgrids," *Applied Energy*, vol. 273, no. February, p. 115231, 2020. [Online]. Available: https://doi.org/10.1016/j.apenergy.2020.115231

[17] C. Leone, C. Peretti, A. Paris, and M. Longo, "Photovoltaic and battery systems sizing optimization for ultra-fast charging station integration," *Journal of Energy Storage*, vol. 52, no. PC, p. 104995, 2022. [Online]. Available: https://doi.org/10.1016/j.est.2022.104995

[18] R. Fachrizal, M. Shepero, M. Åberg, and J. Munkhammar, "Optimal PV-EV sizing at solar powered workplace charging stations with smart charging schemes considering self-consumption and self-sufficiency balance," *Applied Energy*, vol. 307, p. 118139, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S030626192101415X

[19] A. Bartolini, G. Comodi, D. Salvi, and P. A. Østergaard, "Renewables self-consumption potential in districts with high penetration of electric vehicles," *Energy*, vol. 213, p. 118653, 2020. [Online]. Available: https://doi.org/10.1016/j.energy.2020.118653

[20] A. Esfandyari, B. Norton, M. Conlon, and S. J. McCormack, "Performance of a campus photovoltaic electric vehicle charging station in a temperate climate," *Solar Energy*, vol. 177, no. December 2018, pp. 762–771, 2019. [Online]. Available: https://doi.org/10.1016/j.solener.2018.12.005

[21] L. Luo, W. Gu, Z. Wu, and S. Zhou, "Joint planning of distributed generation and electric vehicle charging stations considering real-time charging navigation," *Applied Energy*, vol. 242, pp. 1274–1284, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261919305707

[22] Y. Long, Y. Li, Y. Wang, Y. Cao, L. Jiang, Y. Zhou, Y. Deng, and Y. Nakanishi, "Impact of EV load uncertainty on optimal planning for electric vehicle charging station," *Science China Technological Sciences*, vol. 64, no. 11, pp. 2469–2476, 2021. [Online]. Available: https://doi.org/10.1007/s11431-021-1897-x

[23] A. Allouhi and S. Rehman, "Grid-connected hybrid renewable energy systems for supermarkets with electric vehicle charging platforms: Optimization and sensitivity analyses," *Energy Reports*, vol. 9, pp. 3305–3318, 2023. [Online]. Available: https://doi.org/10.1016/j.egyr.2023.02.005

[24] F. Manríquez, E. Sauma, J. Aguado, S. de la Torre, and J. Contreras, "The impact of electric vehicle charging schemes in power system expansion planning," *Applied Energy*, vol. 262, no. September 2019, p. 114527, 2020. [Online]. Available: https://doi.org/10.1016/j.apenergy.2020.114527

[25] S. Li, T. Zhang, X. Liu, Z. Xue, and X. Liu, "Performance investigation of a grid-connected system integrated photovoltaic, battery storage and electric vehicles: A case study for gymnasium building," *Energy and Buildings*, vol. 270, p. 112255, 2022. [Online]. Available: https://doi.org/10.1016/j.enbuild.2022.112255

[26] H. Mehrjerdi and R. Hemmati, "Stochastic model for electric vehicle charging station integrated with wind energy," *Sustainable Energy Technologies and Assessments*, vol. 37, no. October 2019, p. 100577, 2020. [Online]. Available: https://doi.org/10.1016/j.seta.2019.100577

[27] P. Emrani-Rahaghi, H. Hashemi-Dezaki, and A. Hasankhani, "Optimal stochastic operation of residential energy hubs based on plug-in hybrid electric vehicle uncertainties using two-point estimation method," *Sustainable Cities and Society*, vol. 72, no. June, p. 103059, 2021. [Online]. Available: https://doi.org/10.1016/j.scs.2021.103059

[28] C. Li, Y. Shan, L. Zhang, L. Zhang, and R. Fu, "Techno-economic evaluation of electric vehicle charging stations based on hybrid renewable energy in China," *Energy Strategy Reviews*, vol. 41, p. 100850, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2211467X22000487

[29] U. Fretzen, M. Ansarin, and T. Brandt, "Temporal city-scale matching of solar photovoltaic generation and electric vehicle charging," *Applied Energy*, vol. 282, no. PA, p. 116160, 2021. [Online]. Available: https://doi.org/10.1016/j.apenergy.2020.116160

[30] T. Kobashi, Y. Choi, Y. Hirano, Y. Yamagata, and K. Say, "Rapid rise of decarbonization potentials of photovoltaics plus electric vehicles in residential houses over commercial districts," *Applied Energy*, vol. 306, no. PB, p. 118142, 2022. [Online]. Available: https://doi.org/10.1016/j.apenergy.2021.118142

[31] L. Wang, V. Nian, H. Li, and J. Yuan, "Impacts of electric vehicle deployment on the electricity sector in a highly urbanised environment," *Journal of Cleaner Production*, vol. 295, p. 126386, 2021. [Online]. Available: https://doi.org/10.1016/j.jclepro.2021.126386

[32] C. Kacperski, R. Ulloa, S. Klingert, B. Kirpes, and F. Kutzner, "Impact of incentives for greener battery electric vehicle charging – A field experiment," *Energy Policy*, vol. 161, p. 112752, 2022. [Online]. Available:

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

https://doi.org/10.1016/j.enpol.2021.112752

[33] C. Good, M. Shepero, J. Munkhammar, and T. Boström, "Scenario-based modelling of the potential for solar energy charging of electric vehicles in two Scandinavian cities," *Energy*, vol. 168, pp. 111–125, 2019.

[34] J. A. Domínguez-Navarro, R. Dufo-López, J. M. Yusta-Loyo, J. S. Artal-Sevil, and J. L. Bernal-Agustín, "Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems," *International Journal of Electrical Power and Energy Systems*, vol. 105, no. July 2018, pp. 46–58, 2019. [Online]. Available: https://doi.org/10.1016/j.ijepes.2018.08.001

[35] Y. Yang, C. Lu, H. Liu, N. Wang, L. Chen, and C. Wang, "Optimal design and energy management of residential prosumer community with photovoltaic power generation and storage for electric vehicles," *Sustainable Production and Consumption*, vol. 33, pp. 244–255, 2022. [Online]. Available: https://doi.org/10.1016/j.spc.2022.07.008

[36] L. Novoa and J. Brouwer, "Dynamics of an integrated solar photovoltaic and battery storage nanogrid for electric vehicle charging," *Journal of Power Sources*, vol. 399, no. March, pp. 166–178, 2018. [Online]. Available: https://doi.org/10.1016/j.jpowsour.2018.07.092

[37] M. McPherson, M. Ismail, D. Hoornweg, and M. Metcalfe, "Planning for variable renewable energy and electric vehicle integration under varying degrees of decentralization: A case study in Lusaka, Zambia," *Energy*, vol. 151, pp. 332–346, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544218304821

[38] M. Sedighizadeh, S. S. Fazlhashemi, H. Javadi, and M. Taghvaei, "Multi-objective day-ahead energy management of a microgrid considering responsive loads and uncertainty of the electric vehicles," *Journal of Cleaner Production*, vol. 267, p. 121562, 2020. [Online]. Available: https://doi.org/10.1016/j.jclepro.2020.121562

[39] N. B. G. Brinkel, M. K. Gerritsma, T. A. AlSkaif, I. Lampropoulos, A. M. van Voorden, H. A. Fidder, and W. van Sark, "Impact of rapid PV fluctuations on power quality in the low-voltage grid and mitigation strategies using electric vehicles," *International Journal of Electrical Power Energy Systems*, vol. 118, p. 105741, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061519319994

[40] K. M. Bhargavi and N. S. Jayalakshmi, "A New Control Strategy for Plug-in Electric Vehicle of DC Microgrid with PV and Wind Power Integration," *Journal of Electrical Engineering and Technology*, vol. 14, no. 1, pp. 13–25, 2019. [Online]. Available: https://doi.org/10.1007/s42835-018-00013-9

[41] N. Al Khafaf, A. A. Rezaei, A. Moradi Amani, M. Jalili, B. McGrath, L. Meegahapola, and A. Vahidnia, "Impact of battery storage on residential energy consumption: An Australian case study based on smart meter data," *Renewable Energy*, vol. 182, pp. 390–400, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148121014622

[42] B. Zakeri, S. Cross, P. Dodds, and G. C. Gissey, "Policy options for enhancing economic profitability of residential solar photovoltaic with battery energy storage," *Applied Energy*, vol. 290, p. 116697, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261921002221

[43] M. Herrando, A. Ramos, and I. Zabalza, "Cost competitiveness of a novel PVT-based solar combined heating and power system: Influence of economic parameters and financial incentives," *Energy Conversion and Management*, vol. 166, no. May, pp. 758–770, 2018.

[44] H. Dong, L. Wang, X. Wei, Y. Xu, W. Li, X. Zhang, and M. Zeng, "Capacity planning and pricing design of charging station considering the uncertainty of user behavior," *International Journal of Electrical Power Energy Systems*, vol. 125, p. 106521, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061520307602

[45] A. Dougherty, B. Billings, N. Camacho, and K. Powell, "Improving the economics of battery storage for industrial customers : Are incentives enough to increase adoption ?" *The Electricity Journal*, vol. 34, no. 9, p. 107027, 2021. [Online]. Available: https://doi.org/10.1016/j.tej.2021.107027

[46] S. Varghese and R. Sioshansi, "The price is right ? How pricing and incentive mechanisms in California incentivize building distributed hybrid solar and energy-storage systems," vol. 138, no. July 2019, 2020.

[47] A. Roth, M. Boix, V. Gerbaud, L. Montastruc, and P. Etur, "Impact of taxes and investment incentive on the development of renewable energy self-consumption: French households' case study," *Journal of Cleaner Production*, vol. 265, p. 121791, 2020. [Online]. Available: https://doi.org/10.1016/j.jclepro.2020.121791

[48] R. Khezri, A. Mahmoudi, and M. H. Haque, "Impact of optimal sizing of wind turbine and battery energy storage for a grid-connected household with/without an electric vehicle," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 9, pp. 5838–5848, 2022.

[49] I. D'Adamo, M. Gastaldi, and P. Morone, "The impact of a subsidized tax deduction on residential solar photovoltaic-battery energy storage systems," *Utilities Policy*, vol. 75, p. 101358, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957178722000236

[50] J. Shuai, X. Cheng, L. Ding, J. Yang, and Z. Leng, "How should government and users share the investment costs and benefits of a solar PV power generation project in China?" *Renewable and Sustainable Energy Reviews*, vol. 104, no. March 2018, pp. 86–94, apr 2019. [Online]. Available: https:

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

//doi.org/10.1016/j.rser.2019.01.003https://linkinghub.elsevier.com/retrieve/pii/S1364032119300097

[51] X. Luo, Y. Liu, and X. Liu, "Bi-level multi-objective optimization of design and subsidies for standalone hybrid renewable energy systems: A novel approach based on artificial neural network," *Journal of Building Engineering*, vol. 41, no. April, p. 102744, 2021. [Online]. Available: https://doi.org/10.1016/j.jobe.2021.102744

[52] X. Zhu, B. Liao, and S. Yang, "An optimal incentive policy for residential prosumers in Chinese distributed photovoltaic market: A Stackelberg game approach," *Journal of Cleaner Production*, vol. 308, no. August 2020, p. 127325, 2021. [Online]. Available: https://doi.org/10.1016/j.jclepro.2021.127325

[53] L. Gao, Y. Hiruta, and S. Ashina, "Promoting renewable energy through willingness to pay for transition to a low carbon society in Japan," *Renewable Energy*, vol. 162, pp. 818–830, 2020. [Online]. Available: https://doi.org/10.1016/j.renene.2020.08.049

[54] M. Hájek, J. Zimmermannová, K. Helman, and L. Rozenský, "Analysis of carbon tax efficiency in energy industries of selected EU countries," *Energy Policy*, vol. 134, no. August, p. 110955, 2019. [Online]. Available: https://doi.org/10.1016/j.enpol.2019.110955

[55] A. Kumar, S. Maisanam, A. Biswas, and K. K. Sharma, "Integrated socio-environmental and techno-economic factors for designing and sizing of a sustainable hybrid renewable energy system," *Energy Conversion and Management*, vol. 247, p. 114709, 2021. [Online]. Available: https://doi.org/10.1016/j.enconman.2021.114709

[56] L. Ji, Y. Wu, Y. Xie, L. Sun, and G. Huang, "An integrated framework for feasibility analysis and optimal management of a neighborhood-scale energy system with rooftop PV and waste-to-energy technologies," *Energy for Sustainable Development*, vol. 70, pp. 78–92, 2022. [Online]. Available: https://doi.org/10.1016/j.esd.2022.07.012

[57] J. Liu, X. Chen, H. Yang, and K. Shan, "Hybrid renewable energy applications in zero-energy buildings and communities integrating battery and hydrogen vehicle storage ," *Applied Energy*, vol. 290, no. March, p. 116733, 2021. [Online]. Available: https://doi.org/10.1016/j.apenergy.2021.116733

[58] X. Zhao, J. Yao, C. Sun, and W. Pan, "Impacts of carbon tax and tradable permits on wind power investment in China," *Renewable Energy*, vol. 135, pp. 1386–1399, 2019. [Online]. Available: https://doi.org/10.1016/j.renene.2018.09.068

[59] P. Ifaei, A. Saman, T. Charmchi, J. Loy-benitez, R. Jing, and C. Yoo, "A data-driven analytical roadmap to a sustainable 2030 in South Korea based on optimal renewable microgrids," *Renewable and Sustainable Energy Reviews*, vol. 167, no. July, p. 112752, 2022. [Online]. Available: https://doi.org/10.1016/j.rser.2022.112752

[60] E. Martelli, M. Freschini, and M. Zatti, "Optimization of renewable energy subsidy and carbon tax for multi energy systems using bilevel programming," *Applied Energy*, vol. 267, p. 115089, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261920306012

[61] Y. He, S. Guo, P. Dong, J. Huang, and J. Zhou, "Hierarchical optimization of policy and design for standalone hybrid power systems considering lifecycle carbon reduction subsidy," *Energy*, vol. 262, no. August 2022, 2023.

[62] Z. Ozturk, M. Terkes, and A. Demirci, "Optimal planning of hybrid power systems under economic variables and different climatic regions: A case study of türkiye," *Renewable Energy*, vol. 232, p. 121029, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148124010978

[63] M. Terkes, A. Demirci, Z. Ozturk, and U. Cali, "Strategic integration of second-life batteries: Incentive mechanisms for boosting community energy self-consumption," *IEEE Access*, vol. 12, pp. 125 768–125 785, 2024.

[64] A. Demirci, "Optimal sizing and techno-economic evaluation of microgrids based on 100

[65] Y. J. Choi, B. C. Oh, M. A. Acquah, D. M. Kim, and S. Y. Kim, "Optimal operation of a hybrid power system as an island microgrid in south-korea," *Sustainability (Switzerland)*, vol. 13, no. 9, pp. 1–18, 2021.

[66] M. Terkes, A. Demirci, E. Gokalp, and U. Cali, "Multi-stage and multi-objective feed-in damping-based battery aging-aware energy management strategy for renewable energy integration," *IEEE Access*, pp. 1–1, 2024.

[67] M. Terkes, O. Arikan, and E. Gokalp, "The effect of electric vehicle charging demand variability on optimal hybrid power systems with second-life lithium-ion or fresh na–s batteries considering power quality," *Energy*, vol. 288, p. 129760, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544223031547

[68] J. F. Manwell and J. G. McGowan, "Lead acid battery storage model for hybrid energy systems," *Solar Energy*, vol. 50, no. 5, pp. 399–405, 1993. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0038092X93900602

[69] A. International, "Standard guide for the evaluation of the performance of vibration measuring instruments," *ASTM Standards*, 2023. [Online]. Available: https://doi.org/10.1520/E1049-85R23

[70] Smith, Kandler, Earleywine, Matthew, Wood, Eric, Neubauer, Jeremy, and Pesaran, Ahmad, "Comparison of plug-in hybrid electric vehicle battery life across geographies and drive cycles," in *SAE 2012 World Congress Exhibition*. SAE International, apr 2012. [Online]. Available: https://doi.org/10.4271/2012-01-

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736

0666

[71] M. Terkes, A. Demirci, and E. Gokalp, "An evaluation of optimal sized second-life electric vehicle batteries improving technical, economic, and environmental effects of hybrid power systems," *Energy Conversion and Management*, vol. 291, p. 117272, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890423006180

[72] E. E. Ahmed, A. Demirci, and S. M. Tercan, "Optimal sizing and techno-enviro-economic feasibility assessment of solar tracker-based hybrid energy systems for rural electrification in sudan," *Renewable Energy*, vol. 205, pp. 1057–1070, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148123001660

[73] J.-M. Clairand, M. Arriaga, C. A. Cañizares, and C. Álvarez Bel, "Power generation planning of galapagos' microgrid considering electric vehicles and induction stoves," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 4, pp. 1916–1926, 2019.

[74] A. Demirci, Z. Öztürk, and S. M. Tercan, "Decision-making between hybrid renewable energy configurations and grid extension in rural areas for different climate zones," *Energy*, vol. 262, no. August 2022, p. 125402, jan 2023.

[75] "Nasa prediction of worldwide energy resource (power) database," National Aeronautics and Space Administration (NASA), Tech. Rep., 2023. [Online]. Available: https://power.larc.nasa.gov/data-access-viewer/

[76] "Global solar atlas," Solargis, Tech. Rep., 2023. [Online]. Available: https://globalsolaratlas.info/map

[77] "Renewable power generation costs in 2020," I.R.E. Agency, Tech. Rep., 2020.

[78] M. Terkes, Z. Öztürk, A. Demirci, and S. M. Tercan, "Optimal sizing and feasibility analysis of second-life battery energy storage systems for community microgrids considering carbon reduction," *Journal of Cleaner Production*, vol. 421, p. 138507, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652623026653

[79] A. Demirci, O. Akar, and Z. Ozturk, "Technical-environmental-economic evaluation of biomass-based hybrid power system with energy storage for rural electrification," *Renewable Energy*, vol. 195, pp. 1202–1217, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148122009375

[80] M. S. Javed, T. Ma, J. Jurasz, F. A. Canales, S. Lin, S. Ahmed, and Y. Zhang, "Economic analysis and optimization of a renewable energy based power supply system with different energy storages for a remote island," *Renewable Energy*, vol. 164, p. 1376–1394, Feb. 2021. [Online]. Available: http://dx.doi.org/10.1016/j.renene.2020.10.063

[81] S. M. Tercan, A. Demirci, E. Gokalp, and U. Cali, "Maximizing self-consumption rates and power quality towards two-stage evaluation for solar energy and shared energy storage empowered microgrids," *Journal of Energy Storage*, vol. 51, no. June 2021, p. 104561, 2022. [Online]. Available: https://doi.org/10.1016/j.est.2022.104561

[82] A. Demirci, S. Mirza Tercan, E. E. E. Ahmed, U. Cali, and I. Nakir, "A novel electric vehicle charging management with dynamic active power curtailment framework for pv-rich prosumers," *IEEE Access*, vol. 12, pp. 120 239–120 249, 2024.

[83] K. M. Kotb, M. Elkadeem, M. F. Elmorshedy, and A. Dán, "Coordinated power management and optimized techno-enviro-economic design of an autonomous hybrid renewable microgrid: A case study in Egypt," *Energy Conversion and Management*, vol. 221, p. 113185, oct 2020.

[84] M. Asna, H. Shareef, P. Achikkulath, H. Mokhlis, R. Errouissi, and A. Wahyudie, "Analysis of an optimal planning model for electric vehicle fast-charging stations in al ain city, united arab emirates," *IEEE Access*, vol. 9, pp. 73 678–73 694, 2021.



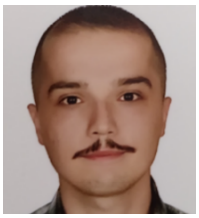
ALPASLAN DEMIRCI received the B.Sc. degree in electrical and electronics engineering from Sakarya University, Turkey, the B.Sc. and M.Sc. degrees in electrical education from Marmara University, İstanbul, Turkey, in 2007 and 2011, respectively, and the Ph.D. degree in electrical engineering from the Graduate School of Science and Engineering, Yildiz Technical University (YTU), İstanbul, in 2023. He is currently an Associate Professor with the Department of Electrical Engineering, YTU. His research interests include power system optimization methods, distributed renewable energy systems, energy economics, electric vehicles, and energy storage systems. He has published several articles related his research areas.



ZAFER OZTURK received the B.Sc. degree in electrical education from Abant İzzet Baysal University, Türkiye, the B.Sc. and M.Sc. degrees in electrical education from Marmara University, İstanbul, Türkiye, in 2007 and 2011, respectively, and the Ph.D. degree in electrical engineering from Electrical-Electronics and Computer Engineering, Duzce University in 2023. He has been working as an Electrical Teacher in the Ministry of National Education since 2014. He is registered with the Chamber of Electrical Engineers (EMO). His research interests include automation systems, power system and optimization methods, renewable energy systems, energy storage systems and electric vehicles. He has published several articles related his research areas.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

This article has been accepted for publication in IEEE Access. This is the author's version which has not been fully edited and
content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2025.3526736



MUSA TERKES received the B.Sc. degree in electrical engineering from Yildiz Technical University (YTU), Istanbul, Türkiye, in 2019, and the M.Sc. degree in electrical power systems from Graduate School of Science and Engineering, YTU, in 2022. He has been studying for a PhD in Electrical Power Systems from the Graduate School of Science and Engineering at YTU since 2023. He assists in power systems, fault analysis, energy transmission, and distribution systems course and teaches electrical power systems, lighting, electrical internal installation, and high voltage laboratories. His research interests include optimal sizing of hybrid power systems, control methods for energy storage systems, energy economics, benefits of renewable energy systems, grid effects of electric vehicles, energy management allocation of microgrids, second-life battery feasibility, and aging. He has published several articles related his research areas.



SAID MIRZA TERCAN received the B.Sc. degree from the Department of Electrical Engineering, Istanbul Technical University in 2012, the M.Sc. and Ph.D. degrees in Electrical Engineering from the Graduate School of Science and Engineering, Yıldız Technical University (YTU), in 2015 and 2022, respectively. He currently serves an Assistant Professor at the Department of Electrical Engineering, YTU. His research interests are energy storage systems, power distribution grid, renewable energy systems, electric vehicles. He has published several articles and conference papers related his research areas.



RECEP YUMURTACI received the B.Sc. degree from the Department of Electrical Engineering, Istanbul Technical University in 1990, the M.Sc. and Ph.D. degrees in Electrical Engineering from the Graduate School of Science and Engineering, Yıldız Technical University (YTU), in 1995 and 2000, respectively. He currently serves an Associated Professor at the Department of Electrical Engineering, YTU. His research interests are power system protection, power quality, power distribution grid, and renewable energy systems. He has published several articles and conference papers related his research areas.



UMIT CALI earned his B.E. degree in Electrical Engineering from Yildiz Technical University, Istanbul, Turkey in 2000, and his M.Sc. degree in Electrical Communication Engineering and Ph.D. degree in Electrical Engineering and Computer Science from the University of Kassel, Germany, in 2005 and 2010, respectively. With over 20 years of experience in both industry and academia, he currently serves as a Professor of Digital Engineering for Future Technologies at the University of York. His research interests encompass energy informatics, artificial intelligence, blockchain technology, renewable energy systems, and energy economics. He holds the position of Chair for the Digital Privacy-Energy Industry TC under IEEE Future Directions and serves as Vice Chair for the IEEE Blockchain in Energy Standards WG (P2418.5).

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/