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Feasibility Analysis of Solar-Powered Electric Vehicle Charging Stations Considering Demand Profiles

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Abstract: The ever-increasing demand for electric vehicles as clean transport is promoted worldwide raises the issue of insufficient charging infrastructure. Moreover, peak charging demand and timing for electric vehicle charging stations (EVCS) vary throughout the day depending on consumer profiles, resulting in risky investment and operational plans. Meeting the stochastic EVCS demand with hybrid power systems (HPS) reduces the use of conventional sources for power generation, increases renewable potential, and supports climate policies. This study analyzes the technical, economic, and environmental impacts of solar-assisted EVCSs for different peak demand periods and investigates minimum-cost hybrid configurations. Also, the effect of variable solar radiation (2.5-6.5 kWh/m^2/day) on HPS based on different peak demand profiles was analyzed. In addition, threshold PV capacities are determined at each solar radiation for morning, midday, and night peak periods based on the variation in the decision criteria. The results show that higher solar irradiation can shorten the payback period by up to 5.4 years and reduce consumers' threshold PV capacities by up to 22.2% and 33.3% in the night and midday peak periods. This study can help investors in clean transportation and energy for climate-based sustainable development policies.

Index Terms **- Electric vehicle, charging station, energy economy, hybrid power system, optimization, renewable energy.**

I. INTRODUCTION

Electric vehicle (EV) sales acceleration has increased the importance of EV charging station (EVCS) installations due to increasing charging demands. Factors such as the probability of different EV brands and models visiting the station, different user driving profiles and priorities [1], EVCS installation points, and charging demands and charging times for EV batteries of different sizes complicate forecasting EV charging demand. Moreover, meeting high EV charging demands with conventional sources will hinder steps to address global temperature concerns. Depending on its intermittent generation profile, renewable energy can meet EVCS demands as an alternative to traditional sources in the clean energy effort. Battery energy storage systems (ESS), filling the valleys in electricity generation, can give hope to consumers and governments by providing energy sustainability and reliability.

Proper capacity optimization and energy management of hybrid power systems (HPS) can provide technical, economic, and environmental benefits for many stakeholders. For instance, it could increase the renewable fraction (RF) to 87%, guaranteeing cost-effective and reliable investments [2]. It can also reduce the cost of energy (COE) by 23.6% [3], CO_2 by 48.7% [4], reserve energy capacity by 84% [5], and maximum power loss by 4.5% [6]. Moreover, high wind and solar energy potential can shorten payback periods, even in challenging operating environments [7]. Smart energy management schemes can provide high-quality stability in optimization [8], improve self-consumption indexed load matching performance [9], reduce peak power demand by a factor of 2 [10], and guarantee lower EV charging costs [11]. However, many criteria must be considered to manage the optimization and realistically determine feasible outcomes properly. Therefore, Different climatic zones, higher radiation variations, and wind speed can deeply affect feasibility analyses. For instance, a 0.2 m/s rise in wind speed and a 1 kWh/m^2/day rise in solar radiation can increase the RF by 1.2% and 6.6% [12]. The higher radiation potential could increase the RF by 4.4%, reducing the net present cost (NPC) by 22% [13]. Moreover, radiation higher than 7.6 kWh/m^2/day does not change the system performance and causes costly investments [14]. Determining the feasible radiation and wind speed can reduce the levelized cost of energy (LCOE) by up to 22.4% [15] and grid imports and exports by up to 66.1% [16]. In addition, optimized energy selling prices, considering radiation and wind speed, can reduce electricity bills by up to 6% [17]. On the other hand, different photovoltaic panel (PV) capacities, depending on technology, purchase price, and demand profiles, lead to local optimization strategies rather than general ones. For instance, PV array sizes of 1-1.5 kWp and PV shares of 50% and 75% in China and the US can promise an efficient system in all locations [18]. Particularly, a 50% share of PV can reduce CO_2 by 18-93% by lowering the grid charging of EVs [19]. Also, a 33.33% increase in PV capacity raises the RF by up to 9.2%, reduces the NPC by 19.72%, and lowers the COE by up to 31% [20]. Can optimization of hybrid configurations in the renewable base be effective under demand stochasticity or variability? Specifically, highly stochastic EV charging can increase renewable energy wastage by up to 36.1% [21], causing undesired investment in PV and ESS capacity [22], [23], rising energy prices [24] and an increase in energy loss by up to 3% [25]. Underestimating EV charging stochasticity can result in risky investments of up to 10% in economic business plans [26]. Moreover, seasonal [27] or daily [28] peak demand periods can significantly impact capacity optimization. Feasible matching of renewable energy generation periods and demand based on solar radiation and wind speed [29] can minimize peak EV charging

demand [30], compensate for demand variability with PV shares higher than 50% [31], reduce the electricity bill by 74.2% and increase electricity sales revenues by 19.86% [32]. Also, integrating distributed energy resources significantly reduces EVs' gross costs, power losses, voltage variations, pollution levels, and electricity costs [33]. ESSs included in collaborative energy management can compensate for demand variability by 30% and reduce system costs by 11.2% [34], [35]. There are many studies in the literature considering optimal sizing [15], [20], [24], [28], [36]–[38] and technical, economic, and environmental feasibility analysis [15], [16], [19], [20], [24], [28], [36]–[41] categorized by EV charging [15], [16], [19], [20], [24], [28], [36]–[41], PV capacity [15], [16], [19], [20], [24], [37], [39]–[41] and solar radiation/wind speed [15], [19], [20], [24], [37], [38] variability and sensitivity, as shown in Table 1.1. Although there are studies addressing variability simultaneously [15], [20], [24], [37], their scope is limited to a specific field. There are also very few studies considering the peak times of EV charging [28] rather than the uncertainty or variability in EV charging. Moreover, the study does not consider PV capacity and climate potential in the variability scenario.

Table 1.1: Comparison of Related Studies Regarding Motivation

Ref.	**Field**	**Planning & Method**	**Analysis**		**Variability / Sensitivity**		
			OS	*FB*	*EV-C*	*PV-C*	*SR/WS*
[15]	House	Technical and economic analysis and optimal sizing for stand-alone residential EV charging load considering reliability	✓	✓	✓	✓	✓
[16]	Transportation network	Optimal control of solar electric bus networks to improve on-site renewable energy consumption and reduce grid dependency		✓	✓	✓	
[19]	Transportation network	Feasibility analysis using an interdisciplinary modeling approach for electricity balance, CO_2, and economic aspects		✓	✓	✓	✓
[20]	Microgrid	Technical, economic analysis and optimal sizing of microgrid integrated solar EVCSs under different solar irradiances	✓	✓	✓	✓	✓
[24]	University campuses route	A technical and economic evaluation of HRES (PV-WT) based EVCSs and finding the optimum scheme	✓	✓	✓	✓	✓
[28]	University	Impact of EV peak demand times and power purchase prices on the optimal scheduling of EVCS	✓	✓	✓		
[36]	Highway	PV and BESS sizing optimization under various energy management strategies for ultra-fast charging station	✓	✓	✓		
[37]	Supermarkets	Optimization and sensitivity analysis of grid-connected HRESs (PV-WT-BESS) for supermarkets with EV charging units	✓	✓	✓	✓	✓
[38]	House	Optimal sizing of grid-connected rooftop PV and BESS considering the new rule-based energy management strategy for residential EV charging load	✓	✓	✓		✓
[39]	Power distribution & transportation network	Using load fluctuation rate to determine feasible capacity ratios in the microgrid, robust optimization to predict EV charging and PV/WT generation uncertainty using kernel density functions		✓	✓	✓	
[40]	Microgrid	Suggesting a cost-effective approach and energy management for EVCS-integrated microgrid communities		✓	✓	✓	
[41]	Communities in the city	Assessing the potential for renewable self-consumption considering vehicle-to-grid in regions with high EV penetration.		✓	✓	✓	
Our Study	General	Optimal sizing and technical, economic, and environmental analysis of solar EVCS depending on EV peak time with variable radiation and PV capacity	✓	✓	✓	✓	✓
***OS:** Optimal Sizing, **FB:** Feasibility, **EV-C:** EV Charging, **PV-C:** PV Capacity*							

The main contributions of this study are as follows:

- Optimal HPS sizes with minimum cost for solar-powered EVCSs are investigated, and technical, economic, and environmental feasibility outputs are analyzed considering peak demand periods (morning, midday, and night) that may vary depending on consumer profiles.

- The impact of varying PV capacity (0-900 kW) and solar irradiance (2.5-6.5 kWh/m2/day) on the feasibility output of the proposed HPSs for different peak demand periods is compared technically, economically, and environmentally without limitation of the study field.
- The threshold PV capacities for each solar irradiation are determined according to the self-consumption rate (SCR) limits for the proposed HPSs for different peak demand periods.
- Based on the optimal threshold PV capacities determined for consumers with different peak demand periods, the feasibility outputs are comparatively evaluated according to the decision criteria (SCR, SSR, RF, COE, and DP).

This paper is organized as follows. The literature review and contributions are described in the introduction in Section 1. Methodology, mathematical modeling, objective function and decision criteria, scenarios, and assumptions are discussed in Section 2, materials and methods. Optimization results and comparative analysis are described in Section 3, optimization results. Finally, conclusions and future suggestions are presented in Section 4, conclusions.

II. MATERIALS AND METHOD

The optimization tool used for optimal sizing, technical, economic, and environmental optimization is introduced in Section 2 under the subheading HOMER Program. The system model is described in Section 2.2 under the heading system modeling. At the same time, the scope of the study and scenarios are discussed in Section 2.3 under the heading description of the scenarios. The mathematical modeling of HPSs is discussed in Section 2.4 under the mathematical system modeling subheading, while the objective functions and decision criteria are presented in Section 2.5.

2.1. HOMER Software

Hybrid Optimization of Multiple Energy Resources (HOMER) has three different sub-programs within the company. HOMER Pro, HOMER Grid, and HOMER Front. The most cost-effective solution for off-grid power systems, microgrids, and islanded utilities can be determined in HOMER Pro. HOMER Grid can be used to reduce energy costs for grid-connected installations and EVCS. HOMER Front can be used to maximize the return of grid-scale storage systems with and without PV or wind turbines (WT). But all these can also be used in grid-connected applications [42]. Design optimization and feasibility analysis can be performed on HOMER, which today has more than 250000 users in 193 countries. In this study, the EVCS demand profile was created in HOMER Grid and exported to HOMER Pro. A feasibility analysis was performed in HOMER Pro.

2.2. System Modeling

The analyses are conducted in the HPS model in Figure 2.1.

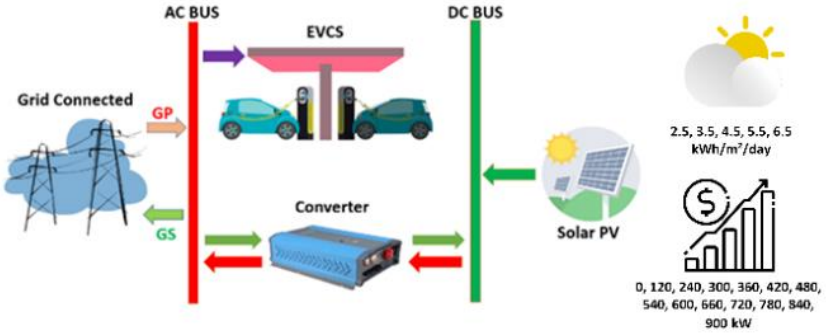


Figure 2.1. HPS model

The study considers that the peak demand periods will vary between morning, midday, and night depending on the consumer profiles. PV power generation is primarily used for different EVCS demands. If there is more demand than energy production, energy is purchased from the grid (GP). The residual energy is sold to the grid (GS). The impact of PV capacity and solar radiation on HPS feasibility is realized through the corresponding model, and HOMER is used as an optimization tool. The installation area of the charging stations should be at least 1600 m^2 according to the regulation on the facilities to be built and opened by the highways in Türkiye [43]. This area is assumed to be maximum of 6000 m^2 for the charging station, considering the charging times and the diversity of electric vehicles (considering that the required area for kW PV is 6.66 m^2). Solar radiation was evaluated as 2.5, 3.5, 4.5, 5.5, and 6.5 kWh/m^2/day, and its effect on feasibility was investigated. In the lower part of the optimization, the temperature data was synchronized depending on the irradiance variation. Although the impact of radiation is observed, location information needs to be included in the optimization. In this context, Antalya province in Türkiye (36° 53.8' latitude and 30° 42.8' longitude) was chosen due to its high radiation potential. In addition, radiation and temperature data were extracted from the National Aeronautics and Space Administration (NASA) database [44]. Antalya's average daily radiation and temperature is 4.5 kWh/m^2/day and 18.23°C [45]. The technical, economic, and environmental optimization inputs used to model the system are summarized in Table 2.1.

Table 2.1: HPS Design Parameters and Assumptions

HPS	Parameter Description		
PV	Manufacturer	Generic	
	Panel type	Flat plate	
	Rated capacity	1	kW
	Capacity range in scenarios	0-900	kW
	Lifetime	20	years
	Derating factor	80	%
	Efficiency	20	%
	Capital cost	1000	$/kW
	Replacement cost	900	$/kW
	O&M cost	10	$/kW/yr
Converter	Manufacturer	Generic	
	Rated capacity	1	kW
	Lifetime	15	years
	Inverter efficiency	98	%
	Rectifier efficiency	95	%
	Relative capacity (rectifier)	100	%
	Capital cost	300	$/kW
	Replacement cost	300	$/kW
	O&M cost	0.02	$/kW/yr
EVCS load	Morning peak time range	07.00-09.00	hours
	PV to load ratio for morning peak demand profile	38	%
	Energy demand for morning peak demand profile	2479	kWh/day
	Midday peak time range	11.00-13.00	hours
	PV to load ratio for midday peak demand profile	48	%
	Energy demand for midday peak demand profile	2505	kWh/day
	Night peak time range	17.00-19.00	hours
	PV to load ratio for night peak demand profile	32	%
	Energy demand for night peak demand profile	2496	kWh/day
	EV charge sessions for all demand profiles	200	sessions/day
	Number of EV chargers	10	
	Peak power due to internal energy demand (heating, cooling) for EVCSs	6.84	kW
	Internal energy demands (heating, cooling, etc.) for EVCSs	50	kWh/day
Grid	Flat tariff (06.00-17.00)	0.10	$/kWh
	Peak tariff (17.00-22.00)	0.16	$/kWh
	Valley tariff (22.00-06.00)	0.056	$/kWh
	Grid sell-back price	0.051	$/kWh
Other	Inflation rate	14	%
	Discount rate	23.3	%
	CO_2 per 1 kWh energy purchase in the grid mix	632	g/kWh
	Project lifetime	20	years
	The range of solar radiation analyzed in the scenarios	2.5-6.5	kWh/m^2/day

The morning peak demand period is 07.00-09.00, the midday peak demand period is 11.00-13.00, and the night peak demand period is 17.00-19.00. PV to load ratios are 38%, 48%, and 32%, respectively. In addition, the daily energy demands are 2479, 2505, and 2496 kWh/day. HPS capital, replacement, and operation and maintenance (O&M) costs are determined according to the future projections of the International Renewable Energy Agency [46]. Depending on the grid mix, the CO_2 value of 1 kWh of energy purchased from the grid proposed by HOMER is 632 g/kWh. For other technical inputs (inverter and rectifier efficiency, PV derating factor, etc.) HOMER recommendations were accepted. The grid tariffs in Türkiye are taken from [47]. Different countries' various time-of-use (TOU) tariffs can directly affect HPS feasibility due to the focus on EVCS peak time. However, the analysis was carried out within the scope of Türkiye. Finally, as a step towards reducing global temperature concerns, the impact of PV capacity and solar radiation on HPS is assessed according to renewable energy potential (self-consumption, RF, etc.) and economic and environmental decision criteria. Although the analysis may vary under different economic conditions (inflation and interest rates, grid tariffs), a general roadmap for the feasibility analysis is presented, and the scope is limited to Türkiye.

2.3. Description of the Scenario

In Section 3, the scenarios created in the study are sorted from 1 to 8 to evaluate the optimization results. The study's main objective is to investigate the possible impacts on PV capacity and solar radiation over the scenarios in the feasibility of the minimum HPS proposed for consumers with different peak demand periods. In this direction, the scenarios considered in the study are evaluated in Table 2.2. The comparison of EVCS demand profiles for HPS at lower PV capacity and lower solar radiation is analyzed in Scenario 1 and Scenario 2 at higher solar radiation. The comparison of EVCS demand profiles for HPS at higher PV capacity and lower solar radiation is analyzed in Scenario 3 and Scenario 4 at higher solar radiation.

Differently, the possible maximum impact of increasing solar radiation on HPS under fixed PV capacity is evaluated in Scenario 5. In contrast, the maximum possible effects of PV capacity under fixed lower solar radiation conditions are analyzed in Scenario 6. The maximum potential impact of increasing PV capacity on HPS under fixed higher radiation conditions is analyzed in Scenario 7. In contrast, the maximum possible hybrid effect of PV capacity and solar radiation is evaluated in Scenario 8.

Table 2.2: Scenarios Considered in the Study

Scenarios	Aim
1	The comparison of EVCS demand profiles for HPS at lower PV capacity and lower solar radiation.
2	The comparison of EVCS demand profiles for HPS at lower PV capacity and higher solar radiation.
3	The comparison of EVCS demand profiles for HPS at higher PV capacity and lower solar radiation.
4	The comparison of EVCS demand profiles for HPS at higher PV capacity and higher solar radiation.
5	The possible maximum impact of increasing solar radiation on HPS under fixed PV capacity.
6	The maximum possible effects of PV capacity under fixed lower solar radiation.
7	The maximum possible impact of increasing PV capacity on HPS under fixed higher radiation.
8	The maximum possible hybrid effect of PV capacity and solar radiation.

2.4. Mathematical System Modeling

In this study, three different formulas are used to represent the PV model. The output power for the PV array is calculated by Eq. 1, while the cell temperature used for the output power under operating conditions is found by Eq. 2. Eq. 3 calculates the PV array's maximum efficiency under normal conditions. All three equations are run in the HOMER background at each time step.

$$P_{PV}(t) = Y_{PV}.f_{PV}.\left(\frac{G_T(t)}{G_{T,STC}}\right).\left[1+\alpha_P.\left(T_C(t)-T_{C,STC}\right)\right] \quad (1)$$

$$T_C(t) = T_a(t) + \frac{G_T(t)}{800}.(T_{NOCT}-20) \quad (2)$$

$$\eta_{mp,STC} = \frac{Y_{PV}}{A_{PV}\,.\,G_{T,STC}} \quad (3)$$

Differently, variable management of the inductor value concerning the load current can reduce switching losses in low-power regions and improve converter efficiency by up to 5% [48]. However, converter management is not considered here. Load following is the optimization controller, which tends to be ideal in systems with much renewable power exceeding the load. At the same time, the converter is operated in the optimization subbase to ensure energy conversion. The converter needs to be managed appropriately and sized for efficient energy flow between DC and AC systems. Unsuitable sizing can lead to excessive and wasted energy. In the converter model consisting of the rectifier and inverter, the inverter and rectifier output powers are calculated in Eq. 4 and Eq. 5, respectively. The DC/AC inverter ratio is formulated in Eq. 6 depending on the PV and converter power fraction.

$$P_{inv}(t) = \eta_{inv}\,.\,P_{DC}(t) \quad (4)$$

$$P_{rec}(t) = \eta_{rec}\,.\,P_{AC}(t) \quad (5)$$

$$\eta_{DC/AC} = \frac{P_{PV}}{P_{Converter}} \quad (6)$$

EV charging time, charging power, and total charging demand can be used for modeling the EV charging profile. The required time for EV charging is calculated in Eq. 7, the charging power in Eq. 8, and the total EV charging demand in Eq. 9.

$$\tau_{e,j} = \left[st_{e,j} + \frac{ER_e}{P_{EV(max)}}\right] \quad (7)$$

$$P_{EV(j)}(t) = \begin{cases} P_{EV(max)}, & if\ t \in \tau_{e,j} \\ 0, & if\ t \notin \tau_{e,j} \end{cases} \quad (8)$$

$$P_{EV}^{t} = \sum_{j=1}^{N_{EV}} P_{EV(j)}(t) \quad (9)$$

2.5. Objective Functions and Decision Criteria

HOMER performs optimal sizing in distributed generation and grid-connected systems with minimum NPC objective. NPC minimization is performed in coordination with COE and offers consumers, investors, and stakeholders hybrid configurations with many possible costs in increasing financial order. Sensitivity analysis extends the study scope and allows for detailed evaluations. Accordingly, the study's main objective is to minimize the total cost at the end of the project lifetime under the highest renewable potential. The second criterion is to minimize COE as much as possible. The third critical criterion is to reduce carbon emissions.

The terms NPC and COE are used to assess costs. NPC is obtained by summing the difference between the discounted cash flows of costs and revenues at the end of each year on a present-day basis. It includes capital cost, replacement cost, O&M cost, fuel cost, and grid purchases. The annual cost is calculated by multiplying the NPC and the capital recovery factor (CRF) by Eq. 10 [49]. While the CRF is formulated in Eq. 11, the annual real discount rate used in the calculations is determined in Eq. 12.

$$NPC = \frac{C_{ann,tot}}{CRF(i,N)} \quad (10)$$

$$CRF(i,N) = \frac{i\,.\,(1+i)^n}{i\,.\,(1+i)-1} \quad (11)$$

$$i = \frac{i' - f}{1 + f} \tag{12}$$

COE represents the average cost per kWh of useful energy the HPS produces [50]. This parameter, as crucial as NPC for consumers regarding energy costs, is formulated in Eq. 13 [51].

$$COE = \frac{C_{ann,tot}}{E_{served}} \tag{13}$$

RF is a fractional expression for the load benefit of RES's total annual energy production. In today's carbon neutrality efforts, it is critical that the RF is represented by Eq. 14 [52], [53].

$$RF = 1 - \frac{E_{nonren}}{E_{served}} \tag{14}$$

It is desired to minimize the potential costs of the EVCS. In this context, the objective function of the sum of the operations and investments regarding the charging station is formulated by Eq. 15. At the same time, the upper and lower limits of the possible number of EVs visiting the EVCS are given by Eq. 16 [54].

$$min_{C_{EVCS}} = \sum_{i=1}^{N_{CS}} \left(C^i_{cap,EV} + C^i_{op,EV} \right) \tag{15}$$

$$0 < N_{CS} \leq N^{max}_{CS} \tag{16}$$

The ratio of PV power generation used in demand to total PV power generation is represented as the self-consumption ratio (SCR). This parameter, a PV-specific measure of how efficiently demand is met in electricity generation, is calculated by Eq. 17. The self-supply ratio (SSR) is calculated by Eq. 18, representing the share of PV energy generation directly transferred to the load and meets the demand. If the SSR is to increase, the share of PV needs to increase according to the EVCS demand [55].

$$SCR = \frac{\sum E^{cons}_{PV}}{\sum E^{gen}_{PV}} \tag{17}$$

$$SSR = \frac{\sum E^{cons}_{PV}}{\sum E_{load}} \tag{18}$$

III. OPTIMIZATION RESULTS

A comparison of the technical, economic, and environmental outcomes of HPS under lower or higher possible PV capacity and solar radiation conditions, depending on different consumer profiles at peak demand time, is shown in Table 3.1. Recalling the scenarios here, lower PV capacity and solar radiation impacts are evaluated in Scenario 1, while lower PV capacity and higher solar radiation impacts are assessed in Scenario 2. Higher PV capacity and lower solar radiation impacts are analyzed in Scenario 3, while higher PV capacity and solar radiation impacts are indicated in Scenario 4. Here, the color green and the numerical value in parentheses show that the profile performs best. Orange indicates the average performance, and red the worst performance. No numerical superiority is stated in parentheses for the worst performances, but it is the basis for determining the superiority of the remaining two profiles. Higher values for SSR and RF and lower for SCR, COE, and DP characterize superior performance. Generally, midday peaks show the best performance, morning peaks show average performance, and night peaks show the worst performance. Moreover, SCR is lower during night peaks when energy production and consumption times do not match.

Table 3.1: Decision Criteria-Based Comparison of HPS Results

Scenarios	SSR (%)	SCR (%)	COE ($/kWh)	RF (%)	DP (yr)	DC/AC (%)
1	Similar	Similar	Midday (%8.4) Morning (%5.05) Night (Base)	Similar	Midday (0.3) Morning (0.1) Night (Base)	Similar
2	Midday (%1.66) Morning (%1.23) Night (Base)	Midday (%8.3) Morning (%6.15) Night (Base)	Midday (%8.95) Morning (%5.05) Night (Base)	Similar	Midday (0.21) Morning (0.14) Night (Base)	Similar
3	Midday (%14.61) Morning (%6.1) Night (Base)	Midday (%21.34) Morning (%12.43) Night (Base)	Midday (%6.4) Morning (%4.92) Night (Base)	Midday (%6.1) Morning (%2.3) Night (Base)	Midday (1.61) Morning (0.73) Night (Base)	Midday (%6.25) Morning (%5) Night (Base)
4	Midday (%8.62) Morning (%8) Night (Base)	Midday (%9.21) Morning (%4.8) Night (Base)	Midday (%29.35) Morning (%20.45) Night (Base)	Midday (%5.8) Morning (%2.7) Night (Base)	Midday (0.62) Morning (0.28) Night (Base)	Similar

Annotation: *The highest performance is in green, and the average is in orange, depending on the base. The base has the worst*

performance.

On the other hand, SCR and RF performances are similar at lower solar irradiance and PV capacities, although they have different peak demand periods. More precisely, the impact of lower PV capacity and solar radiation on HPS is insignificant as the power generation is lower than the consumer demand. As energy conversion is more related to PV capacity than solar radiation, the difference in converter efficiency is remarkable in the proposed HPSs for demand profiles with higher PV capacity and lower solar radiation. A similar relationship holds for RF. The RF results are similar when consumer demand is considered at lower PV capacities, whether low or high solar radiation. Lastly, the numerical advantages of the demand profiles are presented in Table 3.1.

Table 3.2: Evaluation of the HPS Performance

Scenarios	EVCS Demand Profile	INCREASE		DECREASE		
		SSR (%)	*RF (%)*	*COE (%)*	*SCR (%)*	*DP (yr)*
5	*Morning*	17.7	29.3	74.75	35	5.39
	Midday	**39.4**	**31.8**	**82.22**	**40.5**	**5.44**
	Night	14.02	27.8	71.05	31.8	5.26
6	*Morning*	**15.26**	7.41	5.88	7	**1.38**
	Midday	7.61	**7.5**	**6.91**	5.95	0.59
	Night	6.91	7.31	5.77	**8.38**	0.47
7	*Morning*	13.2	16.9	20.5	16.16	**1.52**
	Midday	**23.81**	**18.9**	**27.5**	14.33	0.7
	Night	10	15.8	19.35	**20.92**	0.65
8	*Morning*	47.66	70.81	84	69.13	2.41
	Midday	**56.28**	**73.91**	**85.87**	64.35	**2.73**
	Night	39.7	68.11	81.7	**73.42**	2.14

Annotation: *The highest impact is shown in green. Moreover, the DC/AC inverter ratio, which is not expressed in the analysis section B.4, shows a similar decrease of 59.02% for morning peaks, 58.65% for midday peaks, and 59.02% for night peaks.*

Conversely, the maximum possible impact of increasing solar radiation at fixed PV capacity on the proposed minimum cost optimal HPSs for consumers with different demand profiles is evaluated in Scenario 5 in Table 3.2. In contrast, the maximum possible impact of increased PV capacity at lower fixed solar radiation is analyzed in Scenario 6. The same investigation is repeated at higher fixed solar radiation in Scenario 7. Finally, Scenario 8 assesses the maximum possible impacts of the combined increase of PV capacity and solar radiation. For instance, if the effect of increased solar radiation is questioned, the possible increases are calculated based on the value at lower radiation. The same criterion applies to PV capacity and hybrid assessments. Here, the green color shows which demand profiles are more affected depending on the scenario analysis. As for results, solar radiation has higher impacts than PV capacity. The combined effect has a higher impact than these two individual effects. Under constant PV capacity, increasing solar radiation significantly impacts consumers in the midday peak profile. This is followed by the morning peak and night peak profiles. The impacts of PV capacity increases on HPS under low radiation conditions vary for different peak demand profiles depending on the decision criteria. In contrast, increased PV capacity under high radiation conditions mostly affects consumers with a peak demand profile more. The combined effect of PV capacity and irradiance similarly affects mostly midday peak demand profiles. However, the SCR decrease is higher in night peak demand profiles due to the energy generation and consumption mismatch.

Otherwise, regions with high radiation potential can reduce COE by around 12%, even at low PV capacities. Potential increases in PV capacity can further reduce COE by 66.2%, providing efficient energy production economics. HPSs could become the government's favorite for climate targets under these conditions, increasing the RF by 58.7% and the SSR by 35.7%. However, SCR close to the 30% limit can cause overvoltage problems for HPSs expected to be connected to distribution networks, especially at critical busbars. Moreover, high PV capacities increase essential costs such as investment, extending the DP by up to 3 years. Especially the increased payback periods will not satisfy investors. Conversely, the impact of increasing radiation at low PV capacities shows a similar trend (<5%) for consumers with time-variability in peak demand, especially in terms of self-consumption potential change. However, the beneficial effect of radiation is more apparent in consumer profiles with the peak demand in the nighttime.

Differently, the higher radiation increases the converter capacity, reducing the DC/AC inverter ratio by up to 61.3%. This reduction in the AC/DC inverter ratio can be compensated for up to 6.7% by increasing the PV capacity. Considering the dominance of increased radiation benefits at low PV capacity, the DP for all demand profiles can be shortened to 5.4 years. Moreover, night peak profiles can provide shorter payback periods. Although the three demand profiles generally have similar benefits and drawbacks for the decision criteria regarding increased PV capacity and radiation impacts, significant differences are observed under specific conditions. For instance, the highest SCR decrease and SSR increase are observed in the midday demand profile, while the highest RF increase is observed in the morning demand profile. However, it can be said that SSR and RF outcomes are close to each other. Moreover, the increased PV capacity has made the midday peak demand profile more feasible as the payback period is one year shorter.

On the other hand, the optimal PV capacities for consumers with different peak demand periods depending on each solar horizontal radiation are shown in Table 6. Here, the optimization results are evaluated according to the decision criteria (SCR, SSR, RF, and DP), and the optimal breakpoints are determined. The optimization results are nonsensical for values above the PV capacities specified for each solar irradiance in Table 3.3.

Table 3.3: Optimal PV Capacity for Each Horizontal Irradiance Considering Different Peak Demand Periods

EVCS Demand Profile	Solar horizontal irradiation (kWh/m²/day)				
	2.5	3.5	4.5	5.5	6.5
	Optimal PV capacities (kW) for different peak period demand profiles based on solar horizontal irradiation				
Morning	500	500	500	500	500
Midday	900	900	600	600	600
Night	900	900	900	700	700

Overall, the maximum threshold PV capacity recommended for consumers with morning peak periods is 500 kW. Due to the supply-demand mismatch, a higher threshold PV capacity is recommended for night demand periods. Given the lack of supply-demand matching compared to other demand profiles, higher PV capacities are expected to increase the revenue from the sale of residual energy to the grid. In this way, it is hoped to reduce the higher COE compared to other demand profiles. Therefore, 900 kW of PV capacity up to 5.5 kWh/m^2/day of solar radiation is recommended for consumers with a night peak demand profile. For solar radiation of 5.5 kWh/m^2/day and above, the PV capacity decreases to 700 kW. In contrast, in midday demand profiles, where PV power generation and peak demands match, efficiently meeting peak demands provides the advantage of lower COE. Potential increases in solar radiation do not require an increase in PV capacity. To avoid costly HPS investments, PV capacity is lower for solar radiation of 4.5 kWh/m^2/day and above than for night demand profiles.

HPS outputs of consumers with different peak demand periods for the optimal PV capacities depending on the relevant irradiances in Table 3.3 are given in Table 3.4.

Table 3.4: HPS Outputs of Consumers with Different Peak Demand Periods for Optimal PV Capacities Depending on The Relevant Irradiances

HPS outputs	EVCS Demand Profile	Solar Horizontal Radiation (kWh/m²/day)				
		2.5	*3.5*	*4.5*	*5.5*	*6.5*
SSR (%)	*Morning*	31.15	37.82	42.27	45.5	47.0
	Midday	49.74	56.05	54.31	57.3	59.0
	Night	35.13	40.58	43.38	43.0	44.27
SCR (%)	*Morning*	81.88	65.88	54.18	47.76	46.86
	Midday	72.64	54.24	58.0	50.11	49.0
	Night	51.3	39.27	30.9	32.25	31.55
RF (%)	*Morning*	34.6	46.8	56.0	62.0	63.9
	Midday	56.3	68.4	65.4	71.0	72.8
	Night	50.2	61.7	69.6	68.3	69.8
DP (year)	*Morning*	10.7	8.82	7.76	7.07	6.81
	Midday	11.28	9.6	7.54	6.96	6.7
	Night	12.9	10.68	9.4	8.05	7.74
DC/AC Ratio	*Morning*	2.59	1.68	1.24	1.09	1.07
	Midday	2.52	1.65	1.27	1.09	1.09
	Night	2.40	1.71	1.20	1.09	1.09

The breakpoints where the optimization trade-off is disturbed due to the increase in SSR and RF and the decrease in SCR (minimum 30%) and DP are determined as the PV capacity threshold in Table 3.3, and according to the PV capacities in Table 3.4, higher solar radiation reduced the optimal PV capacity by up to 33.33% for consumers during midday peak demand periods. A similar analysis shows that consumers' optimal PV capacity is reduced by up to 22.22% in night peak demand periods. Higher optimum PV capacity is promising for SSR, SCR, and RF potential while increasing costs extend the payback period to 2.2 years. However, this financial drawback is overcome up to 1.16 years at higher solar radiation. Many decision criteria values can be easily seen and analyzed in the table. When the feasibility results of the threshold PV capacities at each irradiance are evaluated, the SSR is 15.85% higher for the morning, 9.26% higher for midday, and 9.14% higher for the night at higher solar radiation. In contrast, SCR decreases by 35.02%, 23.64%, and 19.75%, respectively. Due to power quality issues, it is not desirable for SCR to fall below 30% at critical bus nodes, and the evaluations were carried out according to the relevant limit [56]. Therefore, while the share of PV capacity-dependent power generation in meeting the electricity demand of the consumer increases, the efficient power generation within the PV capacity itself decreases. Similar to the SSR, for consumers with morning, midday, and night demand profiles, the RF increases by 29.3%, 16.5%, and 19.6%, depending on the threshold PV capacities at higher solar radiation. DC/AC converter efficiency reduces with increasing solar radiation due to decreasing threshold PV capacities. Finally, with the superiority of benefits, the payback periods of HPSs with morning, midday, and night peak demand profiles can be shortened to 3.89, 4.58, and 5.6 years, respectively.

IV. CONCLUSION

This article analyzes technical, economic, and environmental HPS outputs based on EVCS demand profiles for different peak demand periods (morning, midday, and night). In addition, many sensitivity analyses have been carried out for HPS with various PV capacities and solar radiation. The HPS outputs of different EVCS profiles for peak demand periods are comparatively evaluated for higher or lower solar radiation or PV capacity. Moreover, the maximum possible impact of solar radiation or PV capacity on HPS is analyzed for different demand profiles, individually or combined. Also, threshold PV capacities for each solar irradiance condition are determined for consumers in morning, midday, and night peak demand periods based on the decision criteria. The outputs of the HPS for the relevant threshold or optimal capacity installations are evaluated for different demand profiles.

The results support the superiority of midday peak demand periods at lower or higher PV capacity or radiation for many HPS output decision criteria. In addition, the maximum possible impact of increased solar radiation on HPS at fixed PV capacity is higher than increased PV capacity at higher or lower fixed solar radiation. Moreover, higher solar radiation can shorten the DP by up to 5.4 years for all demand profiles at lower PV capacity. Also, higher radiation can reduce the optimal PV capacity of consumers by up to 22.22% and 33.33% in peak demand periods at night and midday. Although higher threshold PV capacity increases the SSR, SCR, and RF potential, the rising costs extend the payback period to 2.2 years. Under these conditions, increased solar radiation can overcome the relevant drawback by up to 1.16 years.

The results of this study can help in the initial phase of climate-based development policies and expand the profile of prosumers with incentives for carbon neutrality provided by governments. The results of this study can be extended in the future using many net zero carbon policies such as net metering, net billing, gross metering, renewable portfolio standard, grid parity, investment subsidies, carbon tax, carbon reduction subsidies, etc. Moreover, fresh and second-life batteries can be compared for the inclusion of ESSs, or the feasibility of HPS with hybrid energy storage systems (supercapacitor, flywheel, battery, etc.) can be investigated at the national level.

NOMENCLATURE AND ABBREVIATIONS

AEF_{EV}	The average emission factor of the fuel mix
A_{PV}	Area of the PV panel (m^2)
$C_{ann,tot}$	Total annualized cost ($/yr)
$C^i_{cap,EV}$	The installation cost of EV station i ($)
$C^i_{op,EV}$	The operational cost of EV station i ($)
$CRF(i,N)$	Capital recovery factor (%)
e	EV type (cars)
E_{nonren}	Conventional energy (kWh/yr)
ER_e	The average required energy for EV type e (kWh)
E_{served}	Total electrical load served (kWh/yr)
f	Expected inflation rate (%)
f_{PV}	PV derating factor (%)
$G_T(t)$	Solar radiation in t (kW/m^2)
$G_{T,STC}$	Measurement of incident radiation at STC (1 kW/m^2)
i	Annual real interest rate (%)
i'	Nominal interest rate (%)
j	EV user index
$min_{C_{EVCS}}$	The objective function for minimizing the EVCS costs ($)
N	Project lifetime (year)
n	Number of years
N_{CS}	Number of selected charging stations
N_{CS}^{max}	The maximum allowable number of chargers at a station
N_{EV}	Number of EVs from each type of e
$P_{AC}(t)$	AC power input (kW)
$P_{DC}(t)$	DC power input (kW)
P^t_{EV}	Total EV load at time t (kW)
$P_{EV(j)}(t)$	Charging power of each j EV of type e at time t (kW)
$P_{EV_{(max)}}$	Maximum charging power in a slow mode (kWh)
$P_{inv}(t)$	The power output of the inverter (kW)
$P_{rec}(t)$	The power output of the rectifier (kW)
$P_{PV}(t)$	PV output power at time t (kW)
P_{PV}	PV output power (kW)
$P_{Converter}$	Converter output power (kW)
$st_{e,j}$	Starting time of charge j EV of type e (hour)
$T_C(t)$	Cell temperature under operating conditions (°C)
$T_{C,STC}$	PV cell temperature under STC (25°C)
T_{NOCT}	Normal operation cell temperature (°C)
$T_a(t)$	Ambient temperature (°C)
Y_{PV}	PV array-rated capacity in STC
α_P	Temperature coefficient of power (0.1%/°C)
$\eta_{DC/AC}$	DC/AC energy conversion efficiency of the converter
η_{inv}	Inverter efficiency (%)
$\eta_{mp,STC}$	Maximum efficiency of the PV panels at STC (%)
η_{rec}	Rectifier efficiency (%)
$\tau_{e,j}$	The time horizon for the charging of each j EV of type e (hour)
$\sum E_{load}$	Total load demand (kWh/yr)
$\sum E^{cons}_{PV}$	Total PV energy directly transferred to the load (kWh/yr)
$\sum E^{gen}_{PV}$	Total PV generation (kWh/yr)
BESS	Battery energy storage systems
COE	Cost of energy ($/kWh)

DP	Discounted payback period (yr)
ESS	Energy storage systems
EV	Electric vehicle
EVCS	Electric vehicle charging station
GP	Grid purchase (kW)
GS	Grid sale (kW)
HOMER	Hybrid optimization of multiple energy resources
HPS	Hybrid power systems
LCOE	Levelized cost of energy ($/kWh)
NASA	National Aeronautics and Space Administration
NPC	Net present cost ($)
O&M	Operating and maintenance cost ($)
PV	Photovoltaic panel
RF	Renewable fraction (%)
SCR	Self-consumption rate (%)
SSR	Self-supply rate (%)
STC	Standard test conditions
TOU	Time of use
WT	Wind turbine

REFERENCES

[1] Min Y., Lee H.W. and Hurvitz P. M. 2023. Clean energy justice: Different adoption characteristics of underserved communities in rooftop solar and electric vehicle chargers in Seattle. Energy Research & Social Science, 96: 102931.

[2] Singh S., Chauhan P. and Singh N. J. 2021. Feasibility of Grid-connected Solar-wind Hybrid System with Electric Vehicle Charging Station. Journal of Modern Power Systems and Clean Energy, 9(2): 295–306.

[3] Shafiq A. vd. 2022. Solar PV-Based Electric Vehicle Charging Station for Security Bikes: A Techno-Economic and Environmental Analysis. Sustainability, 14(21).

[4] Ullah Z. vd. 2023. Optimal scheduling and techno-economic analysis of electric vehicles by implementing solar-based grid-tied charging station. Energy, 267: 126560.

[5] Lai C.S. vd. 2022. Profit maximization for large-scale energy storage systems to enable fast EV charging infrastructure in distribution networks. Energy, 259.

[6] Bastida-Molina P., Hurtado-Pérez E., Moros Gómez M.C. and Vargas-Salgado C. 2022. Multicriteria power generation planning and experimental verification of hybrid renewable energy systems for fast electric vehicle charging stations. Renewable Energy, 179: 737–755.

[7] Kılınç C. 2022. Hibrit Yenilenebilir Enerji Sistemleri ile Sera Sulama Sistemi Tasarımı: İzmir Örneği. Politeknik Dergisi, 25(1): 435–442.

[8] Ji D., Lv M., Yang J. and Yi W. 2020. Optimizing the Locations and Sizes of Solar Assisted Electric Vehicle Charging Stations in an Urban Area. IEEE Access, 8: 112772–112782.

[9] Fachrizal R., Shepero M., Åberg M. and Munkhammar J. 2022. Optimal PV-EV sizing at solar powered workplace charging stations with smart charging schemes considering self-consumption and self-sufficiency balance. Applied Energy, 307: 118139.

[10] Amir M., Haque A., Bakhsh F. I., Kurukuru V.S.B. and Sedighizadeh M. 2023. Intelligent energy management scheme-based coordinated control for reducing peak load in grid-connected photovoltaic-powered electric vehicle charging stations. IET Generation, Transmission and Distribution.

[11] A. K. Karmaker, M. A. Hossain, H. R. Pota, A. Onen, ve J. Jung, "Energy Management System for Hybrid Renewable Energy-Based Electric Vehicle Charging Station", IEEE Access, c. 11, sayı March, ss. 27793–27805, 2023.

[12] Nishanthy J., Charles Raja S., Praveen T., Jeslin Drusila Nesamalar J. and Venkatesh P. 2022. Techno-economic analysis of a hybrid solar wind electric vehicle charging station in highway roads. International Journal of Energy Research, 46(6): 7883–7903.

[13] Boddapati V., Rakesh Kumar A., Arul Daniel S. and Padmanaban S. 2022. Design and prospective assessment of a hybrid energy-based electric vehicle charging station. Sustainable Energy Technologies and Assessments, 53: 102389.

[14] AlHammadi A., Al-Saif N., Al-Sumaiti A.S., Marzband M., Alsumaiti T. and Heydarian-Forushani E. 2022. Techno-Economic Analysis of Hybrid Renewable Energy Systems Designed for Electric Vehicle Charging: A Case Study from the United Arab Emirates. Energies, 15(18).

[15] Al-Buraiki A.S. and Al-Sharafi A. 2021. Technoeconomic analysis and optimization of hybrid solar/wind/battery systems for a standalone house integrated with electric vehicle in Saudi Arabia. Energy Conversion Management, 250: 114899.

[16] Ren H., Ma Z., Fai Norman Tse C. and Sun Y. 2022. Optimal control of solar-powered electric bus networks with improved renewable energy on-site consumption and reduced grid dependence. Applied Energy, 323: 119643.

[17] dos Santos P.D., Zambroni de Souza A.C., Bonatto B. D., Mendes T.P., Neto J.A.S. and Botan A.C.B. 2021. Analysis of solar and wind energy installations at electric vehicle charging stations in a region in Brazil and their impact on pricing using an optimized sale price model. International Journal of Energy Research, 45(5): 6745–6764.

[18] Sierra A., Gercek C., Geurs K. and Reinders A. 2020. Technical, Financial, and Environmental Feasibility Analysis of Photovoltaic EV Charging Stations with Energy Storage in China and the United States. IEEE Journal of Photovoltaics, 10(6): 1892–1899.

[19] Rodriguez A.S., Santana T.D., MacGill I., Ekins-Daukes N. J. and Reinders A. 2020. A feasibility study of solar PV-powered electric cars using an interdisciplinary modeling approach for the electricity balance, CO2 emissions, and economic aspects: The cases of The Netherlands, Norway, Brazil, and Australia. Progress in Photovoltaics: Research and Applications, 28(6): 517–532.

[20] Himabindu N., Santoshkumar H., Deepa B. and Swapna M. 2021. Analysis of microgrid integrated Photovoltaic (PV)

Powered Electric Vehicle Charging Stations (EVCS) under different solar irradiation conditions in India: A way towards sustainable development and growth. Energy Reports, 7: 8534–8547.
[21] Li J., He S., Yang Q., Ma T. and Wei Z. 2022. Optimal Design of the EV Charging Station with Retired Battery Systems Against Charging Demand Uncertainty. IEEE Transactions on Industrial Informatics, 3203: 1–11.
[22] C. Leone, M. Longo, L. M. Fernandez-Ramirez, ve P. Garcia-Trivino, "Multi-Objective Optimization of PV and Energy Storage Systems for Ultra-Fast Charging Stations", IEEE Access, c. 10, ss. 14208–14224, 2022.
[23] J. O. Oladigbolu, A. Mujeeb, A. A. Imam, ve A. M. Rushdi, "Design, Technical and Economic Optimization of Renewable Energy-Based Electric Vehicle Charging Stations in Africa: The Case of Nigeria", Energies, c. 16, sayı 1, 2023.
[24] Li C., Shan Y., Zhang L., Zhang L. and Fu R. 2022. Techno-economic evaluation of electric vehicle charging stations based on hybrid renewable energy in China. Energy Strategy Reviews, 41: 100850.
[25] Alphonse A.R.A., Raj A.P.P.G. and Arumugam M. 2022. Simultaneously allocating electric vehicle charging stations (EVCS) and photovoltaic (PV) energy resources in smart grid considering uncertainties: A hybrid technique. International Journal of Energy Research, 46(11): 14855–14876.
[26] Emrani-rahaghi P., Hashemi-dezaki H. and Hasankhani A. 2021. Optimal stochastic operation of residential energy hubs based on plug-in hybrid electric vehicle uncertainties using two-point estimation method. Sustainable Cities and Society, 72: 103059.
[27] Khan S., Sudhakar K., Bin Yusof M.H., Azmi W.H. and Ali H.M. 2023. Roof integrated photovoltaic for electric vehicle charging towards net zero residential buildings in Australia. Energy for Sustainable Development, 73: 340–354.
[28] Long Y.L. vd. 2021. Impact of EV load uncertainty on optimal planning for electric vehicle charging station. Science China Technological Sciences, 64(11): 2469–2476.
[29] Sureshbabu S., Padmanabhan G., Subramanian A.A., Stonier G.P. and Ganji V. 2022. Design and analysis of a photovoltaic-powered charging station for plug-in hybrid electric vehicles in college campus. IET Electrical Systems Transportation, 12(4): 358–368.
[30] Ghotge R., Snow Y., Farahani S., Lukszo Z. and van Wijk A. 2020. Optimized scheduling of EV charging in solar parking lots for local peak reduction under EV demand uncertainty. Energies, 13(5).
[31] Good C., Shepero M., Munkhammar J. and Boström T. 2019. Scenario-based modelling of the potential for solar energy charging of electric vehicles in two Scandinavian cities. Energy, 168: 111–125.
[32] Domínguez-Navarro J. A., Dufo-López R., Yusta-Loyo J. M., Artal-Sevil J. S. and Bernal-Agustín J. L. 2019. Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems. International Journal od Electric Power Energy Systems, 105: 46–58.
[33] Frri A.A.M. and Guneser M. T. 2022. Yük Belirsizliği Koşullarında Pratik Radyal Dağıtımlı Besleyicide DER'lerin Tekno-Ekonomik ve Çevresel Faydaları. Journal of Polytechnic, 900(2): 731–741.
[34] Sadeghi D., Hesami N. A. and Bahramara S. 2020. Optimal sizing of hybrid renewable energy systems in presence of electric vehicles using multi-objective particle swarm optimization. Energy, 209: 118471.
[35] Fretzen U., Ansarin M. and Brandt T. 2021. Temporal city-scale matching of solar photovoltaic generation and electric vehicle charging. Applied Energy, 282: 116160.
[36] Leone C., Peretti C., Paris A. and Longo M. 2022. Photovoltaic and battery systems sizing optimization for ultra-fast charging station integration. Journal of Energy Storage, 52: 104995.
[37] Allouhi A. and Rehman S. 2023. Grid-connected hybrid renewable energy systems for supermarkets with electric vehicle charging platforms : Optimization and sensitivity analyses. Energy Reports, 9: 3305–3318.
[38] Merrington S., Khezri R. and Mahmoudi A. 2023. Optimal sizing of grid-connected rooftop photovoltaic and battery energy storage for houses with electric vehicle, IET Smart Grid.
[39] Li C., Zhang L., Ou Z., Wang Q., Zhou D. and Ma J. 2022. Robust model of electric vehicle charging station location considering renewable energy and storage equipment. Energy, 238: 121713.
[40] Ahmad F., Alam M. S., Shariff S. M. and Krishnamurthy M. 2019. A cost-efficient approach to EV charging station integrated community microgrid: A case study of indian power market, IEEE Transactions on Transportation Electrification, 5(1): 200–214.
[41] Bartolini A., Comodi G., Salvi D. and Østergaard P. A. 2020. Renewables self-consumption potential in districts with high penetration of electric vehicles. Energy, 213: 118653.
[42] HOMER 2023. https://www.homerenergy.com/products/pro/docs/index.html
[43] Ekren O., Hakan C.C. and Güvel Ç.B. 2021. Sizing of a solar-wind hybrid electric vehicle charging station by using HOMER software. Journal of Cleaner Production, 279: 123615.
[44] NASA, Prediction of Worldwide Energy Resource (POWER) database, 2023.
[45] Solargis, Global Solar Atlas, 2023. https://globalsolaratlas.info/map
[46] I. R. E. Agency, IRENA (2021), Renewable Power Generation Costs in 2020, Abu Dhabi, 2020.
[47] Demirci A., Ozturk Z. and Tercan S. M. 2023. Decision-making between hybrid renewable energy configurations and grid extension in rural areas for different climate zones. Energy, 262: 125402.
[48] Selamoğulları U. S. 2020. Yenilenebilir Enerji Kaynaklarına Sahip Bir Evin Talep Karakteristiğine Uygun Bir İnverter Tasarımının İncelenmesi. Politeknik Dergisi, 23(2): 257–265.
[49] Ozturk Z. and Demirci A. 2023. Yenilenebilir Enerji Kaynaklı Hibrit Güç Sistemlerinin Farklı Penetrasyon ve Şebeke Tarifeleri Altında Optimizasyonu. Journal of Polytechnical.
[50] Ozturk Z., Demirci A., Tosun S. and Ozturk A. 2021. Technic and Economic Effects of Changes in the Location of Industrial Facilities in Industrializing Regions on Power Systems. 2021 13th International Conference on Electrical and Electronics Engineering (ELECO), 11–17.
[51] Terkes M., Ozturk Z., Demirci A. and Tercan S. M. 2023. Optimal sizing and feasibility analysis of second-life battery energy storage systems for community microgrids considering carbon reduction. Journal of Cleaner Production.
[52] Salameh T., Abdelkareem M.A., Olabi A.G., Sayed E. T., Al-Chaderchi M. and Rezk H. 2021. Integrated standalone hybrid solar PV, fuel cell and diesel generator power system for battery or supercapacitor storage systems in Khorfakkan, United Arab Emirates. Int. J. Hydrogen Energy, 46(8): 6014–6027.

[53] C. Li vd. 2021. Techno-economic and environmental evaluation of grid-connected and off-grid hybrid intermittent power generation systems: A case study of a mild humid subtropical climate zone in China. Energy, 230: 120728.
[54] Asna M., Shareef H., Achikkulath P., Mokhlis H., Errouissi R. and Wahyudie A. 2021. Analysis of an Optimal Planning Model for Electric Vehicle Fast-Charging Stations in Al Ain City, United Arab Emirates. IEEE Access, 9: 73678–73694.
[55] Demirci A., Akar O. and Ozturk Z. 2022. "Technical-environmental-economic evaluation of biomass-based hybrid power system with energy storage for rural electrification. Renewable Energy, 195: 1202–1217.
[56] Ahmed E.E.E. and Demirci A. 2022. Assessment of overvoltage and power losses in low voltage distribution networks with high photovoltaics penetration based on prosumers' self-consumption. 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), 1–4.