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Article

Simplified Python Models for Photovoltaic-Based Charging Stations for Electric Vehicles Considering Technical, Economic, and Environmental Aspects

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Abstract: This paper proposes Python models for a photovoltaic-based charging station for electric vehicles considering technical, economic, and environmental aspects. The proposed models consider two main cases of photovoltaic-based charging systems, which are photovoltaic/grid-charging systems and photovoltaic/grid/battery-charging systems. Moreover, additional operational options, such as exporting energy to the grid and zero-export, are added to the proposed models. The proposed techno-economic models can be used to evaluate the location of the electric vehicle charging station and the financial and environmental benefits of the electric vehicle charging station that is installed in a residential, commercial, or industrial context. The models are tested by proposing a simulation based on load demand, and then different cases, including the actual size case and additional trading cases, are investigated.

Keywords: electric vehicles; photovoltaic; modeling; python

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1. Introduction

The transportation industry has often been considered the world's greatest producer of greenhouse gases and a significant cause of local air pollution. According to [1], the transportation industry currently consumes more than 55% of total oil consumption and emits around 25% of total CO_2 emissions. When it comes to decreasing this global and local pollution, electric vehicles (Evs) are expected to be a vital technology. Thus, electric vehicles must be widely adopted by the transportation sector in order to provide significant environmental benefits. Following that, multiple types of electric vehicles have been marketed by automakers, including hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) [2].

In fact, there are two main challenges that the general public may face while switching to electric vehicles: the high cost of electric vehicles and the unavailability of charging stations [3]. On the other hand, the lack of infrastructure for charging Evs can be a huge challenge for their adoption. As a result, the need for more dependable systems with shorter EV charging times is becoming more essential [4].

As the number of electric vehicles on the road may grow at an exponential rate, the infrastructure and operators of distribution networks are confronted with new issues regarding the quality of low-voltage transmission networks [5]. The primary issues that need to be addressed when integrating electric vehicles into the electrical grid are high electrical power demands, network voltages, power losses, stability, harmonic distortion, and system efficiency. Proper development and planning of electric vehicle charging station (EVCS) infrastructures may help to limit the negative impact on the distribution systems [6].

One of the most frequent planning actions of EV charging stations (CS) is the optimal placement and sizing of these stations. Mohsenzadeh et al. [7] discuss the optimal placement and sizing of electric vehicle parking lots, as well as the several levels of charging stations (slow, medium, and rapid). For optimal planning, an objective function that takes into account system reliability, power loss, voltage drop, and the cost/revenue of EV parking lots is suggested. Similar work is carried out in [8] with an aim to minimize the land cost, equipment cost, operating cost, and real power loss cost as objective functions. On the other hand, environmental factors and the service radius of EV charging stations are taken into account to identify the best locations for EV charging stations in [9]. A new method for EV station site selection was proposed in [10]. Meanwhile, by using a multi-objective optimization approach, the authors in [11] were able to find the optimal locations and sizes for distributed generations (DGs), taking into account factors such as the total number of Evs in each zone. A novel approach by [12] is proposed for assessing the effect of integrating a large number of Evs into a power system and their effect on the network voltage profile via reactive power injection into heavily loaded buses. Meanwhile, the ideal location and sizing of charging stations and renewable energy sources (RES) are determined by using a multi-objective optimization problem in [13,14] as well. In the aforementioned research papers, simple models for EVCS were considered. The authors of [7–15] considered the EVCS as a simple load or a simple source of energy, whereas; the most concern was given to the formulation of the objective function. Meanwhile, the model of the EVCS and the accuracy of its output greatly affect the optimization results.

On the other hand, another important topic in EV science is its feasibility. In Ref. [16], the authors conducted an economic analysis of residential photovoltaic systems integrated with electric vehicles, taking into future cost estimates for these technologies. In Ref. [17], a data-intensive technical-economic model is proposed to estimate the cost of charging a renewable-powered battery with a 16-kWh capacity for an average travel distance of 65 km. An optimal PV-EV sizing framework for solar-powered charging stations based on load-matching performance is presented in [18]. The suggested framework in this study includes a unique score, the self-consumption-sufficiency balance (SCSB), which reflects the balance between self-consumption (SC) and self-sufficiency (SS). Similarly, the economic feasibility of a photovoltaic battery (PVB) system for several residential customer groups in Switzerland is examined in [19] using a techno-economic optimization model based on yearly energy consumption, rooftop size, annual radiation, and location. Here also, the accuracy of the adapted model is very critical to ensure that it affects the accuracy of the research output.

In addition to that, the power of EV charging stations by PV systems is a very trending topic nowadays. In Ref. [20], a system that combines an energy storage system (ESS) with a photovoltaic (PV) source and an electric vehicle charger is suggested. In Ref. [21], an office building in southern Italy is analyzed for the implementation of a solar system to meet its electric, heating, cooling, and EV charging needs. An empirical study [22] of the charging and mobility habits of 78 Swiss BEV owners over a decade is presented. Data on the precise roof geometry and PV capacity of each BEV owner's residence are extracted using Switzerland's fine-grained digital surface model. An electric vehicle (EV) charging station powered by solar photovoltaic (PV) canopies is being developed [23] for the parking infrastructure of large-scale shops. Similarly, a solar-powered electric vehicle charging station in India is discussed in detail in [24]. Furthermore, in [25], a 10 kW solar-powered EV charger with V2G for workplaces in the Netherlands is discussed. In Ref. [26], a PEV charging station employing PV panels at a workplace parking garage is analyzed. Photovoltaics systems used for EV charging in Tromso, Norway, and Uppsala, Sweden, are presented in [27] to evaluate self-consumption and self-sufficiency in these two Scandinavian towns. A stochastic model based on survey data was used to construct EV charging schedules. Each scenario has an EV penetration level between ten percent and one hundred percent. Finally, Hybrid solar photovoltaic (PV) and wind turbine (WT) power systems for environmentally friendly electric vehicle (EV) charging stations at five different sites in China are discussed in [28]. The HOMER Pro 3.14 program, which uses a derivative-free algorithm, has searched for the best charging station design. The hybrid PV/WT/battery EV charging station was the best solution for renewable energy charging stations in the five regions studied. Furthermore, the charging station in Nanjing is the most cost-effective, while the charging station in Zhengzhou is the least.

In general, the reviewed literature examines various techno-economic models for electric vehicles coupled with distributed energy resources. Techno-economic models are frequently used to evaluate the financial and environmental benefits of various distributed energy resources installed in residential, commercial, or industrial buildings and optimize them compared to a base scenario with no distributed energy resources. All of these researches are usually conducted based on the EV system model. Here, the model's accuracy is a very important issue that affects the accuracy of the overall results. Thus, this paper particularly aims at developing an EV system model that combines distributed battery storage and renewable power sources. This study will focus solely on the PV-grid charging method and will examine a scenario that integrates a storage battery. Python programming language will be used to develop a model capable of solving various situations involving different PV capacities and storage batteries along with EV demand data.

The rest of the paper comes in three sections, whereas Section 2 presents the steps of developing the proposed model considering technical, environmental, and financial aspects. Meanwhile, Section 3 provides the performance of the proposed model considering different operation scenarios. Finally, a conclusion section is provided as Section 4.

2. Modeling of EV Charging/Discharging System with Renewable Energy Resources

The high current drawn when charging electric vehicles puts an additional burden on the grid. Additionally, if the charging demand occurs during peak hours, the owner may pay a higher tariff. Integrating PV systems in the charging cycle can reduce peak demand and improve grid stability [29].

Both PV-grid and PV-standalone charging methods are already available, and both have their advantages and disadvantages. Using grid electricity to continually charge the EV while the sun isn't shining is a significant benefit of the PV-grid charging method. Moreover, PV-grid charging allows the EV to be constantly charged even when the irradiance is insufficient. On the other hand, the PV-standalone is a better option when grid power is unavailable or too expensive [29].

There are two types of EV chargers: alternating current (onboard) chargers and direct current (out-board) chargers. When using an AC charger, the conversion of grid alternating current (AC) into direct current (DC) for battery charging takes place inside the vehicle; however, DC chargers convert the grid alternating current into direct current outside the vehicle and within the charger circuit itself [30].

EV battery chargers may be classified into three categories based on their power ratings: level 1, level 2, and level 3. On-board battery chargers have physical limitations due to their size and weight. Therefore, they are typically compatible with level 1 and level 2 chargers only [31]. The properties of the three different power levels are summarized in Table 1.

Table 1. EV battery chargers classification.

Power Level	Charger Location	Typical Use	Typical Power	Charging Time
Level 1	On-board	Home	1.3–2.4 kW	40–50 h
Level 2	On-board	Home, Workplace, and Public	6.6–22 kW	4–8 h
Level 3	Off-board	Public DC Fast Station	50–350 kW	<1 h

Level 1 chargers are the slowest of the three types of chargers. They are commonly utilized in domestic applications and have a power output of about 2 kW. The power range for Level 2 is 6.6kW to 22 kW. This charger has charge periods ranging from 4 to 8 h, and it is mostly utilized in commercial and public charging applications. Level 3 is the DC fast charger, which has a charging capability of up to 350 kW. It can charge an electric vehicle in less than one hour in commercial and public fast-charging stations.

EV load profiles are generated by providing information on the number of vehicles, manufacturer, arrival time, the initial and final states of charge, traveled distance, and typical charging periods.

2.1. EV-Load Profile Generation

In this research, HOMER Grid software is used to build the EV-load profile as it can be seen in Figure 1. This software generates the load profile based on multiple inputs. This includes the percentage of vehicles with access to charging stations, the maximum amount of power allowed to charge the electric vehicle, and the average time required to charge the vehicle in minutes. The following table (Table 2) shows the input parameters used in the model generation:

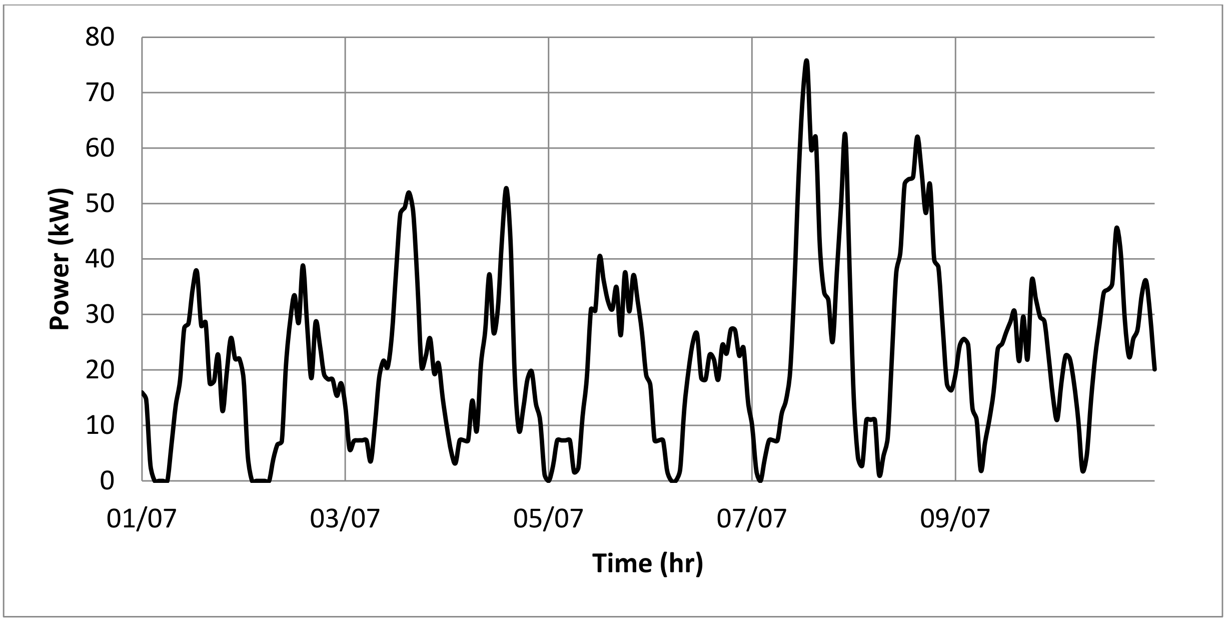

Figure 1. Generated EV-load profile.

Table 2. Input parameters to generate EV load profile [29,30].

Vehicle Model	Number of Vehicles	Maximum Charging Power (kW)	Average Charging Duration (min)	kWh per Kilometer
Tesla Model 3	50	11	240	0.15
Nissan Leaf	50	6.6	240	0.18
Hyundai IONIQ Electric	50	7.2	240	0.16

In this study, it is assumed that the charging station will include 15 identical Level-2 chargers. The manufacturer data for the selected charger type is shown in Table 3 below.

Table 3. Manufacturer data for charger type used in this research [29,30].

Input Voltage	100 V/250 V/380 V (Three Phase)
Input frequency	47~63 Hz
Max. output power	7.6 kW/22 kW (Three Phase)
Max. output current	32 A
Charging interface type	IEC 62196-2, SAE J1772
Environment temperature	−40 °C~+80 °C
Protection degree	IP66
Standby power consumption	<8 W

The total number of chargers was selected based on an iterative approach to minimize the number of missed sessions, as shown in Table 4.

Table 4. Number of chargers selection.

Number of Chargers	Assumed Session per Day	Actual Sessions per Day	Missed Sessions per Day
5	20	12.4	7.6
10	20	18.5	1.5
15	20	19.9	0.1
20	20	19.9	0.1

The load profile peak power is 85 kW, the total number of charging sessions per year is 7253, and the annual energy is 207,211 kWh. The monthly average EV load and daily average EV by month are shown in Table 5 below.

Table 5. Energy consumption of EV based on the generated load profile.

Month	EV Avg Monthly Load (kWh)	EV Avg Daily Load (kWh)
January	17,161	554
February	15,970	570
March	19,000	613
April	16,803	560
May	16,926	546
June	17,208	574
July	16,724	539
August	19,263	621
Sepeptember	16,931	564
October	17,200	555
November	17,103	570
December	16,922	546
Total	207,211	567

2.2. PV System Design

PV sizing software calculates the PV system's hourly output using Typical Meteorological Year (TMY) data. PVGIS software, NASA, and metronome databases offer such data files for many locations in the world. Hourly weather data generated from long-term measurements are included in these files. The key data includes irradiance, ambient temperature, and wind speed. Furthermore, PV module tilt and azimuth angles are critical when designing a PV system. Latitude angle is a key factor in determining the best tilt angles for solar panels. The PV panels are typically tilted to the location's latitude for annual maximum energy generation.

The TMY for any location or city can be obtained from the PVGIS database. Such data will be used to simulate PV systems with different capacities to generate an hourly power profile to use as input into the proposed method. The daily average irradiance, plan of array irradiance, and average ambient temperature adopted in this research are for a city in Palestine called Nablus. These data are shown in the following table (Table 6):

Table 6. Average solar energy and ambient temperature in Nablus city.

Month	Daily Average Irradiance (kWh/m^2/day)	POA Irradiance (kWh/m^2)	Daily Average Temperature (°C)
January	4.20522	130.362	8.69
February	4.10834	115.034	10.55
March	6.03906	187.211	10.31
April	6.32847	189.854	15.3
May	7.64967	237.14	18.72
June	7.7606	232.818	20.37
July	7.89418	244.72	23.57
August	7.67325	237.871	23.18
September	6.96279	208.884	22.25
October	5.78391	179.301	20.35
November	4.19166	125.75	15.17
December	3.70693	114.915	10.03

From the generated load profile, the annual peak demand of the EV charging station is 85 kW. Therefore, the initial size of the PV system is set to 90 kWp. The system capacity will be increased, and a battery will be added to study different scenarios and their impact on the performance of the charging station.

Recent trends in renewable energy system design emphasize the necessity of self-consumption and self-sufficiency at both the individual and community levels. Self-consumption and self-sufficiency are two energy indicators used to assess the utilization of local energy output [32]. The planning of future EV infrastructure should consider both metrics.

The term self-consumption (SC) refers to the quantity of electricity generated and consumed locally (E_{lgc}) in proportion to the overall amount generated locally [32]:

$$SC = \frac{E_{lgc}}{E_{lg}} \tag{1}$$

Self-sufficiency (SS) quantifies the proportion of consumption provided by the local generation to overall consumption. It assesses the user's independence from the grid, and it is determined using the following formulas [32,33],

$$SS = \frac{Elgc}{E_{load}} \tag{2}$$

Both metrics will be investigated for all scenarios in this work.

The average daily energy consumption of the generated load profile over the year is 567 kWh. The daily average generation for a 90 kW PV system is 409 kWh. As a result, a storage battery with a 200 kWh capacity is proposed. The battery capacity is determined after a number of iterations to optimize the system.

The battery state of charge (SOC) is defined as the ratio of the available energy to the maximum energy that can be stored in the battery. The SOC of a fully charged battery is 1, while the SOC of a fully discharged battery is 0. Batteries must not exceed their thermal limits in order to ensure their safety and stability. There is a limit to the amount of energy that can be discharged from the battery, which is commonly referred to as the minimum state of charge (SOC_{min}). On the other hand, there is a limit to the amount of energy that can be stored in the battery, which is the maximum state of charge (SOC_{max}). As a result, the SOC of the battery should always meet the following criteria:

$$SOC_{min} \leq SOC \leq SOC_{max} \tag{3}$$

By using the, and SOC_{min}, as well as the rated energy (E_{rated}) of the battery, it is possible to compute the maximum and minimum energy stored in the battery (Eb_{max}, Eb_{min}) as well as the rated energy (E_{rated}) of the battery.

$$Eb_{max} = E_{rated} \times SOC_{max} \tag{4}$$

$$Eb_{min} = E_{rated} \times SOC_{min} \tag{5}$$

In this research, the selected battery is assumed to have a SOC_{min} value of 0.2 and SOC_{max} value of 0.95.

2.3. EV Charging Station Energy Models

In this research, two charging station configurations will be investigated, which are a PV-grid charging station without a battery and a PV-grid charging station with a battery.

The charging station is equipped with Level-2 AC-type chargers and is directly connected to the AC bus, allowing it to receive power from the PV inverter and the grid. The PV-grid charging configuration is illustrated in Figure 2.

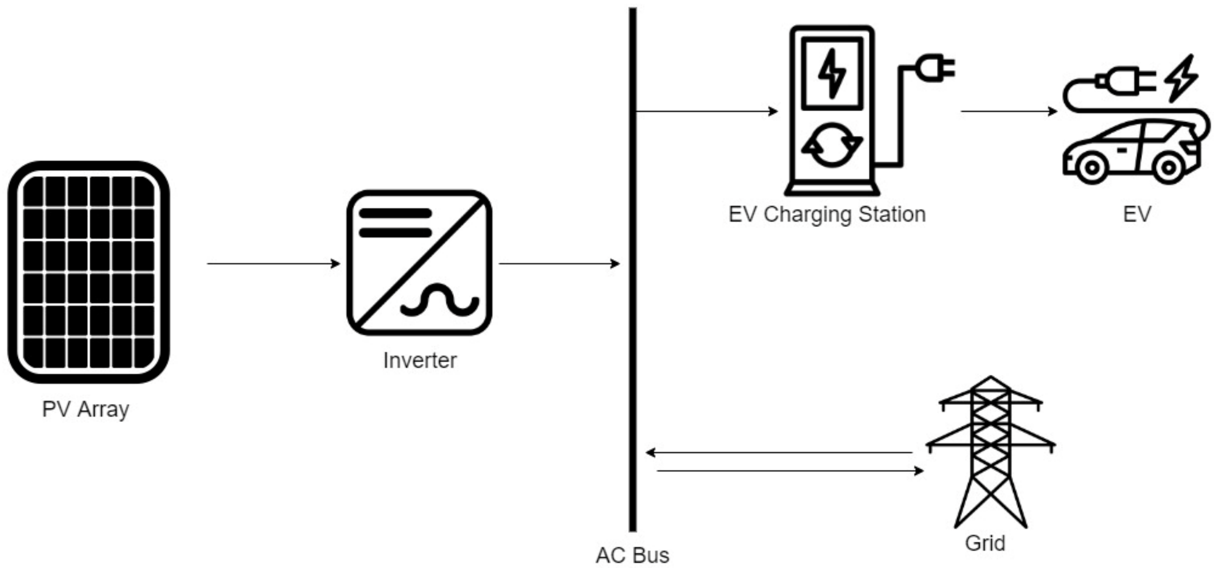

Figure 2. PV-grid charging configuration.

The flowchart illustrated in Figure 3 explains the analysis of the first case. This approach is rather straightforward; the PV system will initially supply the EV load, and if the PV system is unable to supply the entire load, the grid will deliver the reset. On the other hand, if the PV system is able to meet 100% of the load, the excess energy is fed into the grid. The analysis will be performed for each hour of the year. Eventually, the total energy from the PV and the grid will be utilized to compute system self-consumption and self-sufficiency, as well as financial and environmental indicators.

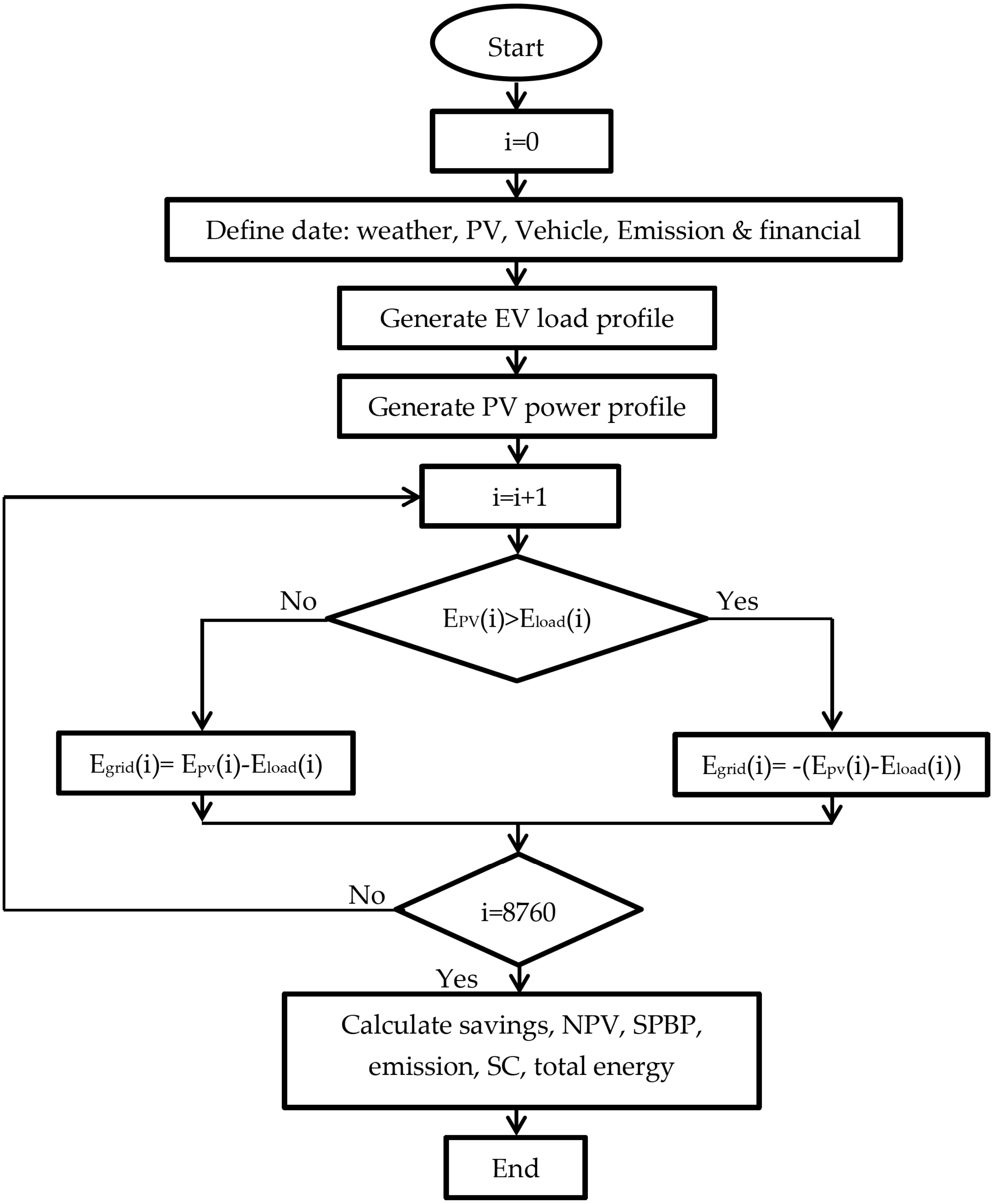

Figure 3. Flow chart of energy flow model of EV–PV−grid.

The second configuration is shown in Figure 4 and it includes a battery equipped with a bidirectional converter that enables the battery to be charged from the PV system AC output power while also injecting energy into the grid to power the EV chargers on the AC bus. The following diagram illustrates how this system is connected.

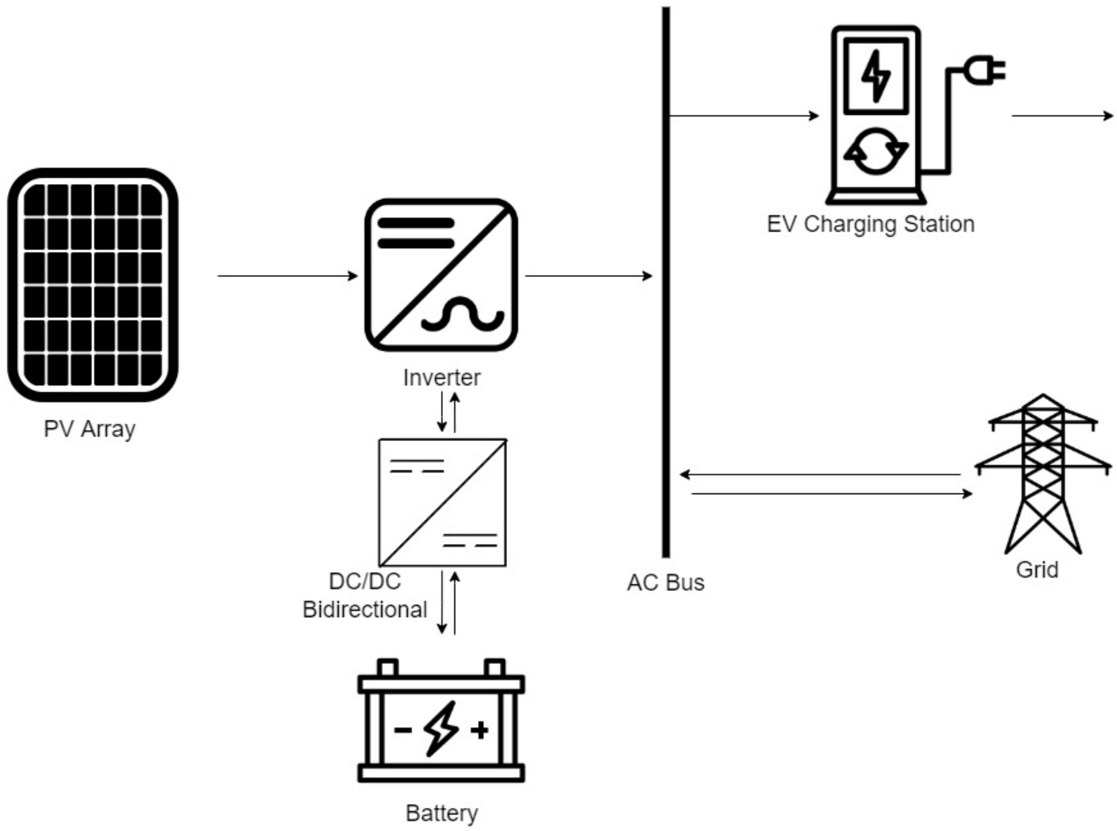

Figure 4. PV−grid battery system.

The energy flow is more complicated in this scenario than in the previous one. First, the PV system will attempt to serve an entire load of local energy. If it is unable to do so, the battery will attempt to supply as much as possible. However, if the battery is unable to cover the entire load, the grid will supply the remaining load, and the battery state of charge will change to SOCmin. On the other hand, if the PV system can totally supply the load, the excess energy will be utilized to charge the battery. Any excess energy above the capacity of the battery will be injected into the grid, and the battery state of charge is set to SOCmax.

The process is illustrated in further detail in the flowchart illustrated in Figure 5.

In the case of having a vehicle-to-grid (V2G) system, the modeling will be very close to this case, as the principle of a vehicle-to-grid system is the ability to import expert power to the grid considering a specific situation. Here, in the case of exporting power to the grid, the code that describes the discharging process of the battery can be used. Meanwhile, in case of importing power from the grid, the code that describes the battery charging can be used. As for the role of exporting and importing power from the grid, they can be also set as the user wishes, considering system specifications.

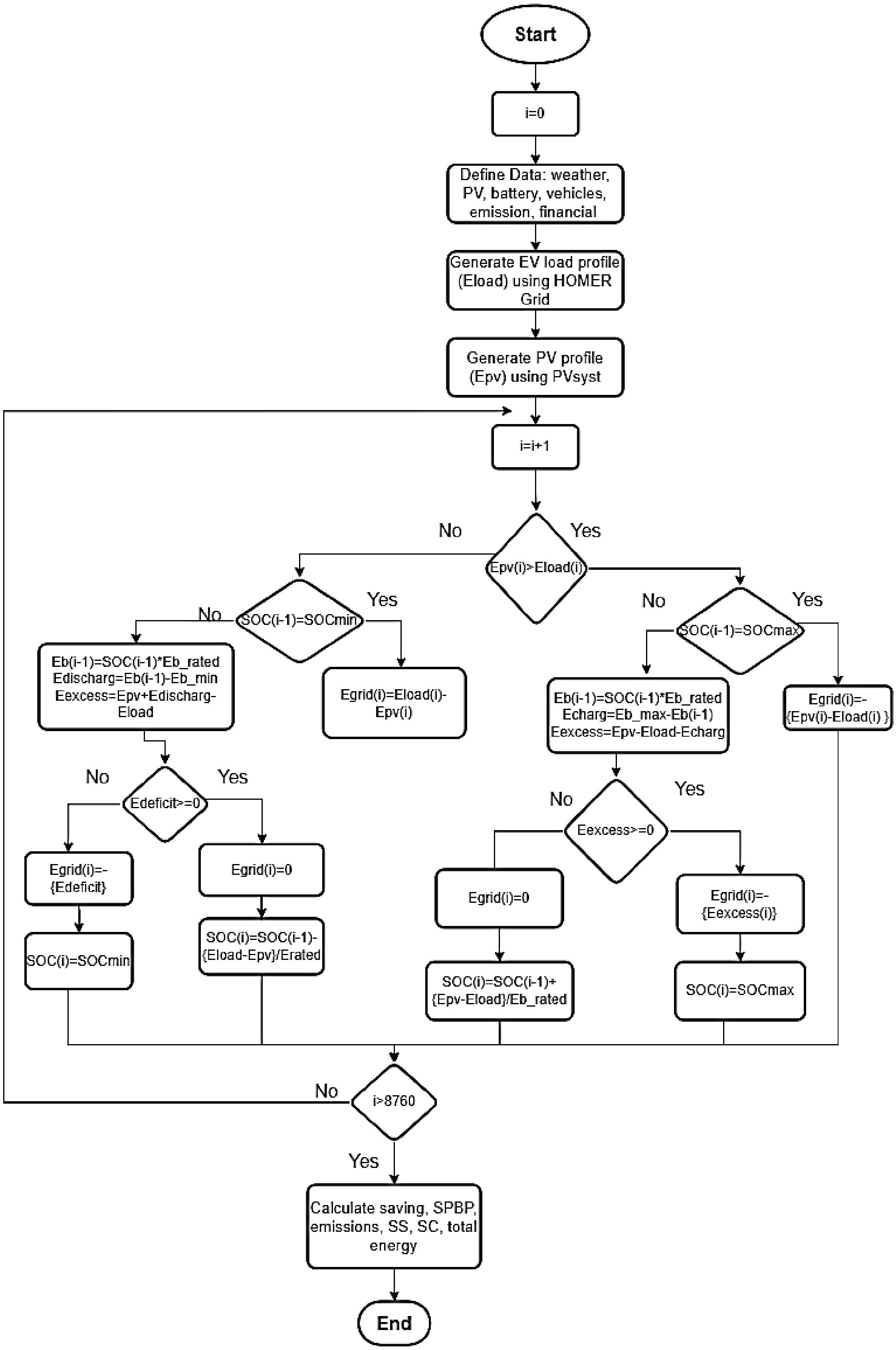

Figure 5. Energy flow model for PV−grid battery charging system.

2.4. Environmental Impact Modeling

The EV may save a considerable amount of CO_2 emissions since it emits less CO_2 compared to a diesel vehicle when traveling the same distance. According to our assumptions, the electric vehicle requires 0.16 kWh/km on average. The total distance traveled may be determined from the generated load profile by dividing the total electricity consumption per year (207,211 kWh/year) by the kWh consumption per km. The total distance traveled per year is calculated to be 1,295,068 km. Given that diesel vehicles can travel on average 12 km/liter, it is estimated that if diesel vehicles are utilized, they will burn 107,922 L/year.

On average, a diesel vehicle emits 2.6 $kgCO_2$ for every liter of fuel burned. This means that diesel vehicles may release 280.59 tCO_2 annually if they travel the assumed distance.

On the other side, the CO_2 emitted by the EV depends on the generating source of electricity. In this research, it is assumed to be 0.7 $kgCO_2$/kWh; therefore, the overall emission, if electric vehicles are used to travel the assumed distance, is equal to 145 tCO_2/year. This suggests that the grid-powered EV vehicles may save 135.6 tCO_2/year, which is comparable to a 48.32% reduction in CO_2/year compared to a diesel vehicle. Now, if a portion of the power consumed by the grid is replaced with PV, the savings will be much greater. The following equation shows the total CO_2 savings associated with integrating a PV system to power the electric vehicle charging station.

$$CO_{2\,Diesel\ Vehicle} = l_{diesel} \times \frac{2.6kgCO_2}{l} \tag{6}$$

$$CO_{2\,EV} = kWh_{grid} \times \frac{0.7kgCO_2}{kWh} \tag{7}$$

$$CO_2SavingEV = CO_{2\,Diesel\ Vehicle} - CO_{2\,EV} \tag{8}$$

$$CO_2SavingPV = kWh_{PV} \times \frac{0.7kgCO_2}{kWh} \tag{9}$$

$$TotalCO_2Saving = CO_2SavingEV + CO_2SavingPV \tag{10}$$

2.5. Financial Parameters

In this research, the assumed initial parameters are PV Station Cost (1100 $/kW), Charger Cost (700 $/charger), Annual Running and Replacement Cost (15 $/kW), Battery Cost (200 $/kWh), Daytime Tariff (0.16 $/kWh), and Battery Tariff (0.2 $/kWh). These values are obtained based on many previous reports and some local figures [4–9].

3. Results and Discussion

In this research, python codes have been developed for two main cases with more than four subcases. The two main cases are a PV-based charging station that is connected to the grid with/without a battery as an additional source.

Each case of these cases is simulated by considering two types of grid interfaces, exporting interface (allowing energy to flow back to the grid) and the zero-export interface, which blocks any reverse power to the grid. The reason behind simulating these cases is to provide information about EV charging stations considering all other technical conditions.

The required size (90 kWp) is simulated first. Moreover, in this research, the advantage of adding more treading options for any PV-based charging stations with more PV array that exports energy to the grid is investigated by adding two trading options (30% (120 kWp) and 50% (140 kWp) more than the required size.

The performance of the two main cases is provided in Tables 7 and 8. From Table 7, the charging size of 90 kWp is suitable for the system with an acceptable payback period and cost of energy. Here the additional trading option does not add that much to the system as it is a net metering system considering the economic issue. However, it makes self-sufficiency higher and contributes positively to the environment by saving more CO2 emissions. As for the zero export system, the optional trading options are not recommended as they did not contribute that much to the system. This situation is the same for PV systems with batteries considering the zero export system; however, the additional trading option might provide some advantages to the system. As a result, adding a battery increases the payback period and the cost of energy but also increases the self-sufficiency ratio. This is to say that the designer should use the proposed model in a trade-off frame between the technical, economic, and environmental issues in order to propose an optimal system.

Table 7. Performance of EV charging station with PV system without battery.

	PV Net-Metering			PV Zero-Export		
System Capacity (kW)	**90**	**120**	**140**	**90**	**120**	**140**
Total PV Generation (kWh)	149,633	199,506	232,752	97,190	103,389	105,788
PV Energy Consumed locally (kWh)	97,190	103,389	105,788	97,190	103,389	105,788
Egrid exported (kWh)	52,442	96,117	126,964	0	0	0
Egrid Imported (kWh)	110,020	103,821	101,422	110,020	103,821	101,422
Self-Consumption Ratio (%)	64.95	51.82	45.45	100%	100%	100%
Self-Sufficiency Ratio (%)	46.90	49.89	51.05	46.90	49.89	51.05
Payback Period (year)	4.47	4.07	3.9	7.18	9.27	10.8
Levelized Cost of Energy ($/kWh)	0.057	0.056	0.055	0.088	0.108	0.122
Total CO_2 Saving (tCO_2)	240.34	275.25	298.53	203.63	207.97	209.65

Table 8. Performance of EV charging station with PV system with battery.

	PV/Battery Net-Metering			PV/Battery Zero-Export		
System Capacity (kW)	**90**	**120**	**140**	**90**	**120**	**140**
Total PV Generation (kWh)	149,633	199,506	232,752	137,099	152,385	156,623
PV Energy Consumed locally (kWh)	137,099	152,385	156,623	137,099	152,385	156,623
Battery Energy (kWh)	39,905	48,993	50,832	39,905	48,993	50,832
Egrid exported (kWh)	12,536	47,123	76,132	0	0	0
Egrid Imported (kWh)	70,111	54,825	50,587	70,111	54,825	50,587
Self-Consumption Ratio (%)	91.62%	76.38	67.29	100%	100%	100%
Self-Sufficiency Ratio (%)	66.16	73.54	75.58	66.16	73.54	75.58
Payback Period (Year)	6.75	6.14	5.90	7.37	8.07	8.85
Levelized Cost of Energy ($/kWh)	0.096	0.085	0.080	0.104	0.111	0.119
CO_2 Saving (tCO_2)	240.34	275.25	298.53	231.57	242.27	245.24

After all, the posted performance in Tables 7 and 8 are examples of the developed models (provided in Appendix A). The user can modify the input parameters of these models in order to simulate any of the aforementioned systems under special circumstances. Moreover, the provided codes can be combined in any size optimization or optimal allocation process of EV charging stations as it provides system performance depending on different types of parameters. Finally, such codes can also be used to conduct feasibility studies, whereas system production can be predicted by running the model, and then the cost of the unit can be calculated. Such models can be implemented in a Python environment or Matlab environment easily.

4. Conclusions

This paper presented the development of Python codes for photovoltaic/grid-based charging stations for electric vehicles considering many operation models. These modes included grid-connected photovoltaic charging stations with/without exporting features to the grid. In addition to that, the case of the PV/grid/battery system was also modeled with/without exported feature to the grid. Following the development of these models, systems performance was generated considering technical, environmental, and economic aspects. Such models are useful for researchers who are working in the field of EV sizing, placement, and control and performance analysis. The proposed techno-economic models can be used to evaluate the optimal location of the electric vehicle charging stations and the financial and environmental benefits of the electric vehicle charging stations installed in a residential, commercial, or industrial context. The models were tested by proposing a simulation of load demand and investigating different cases, including actual size cases and additional trading cases.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. (Python Codes)

Appendix A.1. PV/Grid Charging Station Code

```
tariff=0.15
PV_Capacity=140 # 90, 120 , 140
DCACratio=1 # 1 or 1.2
PVcost=1100 # cost per kW
Charger_cost=700
Chargers=15
investment=PV_Capacity*PVcost + Chargers*Charger_cost
time=pd.date_range(start='1/1/2021', end='1/1/2022',freq='1h')
time=list(time)
del time[-1]
EVload=pd.read_csv('EVLoad.csv')
PV= pd.read_csv( "90kW.csv" )
Data=pd.DataFrame(columns=['Time','PV','EV','Grid'])
Data['Time']=time
Data['PV']=PV['E_Grid']
Data['EV']=EVload['EVLoad']
Data['Grid']=99999
for i in range(len(Data['PV'])):
if Data['PV'].iloc[i] >= Data['EV'].iloc[i] :
Data['Grid'].iloc[i]=-( Data['PV'].iloc[i]—Data['EV'].iloc[i] ) # Export Energy (negative Sign)
elif Data['PV'].iloc[i] < Data['EV'].iloc[i]:
Data['Grid'].iloc[i]=Data['EV'].iloc[i]—Data['PV'].iloc[i] # Import Energy (Positive Sign)
E_grid_export=sum( Data['Grid'][( Data['Grid'] < 0 ) ])
E_grid_import=sum( Data['Grid'][( Data['Grid'] > 0 ) ])
E_Load=sum(Data['EV'])
E_PV=sum(Data['PV'])
E_PV_consumed=E_Load-E_grid_import
SC=E_PV_consumed/( E_PV )*100 #Self-Consumption
SS=E_PV_consumed/(E_Load )*100 #Self-Sufficiency
SPBP=investment/(E_PV*tariff) #SPBP for Net Metering (feed-in System)
CO2=E_PV*0.7/1000
print("E_PV:",E_PV,"kWh")
print("E_PV_consumed:",E_PV_consumed,"kWh")
```

```
print("E_Load:",E_Load,"kWh")
print("Self-Consumption:",SC,"%")
print("Self-Sufficiency :",SS,"%")
print("E_grid_export:",E_grid_export,"kWh")
print("E_grid_import:",E_grid_import,"kWh")
print("SPBP:",SPBP,"year")
print("CO2:",CO2,"ton")
Data.to_csv("Results.csv")
```

Appendix A.2. PV/Grid/Battery Charging Station Code

```
tariff=0.1
PV_Capacity=90 # 90, 120 , 140
PVcost=1000 # cost per kW
Charger_cost=700
Chargers=15
investment=PV_Capacity*PVcost + Chargers*Charger_cost + 200*200
SOCmax=0.95
SOCmin=0.2
Eb_rated=200
SOC_init=0.2
Eb_min=Eb_rated*SOCmin
Eb_max=Eb_rated*SOCmax
timex=pd.date_range(start='1/1/2021', end='1/1/2022',freq='1h')
timex=list(timex)
del timex[-1]
EVLoad=pd.read_csv('EVLoad.csv')
PV= pd.read_csv( "90kW.csv" )
Data=pd.DataFrame(columns=['Time','PV','Eload','Grid','SOC','Eb'])
Data['Time']=timex
Data['PV']=PV['E_Grid']
Data['Eload']=EVLoad['EVLoad']
Data['Grid']=99999
Data['Grid'].iloc [0]=0
Data['SOC']=99999
Data['SOC'].iloc [0]=SOC_init
Data['Eb'].iloc [0]=99999
Ebatt=0
for i in range(1,len(Data['PV']) ):
Data['Eb'].iloc[i-1]=Data['SOC'].iloc[i-1]*Eb_rated
if Data['PV'].iloc[i] >= Data['Eload'].iloc[i] :
if Data['SOC'].iloc[i-1]==SOCmax:
Data['Grid'].iloc[i]=-( Data['PV'].iloc[i]—Data['Eload'].iloc[i] ) # Export All Energy (negative Sign)
Data['SOC'].iloc[i]=SOCmax
elif Data['SOC'].iloc[i-1]<SOCmax:
Echarg=Eb_max-Data['Eb'].iloc[i-1]
Eexcess=Data['PV'].iloc[i]-Data['Eload'].iloc[i]-Echarg
if Eexcess>=0:
Data['Grid'].iloc[i]=-Eexcess # Export part of the Energy (negative Sign)
Data['SOC'].iloc[i]=SOCmax
else:
Data['Grid'].iloc[i]=0
Data['SOC'].iloc[i]=Data['SOC'].iloc[i-1] + ( Data['PV'].iloc[i]—Data['Eload'].iloc[i] )/Eb_rated # Battery carging
```

```
elif Data['PV'].iloc[i] < Data['Eload'].iloc[i]:
if Data['SOC'].iloc[i-1]==SOCmin:
Data['Grid'].iloc[i]=Data['Eload'].iloc[i]—Data['PV'].iloc[i] # Import Energy (Positive Sign)
Data['SOC'].iloc[i]=SOCmin
else:
Edischarg=Data['Eb'].iloc[i-1]—Eb_min
Edeficit=Data['PV'].iloc[i] + Edischarg—Data['Eload'].iloc[i]
if Edeficit >=0:
Data['Grid'].iloc[i]=0
Data['SOC'].iloc[i]=Data['SOC'].iloc[i-1]—( Data['Eload'].iloc[i]—Data['PV'].iloc[i] )/
Eb_rated # Battery discarging
Ebatt+=( Data['Eload'].iloc[i]—Data['PV'].iloc[i] )
else:
Data['Grid'].iloc[i]=-Edeficit # Import Energy (Positive Sign)
Data['SOC'].iloc[i]=SOCmin
Ebatt+=Edischarg
E_grid_export=sum( Data['Grid'][( Data['Grid'] < 0 ) ])
E_grid_import=sum( Data['Grid'][( Data['Grid'] > 0 ) ])
E_Load=sum(Data['Eload'])
E_PV=sum(Data['PV'])
E_PV_consumed=E_Load-E_grid_import
SC=E_PV_consumed/( E_PV )*100 #Self-Consumption
SS=E_PV_consumed/(E_Load )*100 #Self-Sufficiency
SPBP=investment/(E_PV*tariff) # SPBP for Net Metering (feed-in System)
CO2=E_PV*0.7/1000
print("E_Load:",E_Load,"kWh")
print("E_PV:",E_PV,"kWh")
print("E_PV_consumed:",E_PV_consumed,"kWh")
print("Self-Consumption:",SC,"%")
print("Self-Sufficiency :",SS,"%")
print("E_grid_export:",E_grid_export,"kWh")
print("E_grid_import:",E_grid_import,"kWh")
print("Battery Energy",Ebatt)
print("SPBP:",SPBP,"year")
print("CO2:",CO2,"ton")
Data.to_csv("Results_90kW.csv")
```

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