Planning and Optimizing Electric-Vehicle Charging Infrastructure Through System Dynamics

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ABSTRACT One of the key solutions to address the issue of energy efficiency and sustainable mobility is to integrate plug-in electric vehicle (EV) infrastructure and photovoltaic (PV) systems. The research proposes a comprehensive EV infrastructure planning and analysis tool (EVI-PAT) with solar power generation for micro-scale projects for the deployment of EV Charging Stations (EVCS). For the evaluation of the proposed infrastructure, a case study of Qatar University (QU) campus is chosen for the integration of the EV charging infrastructure and PV power generation to evaluate the performance of the presented framework. The model estimates the EV adoption and the number of vehicles based on the inputs related to the country's EV adoption, campus vehicle count, and driving behavior. Economic and environmental indicators are used for evaluating policy choices. The findings in the paper show that the proposed planning framework can find the optimum staging plan for EV and PV infrastructure based on the policy choices. The staging plan optimizes the sizes and times of installing EVCSs combined with solar PV keeping the EV-PV project at maximum economic and environmental targets. The optimum policy can affect the optimum power infrastructure limit to maximize the economic benefit by the solar tariff.

INDEX TERMS Causal loop mapping, energy consumption estimation, EV adoption, solar PV, infrastructure planning, work charging.

I. INTRODUCTION

With the exhaustion of fossil fuel reservoirs, the experts are formulating policies over the globe for emission reduction considering transportation electrification. Consequently, relevant sector stakeholders are becoming interested in incorporating diverse transportation fueling in preparation for transportation electrification [1].

The policies on the adaptation stage of EV technology are not yet fully mature and practical, and the market mechanism of electric vehicles has not yet been formulated. Therefore, the number of electric vehicles still accounts for a low proportion of total vehicles, and the EV industry relies on government subsidies and advocacy. Because of this early stage, any initial investment in the charging stations to

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address all issues related to charging may lead to unnecessary financial expenditure [2].

The installation of EV charging stations in a power system without a suitable framework may cause undesirable effects on the network performance (i.e., grid violations) or on user convenience (i.e., long waiting time) [3]. When planning for the future number of charging infrastructure, overestimating the number of chargers can lead to grid violations, while underestimating can cause a risk of EV users' inconvenience [3]. These risks can affect the EV adoption and market, thus affecting the investments in infrastructure that may be used inefficiently.

The related problems associated with charging are somehow addressed in the literature under EV infrastructure planning, charging station placement and sizing, and charging management [4]. Determining an optimum number of chargers per location depends on the charger cost, annual

operating cost, user's time value, depreciable life, and the average wait time [5]. Reducing the number of chargers can cause an insufficient installation for the EV demands leading to user inconvenience. On the other hand, installing many chargers can lead to network congestion, and this is why it is necessary to estimate the charging demand when planning for EV infrastructure. The vehicle charging demand depends on the number of vehicles, user driving distance, charging habits, and charging network [6], [7]. The demand for EV infrastructure is classified based on socioeconomic indicators, including income, hybrid ownership, tenure, and dwelling type [8]. The necessary charging infrastructure varies according to the geographical parameters and can be explored through software such as the Electric Vehicle Infrastructure Projection Tool (EVI-Pro) using a bottom-up simulation [9], [10].

There are obstacles when it comes to large-scale EV adoption, including infrastructure, battery size and price, model availability, policy, and public awareness [8]. The main obstacles in deploying green technologies in the region are the lack of tools to evaluate policy planning. LEAPP, E3MLab, Panel Data Analysis model, and energy supply modeling are a few tools that have been proposed in the Middle-East and North-Africa (MENA) region to help with energy transition [11]. They are, however, economic-based modeling tools that overlook social and environmental aspects of the region.

Most of the studies in the literature are related to the planning for public charging station infrastructure. At the same time, a more specific method in [12] proposed a deployment strategy at a university campus. The authors define a flexible planning model using the queueing theory and the analytic hierarchy process to find optimum sizes and locations of EVCSs on the campus. The study does not propose a planning framework for infrastructure installation, policy evaluation, or infrastructure impact on the EV deployment. Furthermore, according to a study in [13], universities play a vital role in EV network expansion.

The main contribution of this research is developing a framework for planning and analyzing EV projects with solar energy generation. The outcome can give the annual penetration of EVs on campus with the required number of charging ports and optimum solar PV infrastructure. Other outcomes of this study include recommendations and guidelines for installing EV charging infrastructure over several different policies and charging fees. The model analyzes multiple case studies to obtain optimal solutions for customized case studies. This research uses a Qatar University case study to implement the model, and the output is compared with international universities' EV infrastructure.

The main highlights of this paper are:

1) Define the affecting attributes on the future growth of campus EV and combine a data-set collection valuable for future research.

2) Model a system-dynamic-based tool for EV infrastructure planning and analysis
3) Combine solar PV and EV technologies for economic optimization.
4) Construct a casual loop for EV-PV policy analysis.

The remaining part of this paper is structured as follows: section 2 is a background on EV planning and the relation between charging stations and EV adoption. Section 3 presents the methods and the case study. Section 4 includes model validation and simulation results, discusses the proposed framework outputs, evaluates the model with a real-life case study, and discusses current policies. Finally, section 5 concludes the paper, gives policy implications, discusses limitations and recommendations for future work.

II. BACKGROUND & RELATED WORK

Accurately modeling an EV infrastructure planning framework requires EV adoption to be known [14]. Forecasting is necessary for EV production planning, policy-making, power generation, and supply equilibrium. Multiple methods for EV forecasting have been proposed, but these studies, in [14]–[16], are designed for large-scale country adoption and cannot perform well for the comprehensive models for campus EV infrastructure planning.

A study in [14] uses a logistic growth model to predict long-term sales forecasts using vehicle sales historical data from 2010 to 2018. The author did not consider historical data related to other technology sales such as solar photovoltaics or technology development trends such as battery size or EV range. The growth in the EV numbers is affected by many factors classified as antecedents, mediators, moderators, consequences, and socio-demographic variables [17]. Only a few studies address the repercussions variables of environmental, social, and economic impacts. Other related variables were investigated in the literature, such as the influence of EV infrastructure (fast charging) on EV attractiveness [15]. The charging infrastructure type affects EV adoption for a country-size case study performed in the United Kingdom (UK). The case study in [15] is for a macro-scale adoption and may not be suitable for smaller-scale projects such as university or work charging. Furthermore, EV adoption could increase with the increasing number of chargers instead. Therefore, the study in [16] investigates the casual relation between charging station installation and EV purchases for public charging in the United States of America (USA). There is no evidence of a feedback relation for public charging because most charging occurs at home. On the other hand, there is a relation between installing charging stations at workplaces and the purchases of EVs for commuting areas, and both EV adoption and work infrastructure have a feedback relation [16]. The study does not cover the effect of increasing the number of chargers at one working place on the charging behavior or the EV adoption.

Charging price-related policies affect how people charge and use the infrastructure, and EV adoption is affected

differently with different policies and charging infrastructure [8]. Variable charging prices such as Time-of-Use (TOU) affect users' charging patterns and behavior. For example, low charging price at night makes home charging attractive and convenient for single-users. Even though home charging will be attractive given a policy such as TOU, other policies such as free charging at work may affect the charging behavior and affect the peak demand on the power network.

Many works in the literature apply the system-dynamic approach for EV deployment, planning; however, very few consider combining EV infrastructure with solar PV installation with the consequences variables listed in [17]. Some studies propose a system dynamic approach to solve real-life situations practically because it can combine multiple variables with feedback relations. For instance, the study in [18] presents a novel system dynamic model to predict EV evolution in China. The study quantified the purchase share of EV numbers in China and did not include infrastructure quantity, solar PV potential, or policy implications on the output. The study focuses on EV shares, and no planning strategy for EV infrastructure was proposed. At the same time, another study uses a similar approach but uses the model for impact studies such as oil prices and quantifying emission reduction [19]. Both studies are performed over a country scale and are unsuitable for micro-scale projects such as work charging (institution charging).

Up to the author's knowledge, the previous literature shows a research gap in combining both the technical, economic, and environmental aspects for solar PV and EV technologies together, including policy evaluation. Furthermore, the feedback loops between the number of chargers, EV adoption, charging behavior, and charging demand are not investigated. Moreover, the previous literature does not cover a campus-scale problem combined with solar for EV infrastructure planning.

The previous system dynamic approaches do not implement an optimization method for infrastructure and give only single solutions [18], [19]. Also, mainly EV planning is not combined with solar PV planning. For instance, the study in [20] solves for EV charger placement in an IEEE-33 bus system with solar but does not propose a staging plan.

The proposed work applies system dynamics combined with optimization for obtaining an economical charging infrastructure installation plan with solar. The optimization stage obtains EV infrastructure sizes for charging with solar PV projects for every year. In summary, in the proposed planning analysis tool, the estimation for EV adoption is the central part of the proposed model. The relation between infrastructure and EV adoption concluded in [8] is modeled within the tool. Also, where policy affects the adoption and investment choices, the proposed tool's primary use is to analyze policy effect on the staging plan economically and environmentally to obtain the staging plan. The following section explains the method used in developing the suggested tool.
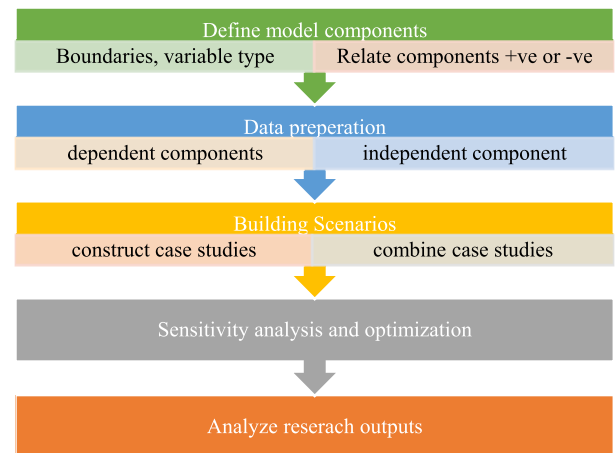

FIGURE 1. Proposed methodology flowchart.

III. METHODOLOGY

The first step in the proposed framework is to define the parameters for the EV infrastructure model, initialize the system's components such as boundaries, input, and output variables, and then model the system mathematically, analytically, or empirically through a graphical relation representation. The main steps followed are summarized in Figure 1. The second step involves the collection and preparation of the required data

The data classification process divides the data into either dependent or independent variables. In the third step, we define case studies for different dependent variables to explore the technical, environmental, and economic indices. Then we build scenarios from different case study combinations. The fourth step is performing sensitivity study, optimization, and obtaining the results using system dynamic software STELLA [21]. Finally, we analyze the results and propose optimal recommendations to plan for on-campus EV infrastructure staging.

A. PROPOSED MODEL

The model solves for the forecasted annual number of EVs on campus, recommends the optimal number of chargers to install every year, solar power plants sizes, and required policy to achieve a set of user-defined objectives. The inputs of the model are the loads, resources, and drivers, which are detailed below:

1) LOADS

two types of loads are input to the study; building loads on the campus and the EV charging loads. The available charging capacity is a percentage of total free capacity in the network (infrastructure %).

2) RESOURCES

two energy sources are in the study; conventional utility power and grid-connected solar PV power. The variable is the ratio of solar PV to the charger capacity (PV %).
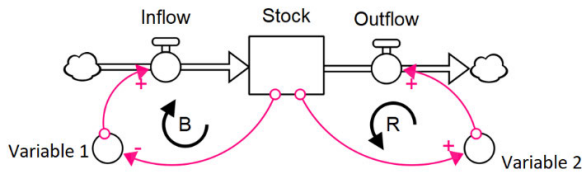
FIGURE 2. System dynamic model definition.

3) DRIVERS

are the objectives to achieve the optimization goals such as maximizing EV adoption, minimizing costs, and minimizing emission.

4) SOLUTIONS

the solutions are the variables considered in the sensitivity analysis that achieve the set goals in the study cases and scenarios. The solutions are reached targets, installation timings, system component sizes, and recommended energy policies (charging prices, feed-in tariffs, and EV incentives).

The model seeks to promote EV deployment and provide insight on the possible behaviors of the system with different policy scenarios and PV plans. The variables that influence policy choices and motivate the promotion of EV uptake are GHG, economic growth, saving, and reputation. The system maps the complete relation between technical, economic, social, and environmental policies related to EV and PV planning.

B. PROPOSED HYPOTHESIS

The model uses a system-dynamic approach initially developed by Jay Forrest and colleagues at MIT in the 1950s [22]. System dynamics studies the time-behavior of a system and allows one to study the system's behavior without experimenting on the existing system [23]. The basis of our proposed model is presented as a connection web between the variables to illustrate the complex system in Figure 2. The system cause and effect relations are circular and not linear because of the feedback loops.

The casual loop diagram (CLD) starts with a diagram of variables and arrows showing the structure of a system (our case in Figure 3). Arrows (loops) transmit information through the main flow either positively as a reinforcing loop (R) or negatively as a balancing loop (B). The CLD consists of balancing loops and reinforcing loops detailed in the subsections below.

1) BALANCING LOOPS (B)

Balancing loops have a resting effect on the system by introducing negative feedback. There are five main balancing loops in the model in Figure 3; each has a balancing effect as follows:

B1: when the number of EVs increase, the number of ICE vehicles decrease in which the total number of vehicles remains constant over the simulation time.

B2: when installed chargers cannot cover the necessary EV demand, the usage rate increases and the consumer attraction to buy reduces. The usage ratio is the percentage of required EV chargers compared with installed.

According to NREL [10], coverage infrastructure requirement has a push and pull relation with the charging demand. The number of stations is proportional to the charging demand, which in turn is coverage-based. When EVs are poorly available, it will be hard to justify investment feasibility, and low-value sales cause a gap in utilization. This gap requires infrastructure installation even though it is unfeasible to affect the consumer's attraction.

B3: the usage rate increases with the increase in EV demand and decreases with the increase in charger installations.

B4: the net income reduces with the installation of solar infrastructure because it is an added value to the EV infrastructure project. This loop allows the model for investigating the effect of policy decisions such as dedicated electricity prices for solar generation and project installation incentives to increase net income. The price of on-campus electric charging is a variable that will affect the net income. Therefore, we consider this value for different scenarios.

B5: GHG emission increases with EV charging from the grid and reduces with solar PV generation. The net emission is the difference between the increasing emissions from conventional power generation consumed by EV load and the reduction from green energy generation from solar PV. Solar PV reduces the net emissions as well as the EV commute length compared with conventional vehicles.

2) REINFORCING LOOPS (R)

Reinforcing loops are positive feedback loops that amplify and reinforce the outcome. There are three main reinforcing loops, in Figure 3, that are explained below:

R1: increasing deployment has a social effect on consumers to buy. Hence, the increased number of EVs reinforces the attraction factor bounded by the usage rate presented in loop **B3**.

R2: the awareness of the environmental effect of EV deployment and the actual benefit from the emission reduction will attract users to buy EVs. Thus, the emission reduction increases attraction.

R3: The increasing number of EVs increases the electricity demand reinforcing the need for EV infrastructure. In addition, it increases the net emission produced from burning the fossil fuel used while generating electricity for charging. The charging load causes an increase in the charging profit, increasing infrastructure investments. Therefore, it reinforces the installation of more chargers as the required demand increases.

The main output of the model is the number of EVs deployed per year. The main affecting component is the attraction factor comprising price attraction, usage rate, and campus adoption.
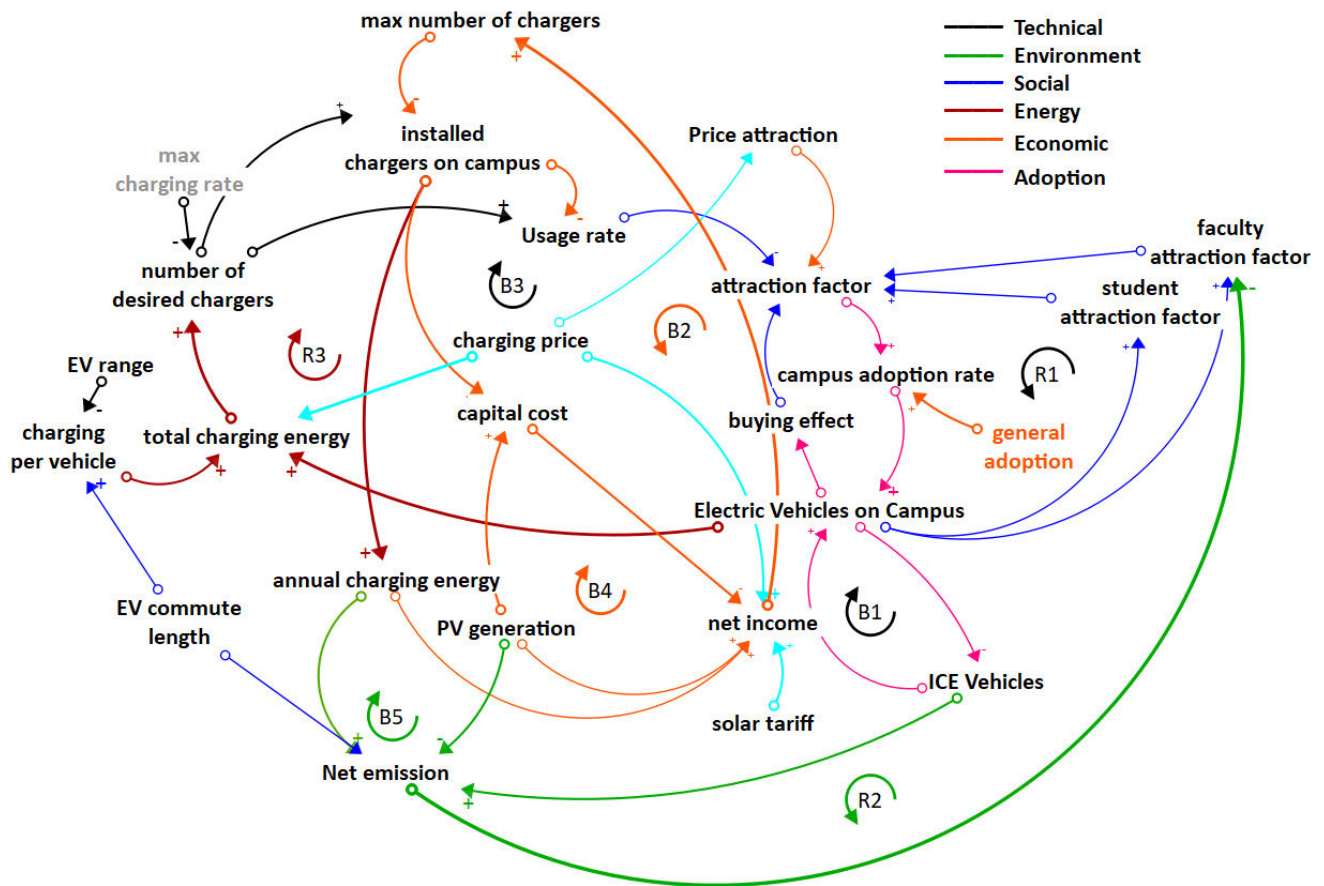
FIGURE 3. High-level mapping of the dynamic hypothesis for EV-PV infrastructure planning tool (EVI-PAT).

C. CASE STUDY

We apply our model to a real-world case educational institute QU. The university spreads over 81 square kilometers of land and is located on the Northern outskirts of the capital Doha. Investigating new technologies as well as addressing sustainable environments are part of QU's research priority. There are 32 parking areas and 6,116 available parking spaces at QU, which are the potential areas for PV installation [24].

D. DATA COLLECTION

The collected data for the case study are from local references Qatar University website, QU statistics booklet, Qatar Mobility Innovations Center (QMIC), Qatar Transportation and Traffic Safety Studies Center, Qatari electric vehicle providers in 2020 (websites), and the ministry of electricity KAHRAMAA. The data is classified into data-set groups A to G, detailed in Table 1. The primary inputs, which are independent variables, are summarized in Table 2, and the dependent variables' equations are in Table 3.

The independent variables are the main inputs obtained by collection method, observation, archival research, survey, calculation, and assumption. References from the literature

TABLE 1. Classification of collected data.

	Data	Dependent independent	Collection method
A	Traveling data	Independent	Observation
B	EV and charger technical data	Independent	Archival research
C	EV adoption rate	Independent and dependent	Secondary/Assumption
D	Campus infrastructure	Independent	Survey
E	EV energy requirement	Dependent	Calculation
F	Environment-related data	Independent and Dependent	Archival/ calculation
G	Economic related data	Independent and Dependent	Archival / simulation

cover some of these assumptions in Table 2. Only few variables are set by model tuning obtained through trial and error. The justification of each variable is explained under its relevant section. Generally, the variables set by

assumptions require investigation through surveys, question-naires, or travel behavior characterizing studies.

1) DRIVING BEHAVIOR DATA (DATASET-A)

This group covers data related to driving behavior into the QU campus. In general, most of the population in Qatar has an average driving distance (round trip) of 40-100 km (2-3 hours) [25]. The number of students, faculty, and staff is 25,067 [24]. The percentage of visitors entering QU at noontime is set to 20%, where this figure is found in a study performed for UAE Sharjah University City [26]. This case is considered because of the similarity in the travel behavior found between these two counties (Gulf region countries).

The cumulative daily number of cars that use the parking area at QU for 30 minutes is 14,005 vehicles, and the average parking hours is approximately 2 hrs. The study assumes 20% wasted time and space at the chargers. The idle time wasted at the charging port can exceed 50% of the overall time [27].

The vehicle life span variable in the model means how long (years) an individual's vehicle is in use on campus. Through logic knowledge, faculty members are available on campus for longer years than students, and students may be at campus for min 4 years and to 7 years. Accordingly, an assumption of 6 years vehicle life span is set for students and 10 years for the faculty, and this variable can be adjusted through a survey in future work.

2) EV AND CHARGER TECHNICAL DATA (DATASET-B)

This data-set is related to EV technical data, including range, battery size, and available charging rates. A survey on passenger vehicle providers in Qatar that sell battery vehicles in the Qatari market in 2020 shows only four vehicle makes. Their median range is 518 km nearest to the Chevrolet Bolt, and its technical specification is chosen in this study. The general EV range is expected to reach 643 km in 2030 [46], which is a 24% increase for Qatar from 518 km in 2020 to 643 km in 2030. The annual range increase will be 2.4% for the coming 10 years. EV development increases with the development of battery sizes in Europe [31]. There is a rapid increase in the EV range between 2020 and 2025 from 350 km to 537 km, and then it starts to settle between 620 km to 660 km in 2050 because the development of battery size saturates at around 100-120 kWh [31]. For work charging, the grid provider KAHRAMAA recommends the maximum charging rates are 11 kW, 22kW, and 20-25 KW-DC with 16A, 32A, and 32A, respectively [32]. The study considers 22 kW chargers for validating the model results.

3) EV ADOPTION (DATASET-C)

There are two significant adoption rates in this study: general adoption R_{adop} and campus adoption R'_{adop}. The model obtains the final attraction amount in years and the value of R'_{adop} is based on that year (final attraction) and its value from R_{adop} plot. An energy transition report in [31], projects passenger EVs in the Middle East and North Africa (MEA) region to reach 10% by 2030, 40% by 2040, and 90% by

2050. In the Gulf region, United Arab Emirates, the Supreme Council of Energy has set a 10% mandate on all new vehicles to be green by 2030 [47]. Therefore, in this paper, we consider 50% adoption by 2050, taking into account the effect of the COVID-19 pandemic on the oil prices, which will reduce the attractiveness of adopting EVs [48].

The projection percentages for the campus EV adoption are presented by the worldwide adoption-related by the attraction factor. The attraction factor for faculty is -5 and students is -7, without a significant difference because both follow the country's adoption rate at the beginning of the simulation (the first year 2020) of campus EV adoption. Faculty members would have a slightly higher attraction because of the environmental awareness and their ability to purchase at the beginning years of low adoption [49]. These values are set by tuning the model to fit the country's current adoption percentage best. Furthermore, these variables can be adjusted through a survey in future work.

The buying effect variable reflects how vehicle purchasing in the gulf region is highly affected by others [50]. Especially with the emerging social media platforms, these platforms significantly affect the impact of automobile purchasing decisions in the oil countries in the Middle East [51]. In the model, the buyer effect from EV adoption is set to 10, and this figure is assumed for the case study to reflect a high value, and this value can be changed based on questionnaires.

4) BOUNDARIES AND CONSTRAINTS (DATASET-D)

EV charger expansion is constrained by the power system infrastructure and available parking spots covered under dataset-D. The charging capacity at the campus is limited to available free power in the transformers at the QU distribution system. QU is a 39-bus the voltage level at buses is 11KV (±6%), the network is fed from the utility with 67 MW through four transformers (40 MW each). A load flow simulation obtains the free capacity (15,378 kW) dedicated for the EV infrastructure project.

Another constraint is the available parking spots that limit the number of chargers. The parking at QU can accommodate 6,116 vehicles. PV installation is constrained by area. Parking areas and building rooftops are proposed for PV installation, and the parking area per slot is 12 square meters [33].

5) EV ENERGY REQUIREMENT (DATASET-E)

The energy consumption of the vehicle E_v [kWh] depends on the commute length traveled d_c [km] in dataset-A, and is calculated by equation (1) in Table 3. The vehicle's efficiency η_{bat} [km/kWh] is related to the EV's technical data in dataset-B, item (7) in Table 2. The charging demand per vehicle d_v in km is dependent on the distance the user drives per day affected by EV range coefficient β_{range}, charging policies ρ_{policy} and commute length d_c. The policy affects the EV user's decision to charge on campus and thus the annual demand, see equation (2). The total charging demand in kWh on campus E_t dependent on the number of EV's connected

TABLE 2. The independent input data and assumptions used in the model – base case.

No.	Independent variable	Dataset -code	Value	Reference
1	Parking hours	A	6:00 am to 3:00 pm	[28]
2	Parking Duration:	A	Average 2 hrs.	[28]
3	Vehicle Count	A	14,005	[29]
4	Visitors	A	20%	Assumption and [26]
5	Vehicle use lifespan	A	Faculty 10 yrs., Students 6 yrs.	Assumption
6	Daily commute	A	50 km (2-3 hours)	[25].
7	EV technical data	B	Chevrolet Bolt, battery capacity 66 kWh	Survey and [30]
8	EV range projection	B	2.4%/yr. (10 years)	[31]
9	Max charger rate	B	22 kW AC, 3 phase, 32 A	[32]
10	Idle time	B	20%	[27].
11	General EV adoption	C	50% by 2050	Assumption
12	Attraction factors	C	Faculty -5, student -7, availability +3, buyer effect +10	Assumption
13	Power System	D	15,378 kW	Simulation
14	Parking areas	D	6,116 slots	Survey
15	Parking slot area	D	2.5 x 5 (square meters)	[33]
16	Free areas	D	117,071 m2	Survey
17	Solar GHI in Qatar	F	5.5 kWh/m2	[34]
18	PV panel data	F	330kW, 1.63m2, 20.2%	[35]
19	Capacity factor CF	F	19.5%	[36] and [34]
20	PV degradation	F	0.7% / yr.	[37]
21	Grid emission factor	F	0.678 tCO2/MWh	[38] and [39]
22	Emission from ICE vehicle	F	1.4 tons of CO2/km	[40]
23	Installation period	G	$t_{install}$ = 1 year	Fiscal year at QU
24	Charging price	G	0	Assumption and [41]
25	Electricity price	G	0.088 USD/kWh for (0.27 USD/Qatari riyal)	[42]
26	Charger cost	G	Decline of 3% per year	[43]
27	Photovoltaic	G	O&M and CAPEX ratio 0.7:100	[44], [45] and [37]

simultaneously on campus N_v and their required charging energy E_v (equation (3)).

6) NUMBER OF DESIRED CHARGERS (DATASET-E)

Number of desired chargers N_{ch} is the number of chargers required to cover the total charging energy on campus E_t, by equation (4). This variable is dependent on the energy of a single charger E_{ch} that depends on the charger rate and hours used from item (9) in Table 2.

The idle effect derates the total charging demand by 20% from item (10) in Table 2; see equation (5). The charging mechanism is an essential factor in planning for EV infrastructure. The peak power for EV charging depends on the number of EVs charging simultaneously. The base case is

an uncontrolled charging setting with a charging time set to one hour (1 hr.). In the study, the annual load for charging considers 261 calendar days per year based on the QU's academic calendar [52].

7) NUMBER OF INSTALLED CHARGERS (DATASET-E)

The total installed chargers N_t on-campus for the ith year is the net installation of chargers at year i, see equation (6). The usage rate λ is the capacity factor of the EV charger usage in equation (7).

8) SOLAR PV GENERATION (DATASET-F)

Dataset-F consists of the environment-related data such as PV power generation and the emission count in the model.

TABLE 3. The dependent data in the model.

Item	Dependent variable	Dataset-code	Equation	No.
1	The energy consumption of the vehicle E_v [kWh]	D	$E_v[kWh] = d_c\ [km] \times (1/\eta_{bat}) \left[\dfrac{kWh}{km}\right]$	(1)
2	charging demand per vehicle d_v in [km]	D	$d_v = d_c \times \beta_{range}(1 + \rho_{policy})$	(2)
3	Total charging demand on campus E_t [kWh]	D	$E_t = E_v \times N_v$	(3)
4	Number of desired chargers N_v	D	$N_v = \dfrac{E_t}{E_{ch}}$	(4)
5	Derated charging demand E_t	D	$E_t = E_t\ (1 - idle\ \%)$	(5)
6	Total installed chargers N_t on-campus for the ith year	D	$N_t^i = \dfrac{N_v^i + N_s^i - N_t^{i-1}}{t_{install}}$	(6)
7	Usage rate λ	D	$\lambda = \dfrac{N_v}{N_t}$	(7)
8	Total generation of a PV array E_A in kWh	F	$E_A = \sum_{i=1}^{365} (PSH)_i\, P_o$	(8)
9	Annual ac power generated to the grid	F	$E_{Grid}\left[\dfrac{kWh}{yr}\right] = CF \times P_o[kW] \times 8760 \left[\dfrac{h}{yr}\right]$	(9)
10	Net emission ($emis_{net}$)	F	$emis_{net} = emis_{ch} - emis_d - emis_{PV}$	(10)
11	Emission produced from EV charging ($emis_{ch}$)	F	$emis_{ch} = E_{ch}[kWh] \times EF_{grid}[tCO2/kWh]$	(11)
12	Emission reduced from EV driving ($emis_d$)	F	$emis_d = d\ [km] \times EF_{ICE}[tCO2/km]$	(12)
13	Emission reduced from PV generation ($emis_{PV}$)	F	$emis_{PV} = E_{PV}[kWh] \times EF_{grid}[tCO2/kWh]$	(13)
14	Net Present Value	G	$NPV = \sum_{n=0}^{N} p_n(1 + i)^{-n}$	(14)

The total generation of a PV array E_A in kWh for a whole year is calculated using the Peak Sun Hour (PSH) approach, in equation (8). Where $(PSH)_i$ is the value PSH for day i, and P_o is the nominal array power under the standard test conditions (STC) [53].

The capacity factor of commercial PV projects depends on system configuration (fixed tilt or single-axis tracking angle) and the installation location (irradiance level). In the USA, for example, low irradiance areas have an average CF of 12.9% (Seattle, WA), and in higher irradiance, the average CF is 19.5% (Daggett, CA). In the MENA region; Kuwait has an average daily global irradiance of 5.319 kWh/m2, and the capacity factor is 19.5 % [36]. Similar to Kuwait, the global solar radiation in Qatar is 5.5 kWh/m2, and therefore the same CF is considered [34].

9) EMISSIONS (DATASET-F)

The Net emission ($emis_{net}$) is the sum of emissions produced from EV charging ($emis_{ch}$), emission reduced from EV driving ($emis_d$), and emission reduced from PV generation ($emis_{PV}$), in equation (10) of Table 3.

The consumed energy demand E_{ch} from EV charging indirectly burns fossil fuels resulting in carbon emission measured by an emission rate known as the grid emission factor (EF_{grid}), see equation (11). This factor is country-specific, defined by the International Energy Agency (IEA). The average grid emission factor in the World is 0.507tCO2/MWh and in the Middle East is 0.678 tCO2/MWh, item (19) in Table 2.

The Carbon dioxide CO2 is the global warming potential considered 95% to 99% of the EV operating emission counting for the carbon dioxide equivalent CO2-eq [54]. The average energy efficiency of light-duty ICE vehicles between 2005 and 2018 is around 7.2 Liters of gasoline per 100 km [40]. Consequently, a gasoline vehicle emits 1.4 tons of CO2 every driven km ($EF_{ICE} = 1.4$ tCO2/km).

The advantage of battery electric vehicles is that no emission is involved during EV operation compared to an ICE, and this difference is called the driving carbon emission saving ($emis_d$), equation (12) in Table 3.

Finally, adding renewable energy to the grid will indirectly reduce the emissions produced from conventional power

generating units. The emissions reduced by solar generation ($emis_d$) depends on the grid emission factor EF_{grid} and the solar energy generated E_{PV}, see equation (13). In this study, we investigate the role of PV power generation in reducing the emissions from EV charging as a vital player in the future charging infrastructure.

10) CHARGER INFRASTRUCTURE ECONOMICS (DATASET-G)
The factors considered in the economic evaluation of EV charger infrastructure are: capital costs, installation costs, maintenance and operation costs, and charging revenue.

Hardware costs will decline in the future at the rate of 3% per year. [43]. Installation costs are a function of the number of chargers per site, composed of labor, materials, permits, taxes, and utility upgrades (material costs) [43]. Maintenance and operation costs include electricity consumption, electricity demand, network fees, maintenance, and station management.

The source of investment in EV chargers is the energy exchange price [55] which is the charger revenue. The investment potential depends on the net present value (NPV) assessment in equation (14). Where i is the interest rate and p_n is the net cash flow at year n, p_0 is the capital expenditure (CAPEX).

The main parameters determining the investment decision's strength are the electricity resale price and the expected energy selling prices at the EVSE [55]. Very few studies consider the carbon credit as part of the economic analysis of EV charging infrastructure. For instance, chargers powered with 100% renewable energy could generate carbon credit revenue of approximately $0.01 per kilowatt-hour sold [56].

Finally, the base case assumption is no charging fee through the campus charging infrastructure as practiced in some universities worldwide [41]. This study considers other charging prices for policy analysis, see Table 4.

11) SOLAR PV ECONOMICS (DATASET-G)
The PV life cycle cost considers the initial costs, installation and engineering of the PV plant, operation & maintenance, equipment replacement, and salvage. There is an annual decrease in the price of commercial PV, including CAPEX and operation and maintenance (O&M) costs. The National Renewable Energy Laboratory (NREL) projects the CAPEX of commercial PV systems from 2020 to 2050 in [44] and [45]. The projection of both O&M and CAPEX are correlated, and their ratio is 0.7:100 based on historical data [37].

The performance of the PV plant has an annual degradation rate of less than 0.7%/yr. with no assumption of improvement [37]. The PV plant degradation is linear 10% for the first (10) years and 10% for the remaining 15 years. The economic analysis considers the energy generated during PV lifespan. All. Every payment which occurs in the future C_f is at its present value using the present value multiplier P, in equation (15).

TABLE 4. Case studies' variables.

Variable	Cases	Base	Unit
Inf. installation	(1 – 100)	100	%
Charging price	0, 0.032, 0.047, 0.088, 0.13	0	USD/kWh
Solar PV	0%, 15%, 30%, 100%	0	%
Solar tariff	0.088, 0.12	0.088	USD/kWh
Charger incentives	0.088, 0	0.088	USD/kWh

E. SCENARIOS
For planning and analyzing EV infrastructure, multiple case studies are developed and combined for sensitivity analysis and objective optimization. The variables of the base case are in Table 2. The other cases consider changing the variables included in Table 4. The flexible parameters in the model include university power infrastructure, PV power parameters, and energy policy. The investigated parameters are EV adoption, energy demand, and costs of RE technology, economic and environmental indicators. The model output undergoes sensitivity analysis to relate the components of the system and use the set of effecting variables into the multi-stage optimization, in Figure 4

Optimizing for both NPV and adoption rate is based on the chosen wight ratio to solve the multi-objective optimization problem [53]. The solution will be the charging rate, power network for EVCSs, NPV, net emissions and adoption rate. The optimization method used is the Evolution Optimization [54], [55] with the following parameters; seed = 0, cr=0.2, population size = 20, generation = 40, cross over type = bin, recombine type = rand.

The final outputs in the staging plan are the number of chargers and corresponding installation years, the size of PV projects, and the corresponding installation years.

IV. RESULTS & DISCUSSION
This section includes sensitivity analysis, model validation, optimization results, staging plan, and behavior validation.

A. SENSITIVITY ANALYSIS & MODEL VALIDATION
Structure validity suggested originally by Forrester and Senge in 1980 involves verifying the structure, parameters, extreme conditions, boundaries, and model dimensions [55]. The proposed system dynamic model structure is divided into the substructures defined in Figure 3.

Each sub-structure is consistent with state-of-the-art models governed mathematically through logic knowledge by the equations in Table 3. The dimensions correspond to real systems and are consistent where each structure is relevant to the descriptive knowledge found in the literature. The output should follow a logical behavior for a valid model when parameters are adjusted to their extremes.

The remaining of this section presents the simulations results with a sensitivity study performed according to the cases in Table 4. Further analysis is performed to see whether
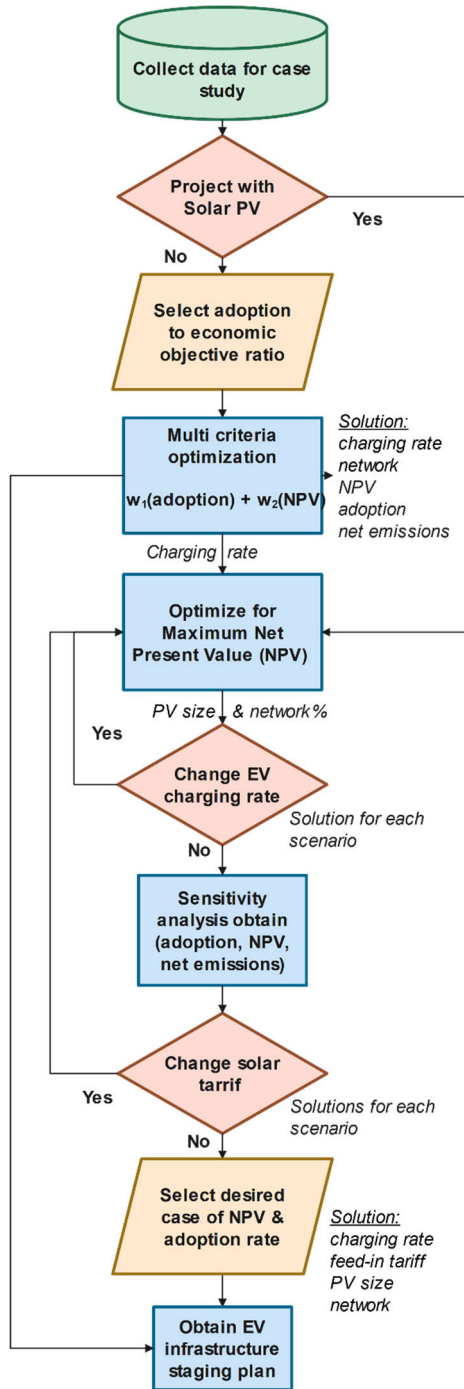
FIGURE 4. Proposed optimization of the planning framework.

adjusting parameters such as the policy for charging prices is endogenous to the system, covered in the economic and environment sensitivity analysis results.

1) EV ADOPTION WITH POWER NETWORK BOUNDARIES

The infrastructure cases Run1 to Run10 are (1, 12, 23, 34, 45, 56, 67, 78, 89, 100)% respectively. Limiting the installed chargers on campus limits the allowed charging infrastructure
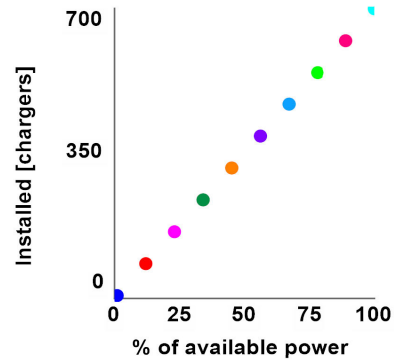

FIGURE 5. Limitation of charger installation affected by % of available power capacity.
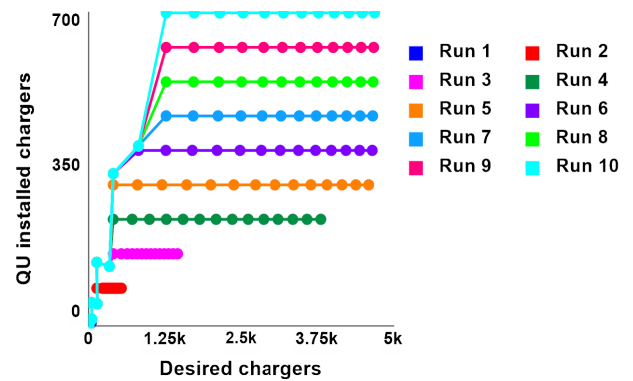
FIGURE 6. Installation chargers versus desired chargers.

even with the increasing requirement of charging, see Figure 5 and Figure 6.

2) EV ADOPTION WITH CHARGING PRICES

The power network constraint affects how adoption changes (increase or decrease) by limiting the installation of desired chargers, discussed in the previous section. This section investigates the effect of different charging rates on the EV deployment, with the power infrastructure limit and the charging rate cases in Table 4. The results in Figure 7 show that EV deployment is at (65%) with no charging rate and reduces as the charging rate increases. At a lower (10%) infrastructure utilization case in Figure 8, a higher charging rate from 0 to 0.047 USD/kWh increases the adoption from 5.98% to 45%, respectively, then stars reducing. The following sub-section investigates the charging price effect on the economic study.

B. EV ADOPTION AND NET PRESENT VALUE WITH CHARGING PRICE AND POWER INFRASTRUCTURE

The case studies for different charging prices and power infrastructure from Table 4 are combined to construct a combination of 60 scenarios in Figure 9. The parameters of 60 scenarios are inputs to the EV planning model to obtain the adoption and NPV.

TABLE 5. NPV (million USD) for different charging prices and PV size ratios, power infrastructure 100%.

PV/EV power %	Charging price USD/kWh, power infrastructure 100%						
	0.13	0.057	0.088	0.047	0.032	0.01	0.00
100.00	-26.81	-0.41	-56.80	17.10	54.50	117.37	119.58
50.00	-12.49	6.45	-24.44	14.62	32.20	60.68	59.75
30.00	-6.77	9.20	-11.49	13.63	23.28	38.00	35.82
15.00	-2.48	11.26	-1.78	12.89	16.59	20.99	17.87
5.00	0.39	12.63	4.69	12.39	12.13	9.65	5.90
2.00	1.25	13.04	6.63	12.24	10.79	6.25	2.31
0.00	1.82	13.31	7.93	12.14	9.90	3.98	-0.08
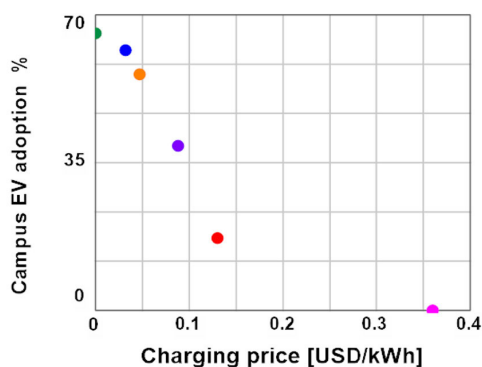
FIGURE 7. Prices effect on adoption (100% infrastructure).

FIGURE 9. Adoption and NPV with power infrastructure and charging prices.

FIGURE 8. Prices effect on adoption (10% infrastructure).

FIGURE 10. Net emission for different charging prices. Run1=0, Run2=0.032, Run3=0.047, Run4=0.057, Run5=0.088, Run6=0.13 USD/kWh (No PV).

Maximum NPV can reach 12.14 million USD at a charging price of 0.047 USD/kWh, and 100% infrastructure and adoption is 56%, Figure 9 and Table 5 (No PV).

A multi-objective optimization solves optimum EV adoption and NPV values with different charging rates and infrastructure utilization percentages in sub-section B.

In Table 6, limiting the power infrastructure (10%) constraint reduces the NPV where for the same case, the NPV is 1.74 million USD, and adoption 45.28% Figure 8 (in orange).
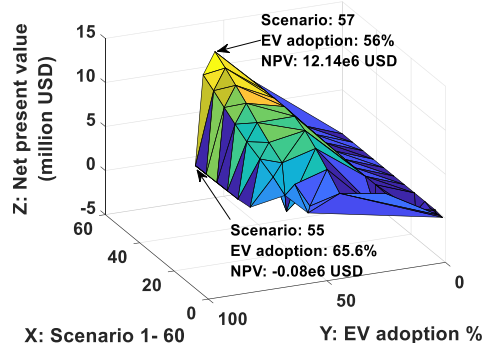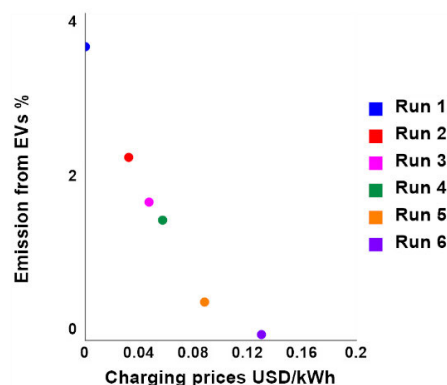
C. EMISSION REDUCTION WITH EV AND PV

The environmental analysis starts with obtaining the effect of decarbonizing the vehicles on campus as a percentage of base case ICE vehicles emissions, Table 7. Next, emissions are obtained for different cases such as commute distances, charging prices, and infrastructure limits. Net cumulative emission from EVs is lowest at low adoption and commute distance because of the grid's reduction in charging burden (Figure 10).

TABLE 6. NPV (million USD) for different charging prices and PV size ratios, power infrastructure 10%.

PV/EV power %	Charging price USD/kWh, power infrastructure 10%						
	0.13	0.057	0.088	0.047	0.032	0.01	0.00
100.00	-6.78	11.50	5.26	11.69	14.25	17.97	16.70
50.00	-2.57	6.78	3.83	6.71	7.76	9.20	8.33
30.00	-0.89	4.90	3.26	4.72	5.17	5.70	4.98
15.00	0.37	3.48	2.83	3.23	3.22	3.07	2.46
5.00	1.22	2.54	2.55	2.24	1.92	1.32	0.79
2.00	1.47	2.26	2.46	1.94	1.53	0.79	0.28
0.00	1.64	2.07	2.41	1.74	1.27	0.44	-0.05

TABLE 7. Average emissions from campus ICE with different commute distances.

Commute km	Base emission (ICE) tCo2e
6	114 K
12	227 K
50	948 K
100	1.9 M

At the base case with different charging prices, maximum emission is approximately 4%, and it is lowest 0.07% at 0.13 USD/kWh (65 % and 17% adoption, respectively). Total emission on campus from passenger vehicles will be the sum emissions from ICE and EV.

Figure 11 shows the variation in EV net emissions with solar PV installations. Negative values of net emissions mean that the EV-PV project contributed to emission mitigation. The cases at which this occurs are when PV sizes are 30% and above. The year for net-zero emissions is at the project's third year, and emission saving is very low until EV uptake increases after 2037 (EV adoption effect). In conclusion, the emission reduction depends on the general EV adoption, charging rate, infrastructure limit, and PV installation.

1) EFFECT OF POLICY ON ECONOMIC AND ENVIRONMENTAL INDICATORS

Three variables present policy in this study: the electricity rate, solar tariff, and charger incentives. The economic and environmental indicators for the cases of different feed-in tariffs, charging rates, power network limitation, and PV sizes, as in Table 8.

At 100% infrastructure (case 8) to (case 5), the NPV decreases from 17.8 to -1.78 million USD/kWh (unfeasible) even with different PV installations. Increasing feed-in tariff to 0.12 makes the project feasible; (case 5) changed to (case1). At 10% infrastructure and 15% solar, increasing the charging rate (case 8) to (case 5) increases NPV to 3.48 million USD then decreases it to 2.83 million USD. In this case, adding solar PV can make the EV-PV project
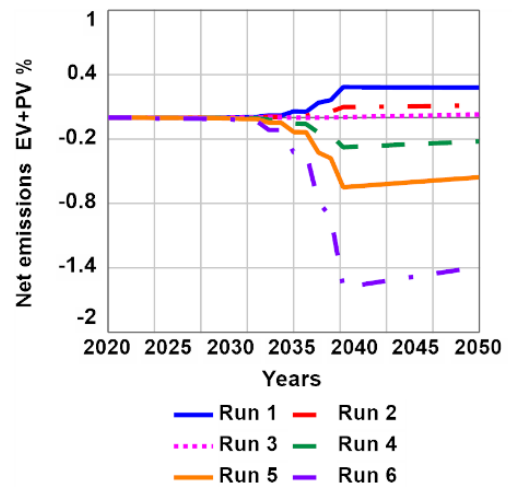

FIGURE 11. Net emission from EV charging as a percentage of bases cases (ICE vehicles) at different PV sizes, No charging rate. Run1=0, Run2=10m Run3=15, Run4=30, Run5=50, and Run6=100%.

profitable at the same feed-in tariff. Changing the project to feasible can be done by increasing the feed-in tariff and solar-PV and sometimes the charging rate depending on the power infrastructure limit.

The results in Table 8 show that the EV net emission project with 15% PV does not reach net zero. Cases with low charging rates have higher emissions than cases with higher rates (lower adoption). Increasing NPV by reducing the charging price for EV-PV projects increases EV adoption and charging emissions. In conclusion, achieving an economic goal has an undesired environmental impact.

For EV-PV planning, the optimum EV infrastructure size and PV size depend on the economic and environmental goals, and policy choices affect these goals. Therefore, the following section solves a multi-stage multi-objective optimization to find the EV-PV staging plan and design parameters.

D. OPTIMIZATION RESULTS OF ECONOMIC AND ENVIRONMENTAL GOALS

The previous cases cover only limited scenarios and are not enough to find the optimum solution for combined targets such as the economic and environmental goals. In this section,

TABLE 8. Effect of policy on the economic and environmental analysis with solar PV.

Case	Policy Feed-in tariff USD/kWh	Policy Charging rate USD/kWh	power network limit=100% NPV million USD	power network limit=100% Cumulative Emissions × 10³ tCO2e	power network limit=10% NPV million USD	power network limit=10% Cumulative Emissions × 10³ tCO2e	PV infrastructure ratio to EV %
1		0.088	1.09	0.12	3.72	0.04	
2	0.12	0.057	18.46	0.54	4.63	0.06	
3		0.032	26.03	0.94	4.50	0.01	
4		0	30.06	1.67	3.86	0.25	15%
5		0.088	-1.78	0.12	2.83	0.04	
6	0.088	0.057	11.26	0.54	3.48	0.06	
7		0.032	16.59	0.94	3.22	0.01	
8		0	17.87	1.67	2.46	0.25	
9		0.088	-5.76	-4.22	5.04	-1.82	
10	0.12	0.057	23.61	-12.88	7.18	-2.74	
11		0.032	42.15	-19.35	7.74	-3.49	
12		0	60.20	-30.73	7.76	-4.18	
13		0.088	-11.49	-4.22	3.26	-1.82	30%
14	0.088	0.057	9.20	-12.88	4.90	-2.74	
15		0.032	23.28	-19.35	5.17	-3.49	
16		0	35.82	-30.73	4.98	-4.18	
17		0.088	-37.69	-24.46	11.19	-10.51	
18	0.12	0.057	47.65	-75.48	19.11	-15.82	
19		0.032	117.40	-114.03	22.82	-19.84	
20		0	200.86	-181.92	26.00	-24.85	
21		0.088	-56.80	-24.46	5.26	-10.51	100%
22	0.088	0.057	-0.41	-75.48	11.50	-15.82	
23		0.032	54.50	-114.03	14.25	-19.84	
24		0	119.58	-181.92	16.70	-24.85	

the cases increase to cover more data: network utilization percentage from 1 to 100 with step size 1, and charging prices 0 to 0.13 with step size 0.001.

1) MAXIMIZE EV ADOPTION

The variables in this simulation are charging prices and power infrastructure to find optimum charging price for maximum EV adoption. The maximum adoption is 66.6%, in Figure 12, when the infrastructure limit is 100%, and the charging price is 0.001 USD/kWh. The solutions are almost similar to the exact solution (zero charging rate and 65.6% adoption) from the sensitivity study in Figure 9 (NPV = −0.08).

2) MAXIMIZE NPV

The variables in this simulation are charging prices and power infrastructure results in Table 5. In Figure 13, when the infrastructure limit is 100% and the charging price is 0.057 USD/kWh, the maximum NPV is 13.313 million USD, and the result is validated in Table 5.
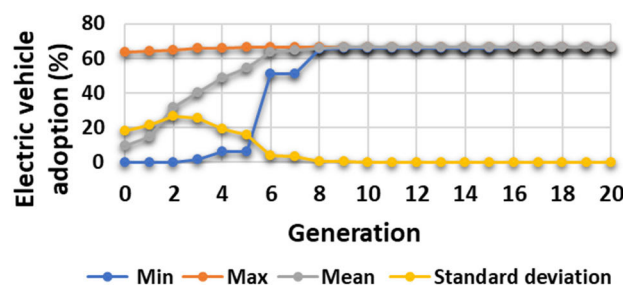

FIGURE 12. Optimizing over electric vehicle adoption (%).

3) MAXIMIZE EV ADOPTION AND NPV

The variables included in this simulation are the charging prices and power network constraints. This simulation solves two objectives in a multi-objective optimization problem and the NPV adoption weights of each objective are in Table 9.

This situation; (case A) assumes that the electricity bill of chargers is not considered and is paid off by an incentive from the grid provider. When the campus goal is to deploy EVs,

TABLE 9. Optimization of EV adoption and net present value for (Case A: with charging incentives).

Case	Adoption weight w_1	NPV weight w_2	Objective	Adoption %	NPV Million USD	Network %	USD/kWh
1	1	0	100	66.6	0.35	100	0.001
2	0	1	100.03	53.9	13.31	100	0.057
3	0.5	0.5	91.41	57.3	12.9	100	0.048
4	0.8	0.2	90.59	62.5	10.4	100	0.033
5	0.4	0.6	92.49	57.3	12.9	100	0.048
6	0.2	0.8	96.19	53.28	13.31	100	0.057

TABLE 10. Optimization of EV adoption and net present value for (Case B: no charging incentives).

Case	Adoption weight w_1	NPV weight w_2	Adoption %	NPV Million USD	Network %	USD/kWh
1	1	0	66.6	-36.8	100	0.001
2	0	1	29.9	0.677	36	0.107
3	0.5	0.5	52.6	-2.06	13	0.048
4	0.8	0.2	57.6	-3.66	16	0.033
5	0.4	0.6	47	-1.05	12	0.065
6	0.2	0.8	35	0.471	48	0.098
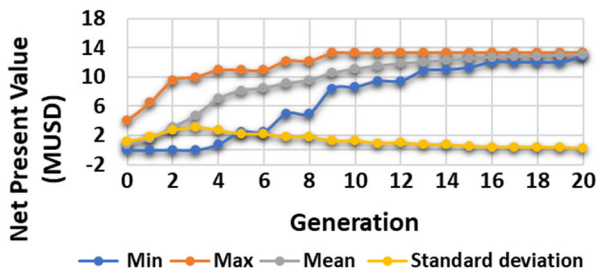
FIGURE 13. Optimizing over net present value (million USD).

the weight of EV adoption is high but not be higher than the NPV for investment attraction and vice versa. The maximum values from the previous optimization results are base values to normalize the NPV and EV adoption to a percentage of their maximums.

With objective payoff weights (0.8 for EV adoption) and (0.2 for NPV): the multi-objective solution is 100% infrastructure and 0.033 USD/kWh; the maximized objective is 90.59, in Table 9. With objective payoff weights (0.4 for EV adoption) and (0.6 for NPV): The solution is 100% infrastructure and 0.048 USD/kWh, and the maximized objective is 92.4882. A similar solution is when the adoption and NPV are equally important (wights are 0.5), Table 9.

Finally, the best economic solution is case 6, 0.057 USD/kWh when payoff weights are (0.2 for EV adoption) and (0.8 for NPV), in Table 9.

4) MAXIMIZE NPV AND EV ADOPTION WITH POLICY CONSIDERATION

The previous studies cover (case A) with charging incentives. Scenarios under (case B) consider no incentives, and the charging burden is on the campus. For the cases without solar PV, results for maximum adoption and NPV for different charging prices and infrastructure are in Table 10. Most of the results are in negative values (not feasible projects).

(Case B) becomes feasible (NPV=0.677 million USD, adoption rate = 29.9%) at a high charging rate of 0.107 USD/kWh and 36% power limit when (adoption weight $w_1 = 0$).

While in (case 6), the optimum charging rate reduces to 0.098 USD/kWh for a higher adoption ($w_1 > 0$) adoption=35%, NPV=0.471 million USD, and 48% power limit when (Adoption weight $w_1 = 0.2$). The infrastructure limit increased with a higher adoption while NPV reduced when increasing the adoption objective. The optimum network size depends on the required set policies, such as the tradeoff between the adoption and economic goals.

5) MAXIMIZE FOR NPV WITH SOLAR PV%

This section optimizes NPV for solar size and power network percentage, with different charging rates, see Table 11. First, the maximum NPV for (case A-1) is 119.58 million USD. Previously in Table 5, increasing the charging rate to 0.047 USD/kWh increased the NPV. But for the case with solar PV, as the charging rate increases, the NPV is reduced, and consequently, the recommended charging infrastructure reduces indirectly. For instance, (case A-1 to A-3) show

TABLE 11. Economic goal optimum PV size and power infrastructure for each charging rate.

No.	Solar tariff USD/kWh	Charging price USD/kWh	Case A (Base) Available incentives for to campus (Electricity rate for chargers = 0 USD/kWh)				Case B No incentives for to campus (Electricity rate for chargers = 0.088 USD/kWh)			
			PV size %	Power size %	Adoption	NPV	PV size %	Power size %	Adoption	NPV
1		0	100	100	65.6	119.58	100	100	65.6	83.2
2		0.032	100	90	61.6	54.82	100	69	61.3	30.22
3		0.047	100	69	55.8	29.013	100	51	55.3	14.90
4	0.088	0.057	100	55	53.6	23.78	100	39	52.7	12.62
5		0.088	0	60	39	7.94	100	7	32.2	3.18
6		0.098	0	48	35	6.52	100	4	11.4	2.87
7		0.13	0	13	17.1	1.83	100	1	2.53	0.99
8		0	100	100	65.6	200.86	100	100	65.6	164.44
9		0.032	100	100	61.6	117.40	100	100	61.6	89.77
10		0.047	100	86	55.9	72.57	100	70	55.8	51.92
11	0.12	0.057	100	71	53.8	59.20	100	71	53.8	42.19
12		0.088	100	17	37.8	12.90	100	16	37.7	9.05
13		0.098	100	10	33.7	9.77	100	10	33.7	7.41
14		0.13	100	3	8.88	2.75	100	2	5.35	2.18

infrastructure reduction from 100% to 69%, and NPV from 119.58 USD to 29.013 USD. The reduction is due to the decrease in the adoption, and therefore forecasted charging demand is reduced. However, the NPV is not affected by the infrastructure size with higher solar tariffs and can accommodate a more extensive power limit as in CaseA-10 86% power infrastructure and NPV=72.57 USD.

Second, for (case B), solar PV always benefits the EV project because of the PV power generation revenue that reduces the charging bills. For instance, in (case5) of Table 11, the optimum PV and charging infrastructure sizes are 0% PV and 60% power (case A). It means the EV project does not need a solar project to increase its revenue. However, with no incentives (case B), a 100% PV will always benefit the EV-PV project because of the solar tariff.

E. SIMULATION & COMPARISON ANALYSIS

The proposed tool is a system-dynamic model that can obtain the estimated EV adoption rate based on the selected policy and solves the optimum EV plan for maximum economic and environmental benefit. The other way around is that the model analyzes the effect of policy on the existing EV infrastructure plan. Economic and environmental indices are the validating measures to compare the case studies defined in Table 12.

First, the solution plan is obtained as the annual chargers per year Figure 14, and cumulative chargers installed Figure 15, annual solar PV installation in Figure 16, and cumulative solar installation to the year 2050 Figure 17.

In Run1 and Run2, the power infrastructure limit 55% and 39% limited the net chargers to 385 and 273, respectively. At the same time, the number of chargers can reach 699 for the case study at 100% infrastructure in Run3 and Run4.

TABLE 12. Cases input to the proposed tool (model).

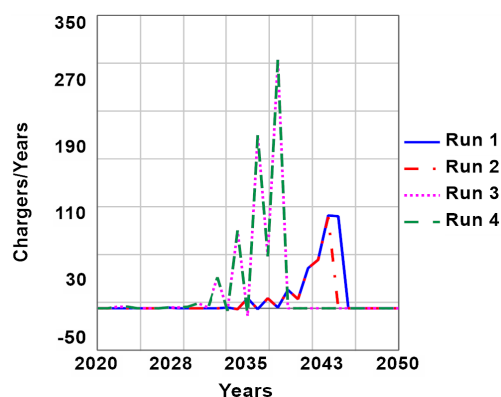|	PV	Power limit	Charging incentive	Charging rate
Run1	100	55	YES	0.057
Run2	100	39	NO	0.057
Run3	100	100	YES	0
Run4	100	100	NO	0

FIGURE 14. Annual charger installation.

The power infrastructure available for EV charging on QU campus is 15,378 kW.

For the results obtained by the proposed model, the total EV adoption on the QU campus case study is plotted in Figure 18. For the comparative cases (1 to 4), adoption is 53.6%, 52.7%, 65.6% and 65.6% respectively. Similarly, the number of EV users for cases (1 to 4) are 7.25k, 7.13k, 8.89k, 8.89k, respectively. The chargers reach a maximum at the year 2039 (699 chargers) for 2.39k users, Figure 15, and the charger to
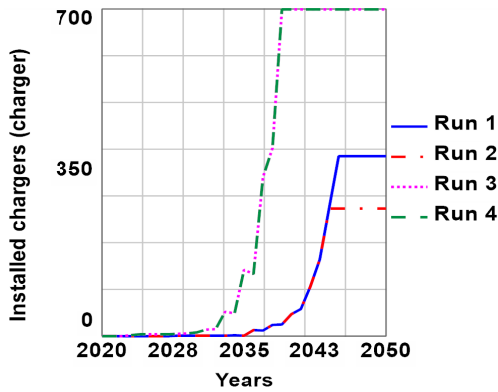
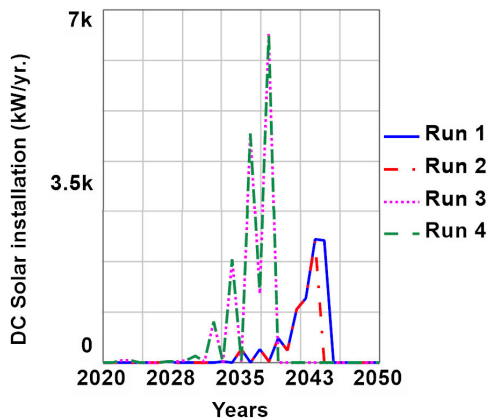**FIGURE 15.** Cumulative installed chargers on campus.

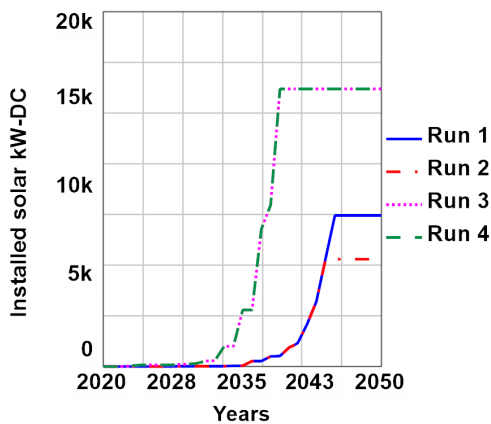**FIGURE 16.** Annual solar PV installation.

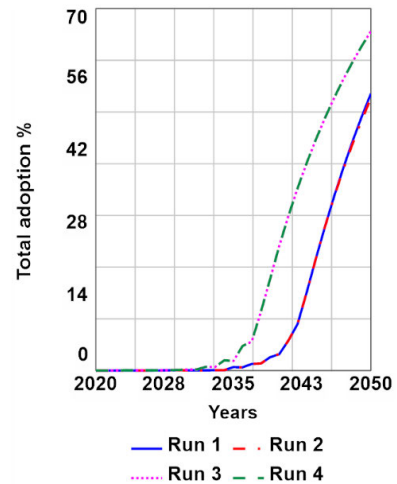**FIGURE 17.** Commutative installed solar PV projects.

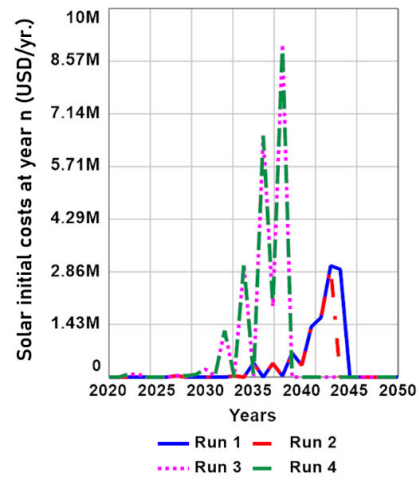**FIGURE 18.** Estimated electric vehicle adoption at QU campus.

FIGURE 19. Initial costs EV infrastructure staging plan – case study QU campus.

Cases without charging incentives have lower NPV even if solar PV is installed at 1:1 ratio with EV infrastructure (PV=100%). The cases of 100% infrastructure and 100% PV (no charging rate) have high initial costs exceeding 3 million (Run3 and Run4). The choice to limit the annual budget is kept for future work, which can be added to the EVI-PAT dynamic model. Reducing the annual budgeting results with reducing the NPV as in Run1 and Run2 compared with Run3 and Run4.

1) BEHAVIOR VALIDATION

Behavior validity assesses how the model-generated behavior mimics the observed behavior of the real system to achieve the overall validity of the model or to build confidence in the model [57]. The methodology includes finding the overall behavior similarity in the output shape such as growth, oscillation or specific patterns such as in inflection points, periods.

Real-life campus charging infrastructure installations at The University of Massachusetts (UMass) Medical
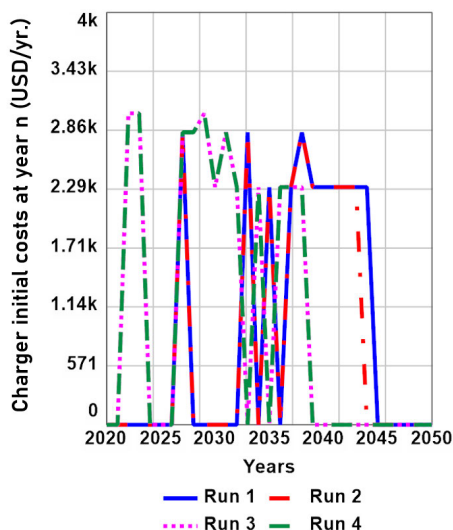
EV ratio is 1 to 10. A charger in this study has 22 kW that can charge 3 vehicles considering a single-vehicle user's average charging as (6.6 kW), and consequently, 699 chargers serve 2,097 charging sessions per hour.

Finally, the staging plan obtains the number of chargers and solar sizes to be installed at years n. The initial costs for the annual installation of the EVCSs and PV solar installations for every year n, are in Figure 19 and Figure 20, respectively. The total NPV of the cases (1 to 4) for 30 years is 23.78, 12.62, 119.58, and 83.16, respectively, see Table 11.

FIGURE 20. Initial costs for solar projects associated with EV infrastructure staging plan – case study QU campus.

FIGURE 21. Annual ports at massachusetts medical school.

FIGURE 22. Cumulative number of ports on campus at massachusetts (UMass) medical school.

School [58], [59] is plotted in Figure 21 and Figure 22. A plot of the number of charging ports installed versus the installation year Figure 21. In 2021, the total number of chargers is 44, 77 charging spaces (ports), and the number of unique users is more than 50 users, see Figure 22. The average power drawn per port is 6.6 kW. All stations are set up to be able to draw voltage from a range of 208-24, and can draw up to 30 A. There are 80% level 2, 13% level 1, and 7% DC fast chargers on campus.

For the proposed model's output, the cumulative charger installation pattern in Figure 15 is compared with the real-life situation in Figure 22. The results mimic real-life campus infrastructure at the University of Massachusetts Amherst [60] and [61]. The plots show similarities in the overall S-shape-growth behavior.

F. POLICIES SUPPORTING SOLAR CHARGING

This section discusses the policies supporting solar power generation for EV charging that promote EV adoption and maximize EV and PV synergies. Policies related to PV alone aim to reduce the financial burden to encourage PV projects into the electricity generation market and facilitate integration. The current policies related to PV include tax incentives, feed-in tariffs, Levelized cost of energy (LCOE), and subsidies [62]. PV-related policies are different between regions, which in return will require PV projects to undergo planning studies.

Realizing PV infrastructure combined with EV chargers is an advantage to reduce CO_2 emissions substantially. A dedicated task by the International Energy Agency (IEA), namely subtask 2 of Task 17, includes analyzing the performance of PV-powered charging stations (PVCS) projects [63]. One of the recommendations from this task is to perform technical and economic optimization of the PVCS projects under the local site condition over the entire 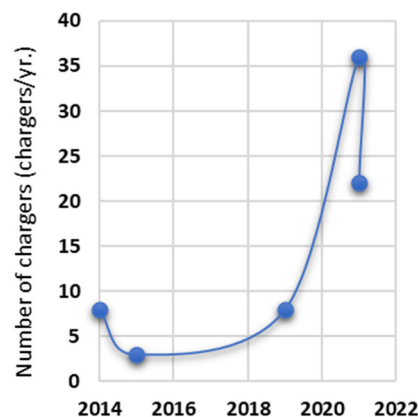lifespan of the PV. Furthermore, the IEA report recommends developing new methodologies and tools for optimizing the PV infrastructure for EV charging [64].
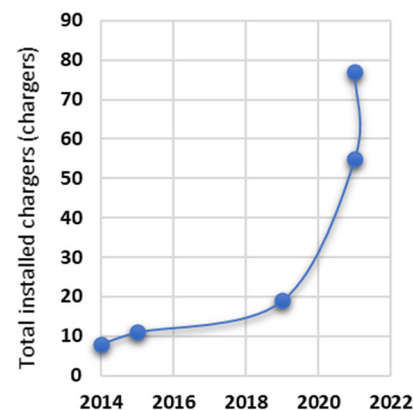
In a recent study by National Renewable Energy Laboratory (NREL), the scope evaluates the utility cost savings considering the net-metering policy at EV chargers with grid-connected PV [65]. They recommend reducing the PV and storage sizes proportionally when the number of EV chargers is reduced from 6 to 3 in a grid-case scenario (for the case study). Also, adding PV to EV load alone (no building load) is not as beneficial as adding the building load to the overall study.

To realize EV/PV synergy, investigating the correct charging prices and feed-in tariffs for a particular region is crucial for a profitable project. An efficient EV/PV synergy requires certain levels of EV and PV in the system for the same region [66]. On the other hand, virtual net-metering allows EVCS to benefit from off-site solar rooftop photovoltaic (SRTPV) [67]. It means that the energy generated in a community can offset the energy consumption of an EVCS at another site. The EVCS has ownership shares of the STRPV but cannot accommodate the space required for PV installation on-site.

Workplace charging initiatives include funding, free charging, and charger price reduction, which is very helpful in EV uptake [68]. Combining work charging with solar causes dips in daytime power and high peaks during night [69]. The smart charging policy allows for flexibility charging (peak reduction/load shifting) to adopt both the power system conditions and the vehicle user's needs. One of the smart charging policy objectives is to harness renewable energy while scheduling EV charging [70]. It involves shifting the charging load to specific times during the day such as during high solar energy generation. In other words, smart charging is the core solution to maximize the benefit of solar PV at EV charging points.

In order to meet smart charging policies, further modifications and requirements should be placed on EV chargers' stakeholders, including charging infrastructure operators, electricity aggregators, and electricity suppliers, and such requirements can include:

1) Smart meters requirement to allow sending and receiving information.
2) Mandate smart charging on new EV chargers.
3) Smart functionality includes the ability to increase/decrease charging rate and change charging times and duration.
4) Mandate monitoring system requirement on chargers to calculate exported and imported electricity to allow for bi-directional flow.
5) Chargers' internet of things (IoT) devices must include cyber security as a minimum requirement to protect against cyber-attacks.

V. CONCLUSION

This paper proposes a model that combines optimization with system-dynamics for EV infrastructure planning and analysis of micro-scale projects. The model is validated with historical data for EV installation on campuses to illustrate how the model results are practical. The output of the tool is the sizes and installation times for EV chargers and solar PV infrastructure. The staging plan is evaluated with a case study Qatar University, and the evaluation is done through comparative plots of the economic and environmental indicators for different staging plans.

The feasibility of EV infrastructure project depends indirectly on the EV adoption rate of the country. The charging rate can affect EV adoption where the optimum case is when the charging rate is almost zero with available charging incentives and no solar PV. For this case, the project is not feasible; therefore, installing solar PV is recommended.

Depending on the charging rate, EV-PV project sizes and years of installations can be chosen using the proposed method with the economic and environmental assessments. The economic optimization of the solar size and power network limit % for the EV-PV infrastructure project is highly dependent on policy. The recommendation is that if the EV chargers have no charging rate, the optimum PV size is 100%, and increasing the charging rate will reduce the NPV by indirectly reducing the adoption. In this case,

increasing the solar tariff will increase the NPV where the optimum values can be defined using the proposed model. When there is no charger incentives policy for universities, the recommendation is 100% PV installation with smaller charging infrastructure (at an optimum size) to reduce the charging burden and benefit the EV-PV project by maximizing the NPV.

Thus, the model allows for policy analysis where policies can affect the optimum limit of power infrastructure for maximum economic benefit by the solar tariff. A project with a lower solar tariff requires limiting the power infrastructure as the adoption attraction reduces and vice versa. Solar PV is not always feasible with EV, depending on the charging rate, charging incentive, and power infrastructure limit constraint.

Finally, the proposed planning framework finds the optimum staging plan for EV and PV based on predefined policy choices. However, the EV infrastructure will be based on highly uncertain and dynamic polices, and existing approaches cannot perform well in the future. As a result, in the future, we aim to research the novel concept of deep learning (DL) to find more accurate and realistic PV forecasting to optimally balance the performance.

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