Technical and Economic Feasibility Analysis of a Solar-Powered Electric Vehicle Charging Station

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***Abstract*—This paper presents a comprehensive study evaluating technical and economic aspects of integrating solar generation in an electric vehicle charging station in a commercial building. The analysis applies Monte Carlo simulation in order to properly consider the stochastic nature of solar generation and electric vehicle demand, using meteorological and load data from a location in Texas, USA, and electricity prices from an electric power utility company. Two vehicles arriving time profiles are analyzed: coincidental and non-coincidental with maximum solar generation availability. The results show that the solar charging station project is an attractive investment with an average cost reduction of 6.5% in the monthly energy electricity bill, and payback time of 9 years considering the federal solar tax credit and the electric vehicle rebate program offered by the local utility.**

***Index Terms*— economic analysis, Monte Carlo simulation, plug-in electric vehicles, probabilistic analysis, solar generation.**

I. Introduction

Plug-in electric vehicles (PEV) are becoming increasingly popular worldwide due to their potential for reducing petroleum use and CO_2 emission. According to the International Energy Agency, plug-in electric vehicles sales surpassed 1 million units in 2017, representing a growth in new electric car sales of 54% compared with 2016 [1]. The charging infrastructure for PEVs is also growing considerably. By the end of 2017, the number of public and workplace charging points had surpassed 47,000 in United States with an increase of 18% since 2016 [2].

Although seen as an environmentally friendly option, PEVs demand represent a significant increase on the existing load and can still contribute with indirect greenhouse gas emissions depending on the energy source used for charging the vehicles [3]. The continuous drop in solar panel price makes solar energy an attractive solution to charge PEVs. It can be a very favorable scheme for daytime charging at workplaces and commercial buildings, where the parking duration time is usually much longer than the charging time needed.

Several papers have been proposed addressing solar energy use to charge PEVs [4]. Reference [5] proposes a smart charging method for a solar parking lot with stationary storage battery, considering average profiles of seasonal photovoltaic production from Portugal. Reference [6] investigates the use of solar energy to charge PEVs with local battery at a workplace in the Netherlands. The study evaluates different smart charging schemes under deterministic analysis. In [7], the potential benefits of using solar generation to charge PEVs is examined considering different geographical locations in Italy. In [8], a solar-powered PEV charging station is designed with maximum power point tracking (MPPT) controller and vehicle-to-grid technology. In [9], a charging algorithm is proposed to an electric vehicle charging station with solar generation for a car-share service in a parking lot. The objective is to increase the use of solar energy and maintain similar battery levels for all cars, considering different demand profile.

Although some work has been done, there is still need to investigate the use of solar energy to charge PEVs probabilistically, since solar energy is very intermittent in nature and PEV demand has stochastic behavior. This paper presents a comprehensive study analyzing technical and economic benefits of integrating solar generation in a PEV charging station in an existing non-solar parking lot facility. A stochastic approach based on Monte Carlo simulation is adopted to consider the uncertainties from solar generation, load and PEV demand. The analysis considers time-of-use (TOU) pricing, meteorological and load data from a location in Texas based on uncontrolled charging scheme, which is a more realistic scenario for nowadays. Two vehicles arriving time profiles are considered: coincidental and a non-coincidental PEV demand with maximum solar generation availability. The solar charging station is grid-connected, and the power generated by solar panels can be used to charge PEVs without the need for storage system. The solar energy surplus can be used to meet building load, and the grid can attend the exceeding PEV demand. The main contributions of this paper are: perform a probabilistic analysis of the benefits obtained with a solar-powered PEV charging station and assess the economic viability of the project based on real data.

The remainder of this paper is organized as follows. Section II shows PEV load and solar energy modeling. Section III presents the Monte Carlo methodology and main evaluation metrics adopted. Section IV discusses simulation results and Section V addresses the main conclusions achieved.

II. PROBABILISTIC MODEL

The system under consideration consists of a commercial building assumed to be integrated with a solar-powered PEV charging station with capacity for 7 vehicles. The solar panels can be installed on the rooftop of the building or as a solar carport. In both cases, the facility is connected to the grid. The solar generation is used for supplying PEVs charging and building demand. If solar energy is not enough to supply these loads, the grid must supply this extra power. The stochastic model for solar generation, PEV demand and building load is described next.

Figure 1. System under study.

A. Solar Generation Modeling

In this study, historical data of irradiance and ambient temperature was collected over a year for Austin, Texas, using PVWatts calculator developed by the National Renewable Energy Laboratory (NREL) [10]. Fig. 2 shows the average daily solar irradiance over a one-year period. In order to capture data dependency to weather conditions, the available data is divided into four seasons: winter (November to January), spring (February to April), summer (May to July) and autumn (August to October), and one day is split into 24-h periods. Based on historical irradiance data, mean μ^t and standard deviation σ^t values are calculated for each hour of the day in order to consider hourly fluctuations of solar irradiance. Beta probability density function (PDF) is commonly used to model solar irradiance, and is represented by [11]:

$$f_s^t = \frac{\Gamma(\alpha^t+\beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)}(s^t)^{(\alpha^t-1)}(1-s^t)^{(\beta^t-1)},\ 0\le s^t\le 1,\ \alpha^t,\beta^t\ge 0 \quad (1)$$

$$\beta^t = (1-\mu^t)\left[\frac{\mu^t(1-\mu^t)}{(\sigma^t)^2}-1\right] \qquad \alpha^t = \frac{\mu^t\beta^t}{(1-\mu^t)} \quad (2)$$

where s^t is the random variable of solar irradiance at time t in W/m^2, Γ represents the Gamma function, α^t and β^t are the parameters of Beta pdf at time t obtained using μ^t and σ^t according to (2). Finally, random samples of irradiance are generated according to the pdf to each hour interval, to each season.

The hourly PV output power can be evaluated by (3) and (4) using the irradiance data generated [5]:

$$P_{PV}^t = \left(\frac{N\,\eta\,P_r\,s^t}{s_{ref}}\right)\left[1+\lambda(T_{cell}^t - T_{ref})\right] \quad (3)$$

$$T_{cell}^t = T_a + \frac{s^t}{800}(NOCT-20) \quad (4)$$

where N is the number of solar panels, η is the efficiency, P_r is module nominal power in W, λ is power temperature coefficient in %/°C, T^t_{cell} is temperature of cells in °C at time t, T_a is ambient temperature in °C, $NOCT$ is the normal operating cell temperature in °C, s_{ref} and T_{ref} are irradiance and cell temperature values under standard test condition (STC), which are 1,000 W/m^2 and 25°C respectively.

To illustrate hourly fluctuations of solar irradiance, Fig. 3 (a) shows the beta PDF to different day hours. Note that at 8:00 h the probability of having lower values of irradiance is higher than at 16:00 h. The Beta cumulative distribution function (CDF) obtained using measured solar irradiance data is compared with the Beta CDF obtained with generated random data for different day hours, as shown in Fig. 3 (b). It can be observed from the figure that Beta distribution gives a good fit to solar irradiance. The Chi-Square test was also conducted to check the goodness of fit of Beta PDF for modelling solar irradiance. The solar system adopted in this study consists of 72 poly-crystalline panels from Canadian Solar model CS6K rated at 275W at STC, with total installed power of 19.8kW [12]. The specifications are shown in Table I.

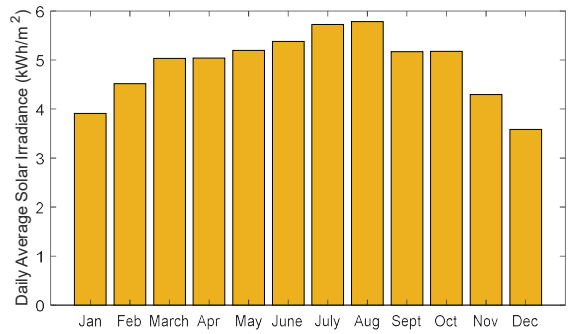

Figure 2. Daily average solar irradiance in the study area.

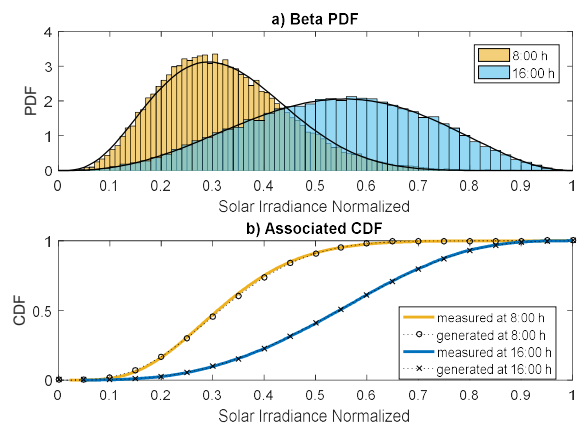

Figure 3. Solar Irradiance: a) Beta PDF b) Associated CDF.

TABLE I. SOLAR MODULE DATA

Parameter	Value
Nominal operating cell Temperature (NOCT)	43 °C
Voltage at maximum power point (V_{MPP})	28.5 V
Current at maximum power point (I_{MPP})	7.08 A
Open circuit voltage (Voc)	35.4 V
Short circuit current (Isc)	7.63 A
Power temperature coefficient (γ)	-0.41 % /°C

B. Plug-in Electric Vehicles Modeling

Since PEV demand depends on several factors such as mobility behavior, vehicle characteristics and charging start time, a probabilistic model is employed. Three factors play a crucial role in determining PEV demand: charging duration, vehicle arrival time and charging power. The charging duration can be evaluated as shown in Algorithm 1 [13], based on

vehicle data, initial state-of-charge (SOC) and daily driving distance. Using actual NHTS 2017 data [14], the histogram of the daily driving distance in U.S.A. is shown in Fig. 4 (a), with mean value of 29.5 miles. After applying the Chi-squared test, the results showed that the observed data fit a Weibull distribution with parameters $\alpha = 31.4$ and $\beta = 1.24$, and random samples can be generated. The associated initial SOC is evaluated and its histogram is presented in Fig. 4 (b).

The vehicle arrival time depends on the building type and occupants' behavior. As an example, in residential buildings most cars arrive at the end of the day. In schools, most cars arrive at the early morning. This paper considers two different arriving time profiles for the commercial building and their PDF are shown in Fig. 5: a) case 1: non-coincidental arrival and b) case 2: coincidental arrival. In both cases vehicles arriving time is assumed to follow a normal distribution, which is commonly used to model this variable [15]. In case 1, most cars arrive around 8 a.m. and PEV peak-demand does not coincide with maximum solar generation availability. In case 2, most cars arrive at noon, and PEV peak-demand coincides with maximum solar generation availability.

Algorithm 1: Evaluation of PEV charging duration.

Input: C_b: vehicle battery capacity in kWh, d: daily driving distance, E: energy consumption in kWh/100 miles, η: charger efficiency considered 90%, P: charging power.
Output: $Ch_{duration}$: PEV charging duration in hours.
{1}**Begin**
{2}**Generate** random numbers for driving distance based on Weibull distribution with α the shape factor and β the scale factor, given by:

$$f_d = \frac{\alpha}{\beta}\left(\frac{\alpha}{\beta}\right)^{\alpha-1} exp\left[-\left(\frac{d}{\beta}\right)^{\alpha}\right]$$

{3} **Evaluate** energy consumed given by: $E_{cons} = (d \times E)/C_b$
{4} **Set** $SOC_{\%}^{max} = 100\%$ and $SOC_{\%}^{min} = 5\%$ to avoid battery degradation.
{5} **Evaluate**: $SOC_{\%}^{ini} = max\{SOC_{\%}^{min}, 100 \times (1 - E_{cons})\}$
{6} **Evaluate**: $E_{req} = \left(100 - SOC_{\%}^{ini}\right) \times C_b/(\eta \times 100)$
{7} **Evaluate** charging duration: $Ch_{duration} = E_{req}/P$
{8} **end**

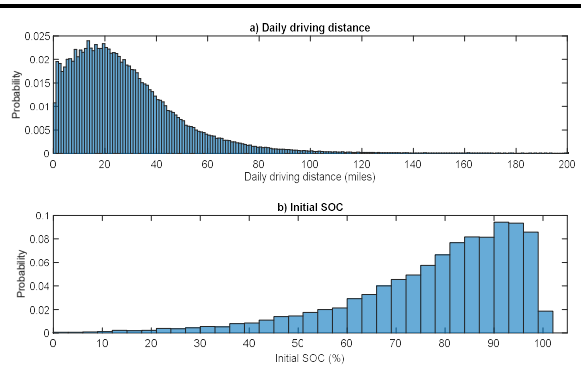

Figure 4. Histogram: a) Daily driving distance b) Initial SOC.

Simulations consider vehicle parameters from Nissan Leaf 2018 with Cb = 40kWh, E = 30kWh/100miles, charger efficiency of 0.8 and on-board charger of 6.6kW. The charging power is assumed constant throughout the charging period. The power consumed by the electric vehicle fleet is the sum of the power drained by each vehicle. Also, PEV consumption was considered 20% higher in winter season since electric vehicles experience efficiency losses in cold temperatures and require additional power for heating [16].

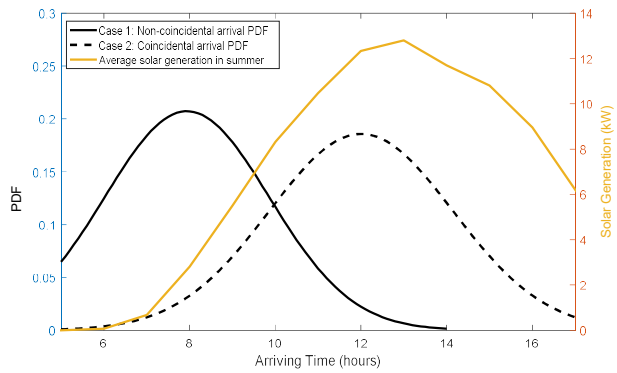

Figure 5. Vehicle arriving time and solar generation availability.

C. Load Modeling

The building load data was obtained from Electric Reliability Council of Texas website (ERCOT) for the South Central region and is shown in Fig. 6 [17]. A constant power factor of 0.95 is considered. Based on this data, the building load is modeled by the commonly used normal distribution. The random variables are generated to each hour of the day for each season, with mean values based on the hourly load data.

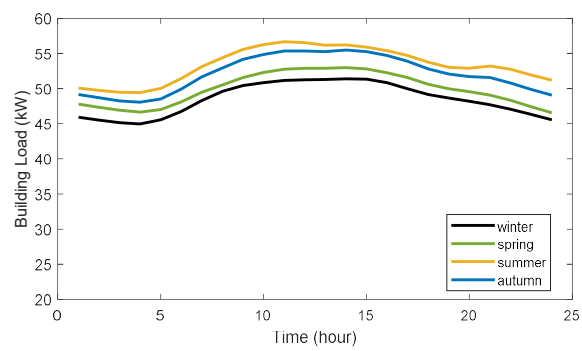

Figure 6. Building load for different seasons.

III. METHODOLOGY

Monte Carlo simulation is a statistical technique that consists on generating random samples repeatedly, computing the output to each sample to perform a statistical analysis [18]. An important aspect is to define the number of iterations required to reach convergence since the precision improves with the increase in the number of iterations. The Monte Carlo procedure applied in this study follows these steps:

1. Generate random numbers for building load based on its distribution function for each hour of the day, for all seasons;
2. Generate random numbers for solar irradiance based on its distribution function and obtain solar generation for each hour of the day, for all seasons;
3. Generate random numbers for driving distance and arriving time based on their distribution function and obtain PEV demand for each hour of the day, for all seasons;
4. Compute the proposed metrics;
5. Perform statistical analysis of results.

In this study, two metrics are used to verify the technical feasibility of the solar-powered charging station. The first one is the daily savings in electricity consumption cost ($S_{daily,\%}$), evaluated comparing the daily costs with and without solar generation as shown in (5)-(7):

$$S_{daily,\%} = 100 \times \left(1 - \frac{C_{daily,with\,PV}}{C_{daily,no\,PV}}\right) \quad (5)$$

$$C_{daily} = \sum_{t=1}^{N} P_{cons}^{t} \times \Delta t \times T_{f}^{t} \quad (6)$$

$$P_{cons}^{t} = P_{L}^{t} + P_{PEV}^{t} - P_{PV}^{t} \quad (7)$$

where C_{daily} is the daily electricity consumption cost in \$, P^{t}_{cons} is the power consumed from grid at time step t in kW, ΔT is time interval, T_f^t is the energy tariff at time step t in \$/kWh, N is the number of intervals during simulation, P_L^t is the building load at time step t in kW, P^{t}_{PEV} is the aggregated electric vehicle demand at time t in kW, P_{PV}^t is the solar generation at t in kW. The energy tariff considered in this study is presented in Table II, which is a time-of-use (ToU) tariff applicable to commercial users by a power utility from Texas [19].

TABLE II . COMMERCIAL TOU RATES

	On-peak hours (3p.m.–8 p.m. from May to Oct.) (6p.m.–8 a.m. / 3p.m.–8p.m. from Nov. to Apr.)	**Off-peak hours**
\$/kWh	0.166989	0.073605

The other metric evaluated in this study is the percentage of PEV demand expected to be covered with PV given by:

$$DC_{\%} = 100 \times \frac{\left(\sum_{t=1}^{N} P_{PEV,PV}^{t}\right)}{\sum_{t=1}^{N} P_{PEV}^{t}} \quad (8)$$

where $P^{t}_{PEV,PV}$ is the aggregated PEV demand at time step t supplied by solar generation, P^{t}_{PEV} is the aggregated PEV demand at time t, and N is the number of intervals in simulation. Fig. 7 illustrates this concept. If PEV demand is higher than solar generation, the difference will be taken from the grid since the system is grid connected. If solar generation is higher than PEV demand, the overproduction will be used to attend building demand.

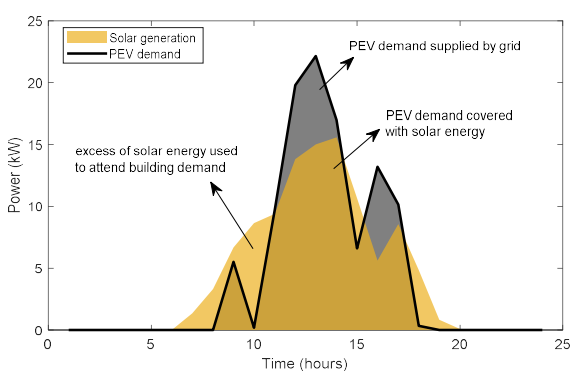

Figure 7. PEV demand covered with solar generaton

To verify the economic feasibility of the project, three investment indicators are evaluated: Net Present Value (NPV), Internal Rate of Return (IRR) and Payback Time (PT). The NPV is the difference between the present value of cash inflows and cash outflows over a time period. The IRR is a discount rate that makes NPV equal to zero, and the PT is the necessary time to recover the cost of an investment, when the cumulative cash flow becomes a positive number [20]. These metrics are evaluated by:

$$NPV = -C_0 + \sum_{t=1}^{T} CF_t (1+r)^{-t} \quad (9)$$

$$-C_0 + \sum_{t=1}^{T} CF_t (1+IRR)^{-t} = 0 \quad (10)$$

where C_0 is the cost of the investment in \$, r is the discount rate in %, T is the total number of years the investment is evaluated, and CF_t is the cash flow at time t in \$, defined as the difference between cash inflow and cash outflow. Table III shows the data summary used in the economic analysis [21,22,23].

TABLE III . EQUIPMENT COST AND FINANCIAL PARAMETERS

Parameter	**Value**	**Parameter**	**Value**
PV module	\$200/unit	O&M cost	0.5%/year
Pedestal charging st.	\$1,285.00/unit	Inflation rate	1.6%/year
Inverter	\$0.15/Wac	Discount rate	5.0%/year
Installation cost	15%	Energy increase	2.5%/year

IV. SIMULATION RESULTS

This paper analyzes the potential savings and the percentage of PEV demand covered with solar generation when using a solar-powered electric vehicle charging station. This study adopted 50,000 Monte Carlo iterations to obtain the convergence of the method, which occurs when the mean value of output results doesn't change significantly with each new run, and the variance lies to a confidence interval. The analysis is performed considering data divided into four seasons (winter, spring, summer, and autumn). Simulation time step was set to 1 hour and focuses on commercial customers considering different vehicles arriving time profiles: a) Case 1: non-coincidental arrival; b) Case 2: coincidental arrival.

Fig. 8 shows the box-plot of PEV demand covered with solar generation for each season for cases 1 and 2. In each box, the red mark in the central indicates the median, and the blue edges at the bottom and at the top indicate the 25th and 75th percentiles, respectively. The black whiskers are extreme data points not considered outliers, and the outliers are plotted using the '+' symbol. As expected, PEV demand covered with solar generation is bigger during summer due to high irradiance levels. Also, since in case 2 PEV peak-demand is coincidental with solar generation, the percentage of PEV demand covered with solar generation is bigger than in case 1. The annual average demand covered with solar generation is 29.75% for case 1 and 65.47% for case 2.

The statistical analysis with minimum, maximum, mean and standard deviation values of the daily savings in electricity consumption cost obtained installing the solar-powered charging station is presented in Table IV. As expected, in both cases savings are bigger during summer season due to high irradiance levels. Also, the average annual savings are 6.57% in both cases 1 and 2. Although PEV demand covered with solar generation is bigger in case 2, the excess of solar generation is used to supply energy to the local building, and cost savings can still be achieved.

The installation of the solar charging station represents an average cost reduction of \$188.76 in the monthly electric energy bill. Considering that the facility offers free charging and a project duration time of 25 years (solar panels lifetime), the NPV, IRR and PT were evaluated. Fig. 9 shows the cumulative cash flow, which leads to a NPV of \$7,957.59, IRR of 7%, and payback time of 13 years. If the cash flow analysis considers the rebate of \$4,000.00 currently offered by Austin Energy for installing Level 2 charging stations, and the federal solar tax credit of 30%, the payback time can be reduced to 9

years with NPV of $18,211.81 and IRR of 11%, becoming a more attractive investment.

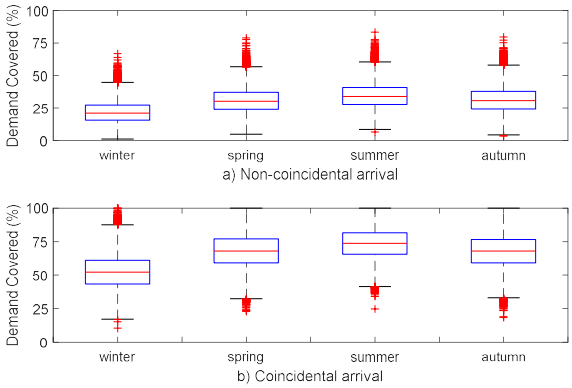

Figure 8. Box-plot of PEV demand covered with solar generatoin. a) Non-coincidental arrival b) Coincidental arrival.

TABLE IV . STATISTICAL ANALYSIS OF POTENTIAL DAILY SAVINGS

Season	Potential Daily Savings (%)					
	Case 1: Non-coincidental			Case 2: Coincidental		
	Min.	Mean	Max.	Min.	Mean	Max.
Winter	1.62	5.45	9.82	1.65	5.54	10.19
Spring	2.67	6.72	10.11	2.73	6.81	10.33
Summer	4.04	7.50	10.35	4.03	7.40	10.22
Autumn	2.29	6.59	10.54	2.25	6.50	10.37

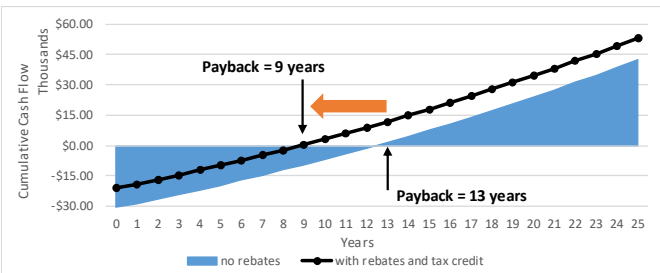

Figure 9. Cummulative Cash Flow for coincidental arrival scenario.

V. CONCLUSION

This paper presents a technical and economic feasibility study for installing a solar-powered charging station in a commercial building. The system is grid-connected and does not require stationary battery system, since solar energy surplus can be used to meet local demand of the building. A stochastic approach based on Monte Carlo simulation is implemented to consider the uncertainties from solar generation, load and PEV demand. The analysis considers TOU pricing, load and meteorological data from a location in Texas based on uncontrolled charging scheme, which is a more realistic scenario. The conclusions are as follows:

- The average demand covered with solar generation is bigger for the coincidental arrival time scenario, around 65.47%;
- The solar charging station installation represents an average cost reduction of 6.5% in the monthly energy electricity bill even for non-coincidental arrival time scenario;
- The cost reduction in the monthly energy electricity bill is around 5.5% during winter, which is still satisfactory;
- The project proved to be an attractive investment even without payments for customers to charge their PEVs, with a payback time of 9 years considering federal solar tax credit and rebates currently offered by local power utility.

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