Proceeding Paper

Optimal Planning of a Photovoltaic-Based Grid-Connected Electric Vehicle Charging System Using Teaching–Learning-Based Optimization (TLBO) †

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Abstract: In this paper, an energy management schedule is proposed for a renewable energy (RE)-based grid-connected electric vehicle (EV) charging system (commercial charging station). This energy management schedule was converted into an energy management algorithm (EMA) on which teaching-learning-based optimization (TLBO) was used to determine the optimum size of the photovoltaic (PV) array and energy storage unit (ESU) required to charge electric vehicles with the help of the proposed energy management scheme. It was designed in such a way that the EVs are charged without incurring economic losses to the station owner. The objective function of the TLBO was formulated based on a financial model that comprised the grid tariff, EV demand, and the purchasing as well as selling prices of RE and ESU energy. By integrating the financial model with the energy management algorithm (EMA), the TLBO computed the minimum number of PV modules (Npv) and ESU batteries (Nbat) for various vehicles.

Keywords: energy management; optimization; power grid; objective function

1. Introduction

The volatile prices of oil and increasing emissions of greenhouse gases associated with conventional vehicles have created a shift in the automobile industry towards electric vehicles [1–3]. In this regard, various large-scale automobile manufacturing companies have developed electric vehicles; some of them have already taken over the automobile market [4,5], whereas many are on the way to being launched.

There are a number of applicable approaches that can be taken into consideration for the purpose of developing an EV charging system, as discussed in previous studies [6–8]. The first approach is a grid-connected electric vehicle charging station without renewable energy (RE) resources and electrical storage units (ESUs). The advantage is in its simplicity; however, this technique is not much appreciated due to increased grid burden, power quality problems in the distribution system, and the limited number of EVs which can be connected [9–13]. Another approach available is grid-connected electric charging stations with ESUs, which are only advantageous in terms of system flexibility and reductions in load peaks in the grid, although this technique is more expensive to employ with ESUs relative to batteries connected to EVs [14–18]. Comparing grid-connected electric charging stations with renewable energy (RE) resources only, these reduce the peak load demand on the grid, although require advanced optimal system designs for RE and control strategies for power fluctuations and voltage instability caused by RE [19,20]. In this paper, grid-connected electric charging stations with renewable resources and ESUs are proposed. The advantages of this method are: it encompasses peak power flow shaving, reduced power losses of the connected grid, and better power quality [21]. In this paper, an optimized energy management schedule is proposed for EV charging stations.
2. Methodology

Figure 1 presents the general scheme of the suggested PV–ESU–grid charging system [22,23]. As earlier discussed, the main electrical components are RE sources, power grids, electric vehicles, and electric storage units (ESUs), which can be interconnected as shown in Figure 1.

![Figure 1. General scheme of the proposed system.](image)

Mathematical models for each of the following components were established in MATLAB. The single-diode model was used to calculate the PV output power. The output current of PV, ie, Ipv, are written as [21]:

\[
I_{pv} = \left[ (I_{sc, stc} + K_i (T - T_{stc})) \frac{G}{G_{stc}} \right] - \left[ I_0 \left( e^{\frac{V_{pv} + I_{pv} R_s}{V_T}} - 1 \right) \right] - \left( \frac{V_{pv} + I_{pv} R_s}{V_T} \right)
\]

where \(I_{sc, stc}\) is the short circuit current at standard test conditions, \(K_i\) is the temperature coefficient of the current, \(G\) is the instantaneous irradiance, \(G_{stc}\) is the irradiance during standard test conditions, \(I_0\) is the saturation current, \(V_{pv}\) is the instantaneous voltage, \(V_t\) is the thermal voltage, \(R_s\) is the series resistance, and \(R_{sh}\) is the shunt resistance.

Thus, the PV output power can be obtained as:

\[
P_{pv} = \max (I_{pv} \times V_{pv})
\]

\[
P_{pvwr} = P_{pv} \times N_{pv}
\]

In order to obtain the irradiance and temperature used in the single-diode model, meteorological data of Southern California were obtained from the official website of the NREL (National Renewable Energy Laboratory), USA.

The ESU model is represented by its state of charge equation, which is written as [21]:

\[
SOC(t) = SOC(t-1) \times (1 - \delta_{bat}(t)) + (PE(t)/V_{bus}) \times \eta_{bat} \Delta t
\]

In the above equation, \(\delta_{bat}(t)\) indicates the self-discharge rate on an hourly basis, which is normally taken as 0.29; \(\eta_{bat}\) represents the efficiency of charging and discharging of the battery, which is assumed to be 100%. \(V_{bus}\) is the DC common bus voltage; for this study, it was considered to be 500 V [21]. To increase the life of batteries, their SOC was limited within the defined values of SOCU and SOCL, which were fixed at 90% and 10%, respectively [21].

As far as the EV demand is concerned, site data have been collected by Muratori et al. [24]. This dataset includes at-home plug-in electric vehicle recharging profiles for 348 vehicles.
associated with 200 households randomly selected among those available in the 2009 RECS dataset for the Midwest region of the United States.

Levelized costs of electricity (LCOEs) for the PV array (abbreviated as PV_Pr) and ESU (abbreviated as ESU_Pr) were considered, as in previous studies [21], i.e., USD 0.167/kWh for PV and USD 0.15/kWh for ESUs. Nevertheless, the electricity prices of the grid energy (called GE_Pr) were hypothetically generated with the help of the random function in MATLAB.

2.1. Operating Modes

There are six possible operating modes depending upon the real-time situations, which are presented subsequently.

2.1.1. First Operational Mode (PV 2 EV)

This operating mode works when the EV demand is greater than or equal to the PV generation. In either case, energy is transferred from PV to the EV.

2.1.2. Second Operational Mode (ESU 2 EV)

This operating mode starts when the EV demand is greater than the PV generation. In this case, energy will be transferred from the ESU to the EV.

2.1.3. Third Operational Mode (GRID 2 EV)

This operating mode starts if the EV demand is greater than the cumulative energy of PV generation as well as the ESU. In this condition, the remaining deficit of EV demand shall be fulfilled by the grid.

2.1.4. Fourth Operational Mode (PV 2 ESU)

This mode works when the EV demand is less than the PV generation. In this condition, the remaining PV energy, after fulfillment of the EV demand, shall be fed to the ESU.

2.1.5. Fifth Operational Mode (PV 2 GRID)

This mode is activated when the PV energy is still surplus after fulfillment of the EV demand as well as the charging of the ESU up to its highest limit. In this condition, the excess PV energy shall be transferred to the grid.

2.1.6. Sixth Operational Mode (GRID 2 ESU)

This mode works when the PV-generated energy is insufficient to completely charge the ESU up to its highest limit. In this condition, the remaining requirements of the ESU, after taking PV energy, shall be supplemented by the grid. This is called the valley-filling phenomenon.

2.2. Proposed Energy Management Schedule

In the proposed EMA, the operation of the PV–grid system is divided into four main scenarios. These four scenarios work according to previously described operating modes which are controlled by the central EMA, categorized as the overload scenario, underload scenario, no-load scenario, and idle condition. The EMA-based operation of the charging system is shown in Figure 2. The objective is to charge the EV without interference at a specified constant price. This charging price (Chrg_Pr) was taken to be USD 0.01 lower than PV_Pr (Chrg_Pr = PV_Pr − USD 0.01/kWh) to hold it below the Avg_GE_Pr under the conditions of par as well as the below parity. The charging price can also be set to any other value. The GE_Pr is directly proportional to grid overloading; therefore, the off-peak conditions (in this study) were based on GE_Pr. Thus, off-peak conditions commenced when GE_Pr < Avg_GE_Pr. The off-peak conditions can also be written as GE_Pr ≤ ESU_Pr, because the assumed value of ESU_Pr is already less than Avg_GE_Pr = PV_Pr. Notably, the EMA was designed to operate on the basis of no profit, no loss. The “no profit” aim
facilitates the EV clients with the minimal conceivable charging price, whereas the “no loss” condition protects the charging stations from financial losses.

Figure 2. Flow chart of the proposed energy management scheme.

The EMA tracks and directs the energy flow among various components of the system by means of the power converter switching. In addition, it records the respective prices of energy purchasing and selling. The profit is simply the difference between selling and purchasing prices [17]. All the energy costs are taken in cents; therefore, the amount of profit is:

\[
\text{Profit (cents)} = S_{\text{eng}} - P_{\text{eng}}
\]

3. Results and Discussions

The results obtained by teaching–learning-based optimization (TLBO) are summarized in Table 1.
Table 1. Observations from the TLBO.

| Parameters                  | TLBO   |
|-----------------------------|--------|
| Number of Iterations        | 100    |
| Optimum Number of PV Panels | 100    |
| Optimum Number of ESUs      | 12     |
| Daily Profit                | USD 9  |
| Annual Profit               | USD 3286 |
| Percentage Reduction in Grid Burden | 52%     |
| Annual Reduction in Carbon Footprints | 42 lbs./annum |

It is envisaged that this research shall not only guide the installers of electric vehicle charging stations with the optimum number of PV arrays and ESUs for profit maximization, but also contribute to the global reduction in carbon footprints. Additionally, it shall help to create more opportunities for future loads by decreasing the burden on the utility grid as well as by providing excess energy generated by renewable resources.

4. Conclusions

The optimized number of PV panels (Npv) and optimized number of ESUs (Nbat) of the PV–ESU–grid system of commercial charging stations were determined in this study. The proposed PV–ESU–grid system enabled charging of all connected vehicles without incurring annual economic losses. Notably, the owner of the charging station earns more profit when grid electricity prices increase. The resiliency of the system in providing constant price charging (which is lower than the price of average grid electricity) was verified with different EV fleet sizes; the station owner still earned some profit. Furthermore, the superiority of the proposed charging system over the utility grid system was validated with reduced charging burden (i.e., 52%) and reduced carbon footprint (i.e., 42 lbs./annum reduction).

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