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DOI
10.1109/ITEC53557.2022.9814016

Publication date
2022

Document Version
Final published version

Published in
Proceedings of the 2022 IEEE Transportation Electrification Conference & Expo (ITEC)

Citation (APA)
Vermeer, W., Chandra Mouli, G. R., & Bauer, P. (2022). A Multi-Objective Design Approach for PV-Battery Assisted Fast Charging Stations Based on Real Data. In *Proceedings of the 2022 IEEE Transportation Electrification Conference & Expo (ITEC)* (pp. 114-118). Article 9814016 IEEE. https://doi.org/10.1109/ITEC53557.2022.9814016

A Multi-Objective Design Approach for PV-Battery Assisted Fast Charging Stations Based on Real Data

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***Abstract*—This paper presents a multi-objective approach to designing an optimal PV-BES assisted EV fast charging station. The trade-offs between lifetime net present value (NPV), energy independence, and grid power reduction are analyzed using particle swarm optimization and real 50kW fast charging data. Our results show a maximum lifetime profit of close to 4M euro. Furthermore, for only a 8% decrease in profit the we can achieve up to 62% of the maximum energy independence and 46% peak power demand reduction. This show that EV fast charging stations can become more significantly more sustainable and have a less fluctuating demand, for very little reduction in profits.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Battery energy storage (BES) and solar photo-voltaïc (PV) systems can be used to reduce the grid energy demand of EV (fast) charging, while potentially also improving profitability and sustainability. However, appropriate design methodologies are required to find the best trade-off's between profitability, sustainability, and demand intermittency. To achieve this, various optimal design approaches have been investigated in literature. However, most literature focuses only on cost-optimal designs [1]–[5], use artificially generated demand profiles [6]–[8] and often do not take into account the effect of battery degradation on available BES capacity, or lifetime system costs. To this extend, the main contributions of this paper are: 1. A techno-economical feasibility analysis of a PV-BES-assisted EV fast charging station, using a multi-objective particle swarm optimization, 2. The inclusion of a battery degradation model, 3. The use and analysis of real 50kW data measured at a fast charging station (FCS) in the Netherlands.

II. System Description

A schematic representation of the PV-BES assisted fast charging station is shown in Figure 1. The BES, PV, and EV chargers are all interconnected on DC to reduce the amount of DC/AC conversion steps. The EV charging demand is based on data obtained from 2 50kW FCS in Netherlands. The battery operates as peak shaving device, and is discharged whenever the charging demand exceeds the grid connection. Similarly, it is charged whenever the battery is below its maximum set capacity and the charging demand is lower than the maximum grid connection. The PV system operates in its maximum power point, or reduces its power to not exceed the maximum grid power. Two example days are shown in Figure 1, representing a day with high demand - low PV production (middle), and a low demand - high PV production (right).

III. Demand Analysis & Extrapolation

To provide a generic optimization tool for FCS design, it is necessary to be able to extrapolate data from the two FCS to as many chargers as required. To do so, the data must first be analyzed. This analysis can also be a useful reference for future studies which generate their own demand profile. Figures 3(a)(b)(c) show the data used.

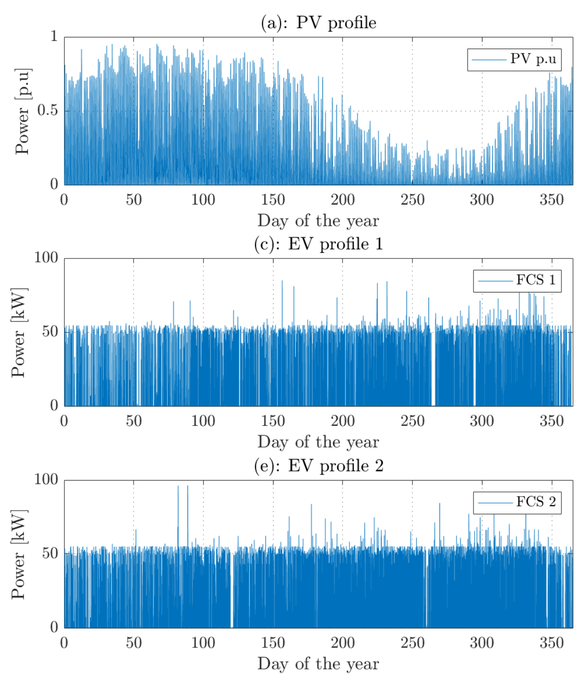

Fig. 2: (a) Measured PV power per unit (b) Charging profile of the first FCS and the second (c).

To extrapolate the data to N chargers while maintaining diurnal and seasonal variations, the data is first divided into weeks, then N days from each week are randomly sampled and added to the same week in the final profile. As a result, the final profile maintains the stochasticity of the

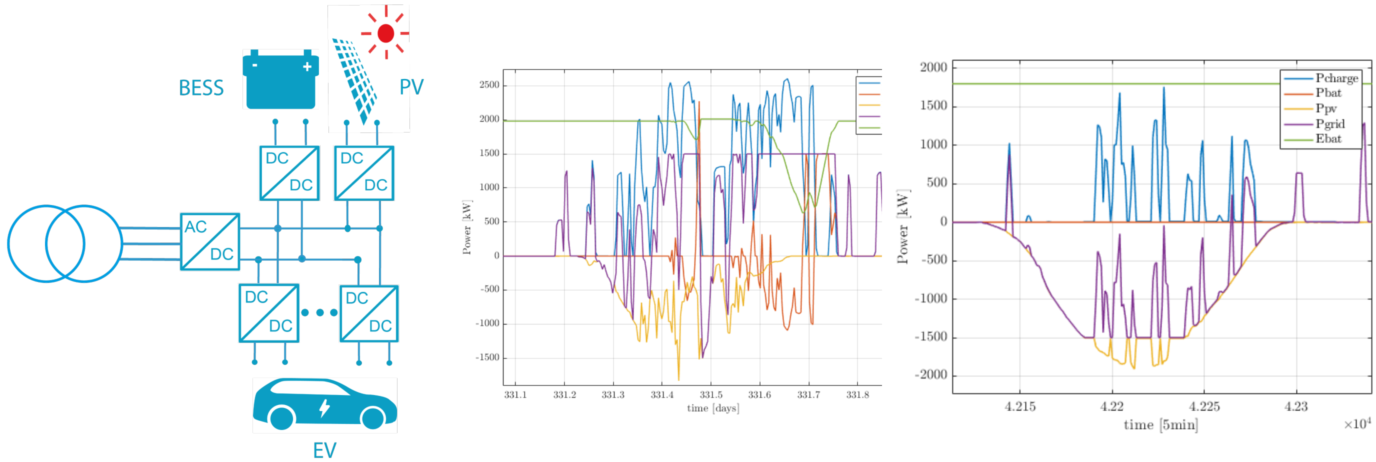

Fig. 1: (left): Schematic representation of the PV-Battery assisted fast charging station. (middle): Power flows for a day with high demand (extrapolated to 12 chargers), and low PV production. (right): Power flows for a day with low demand and high PV production.

data, while accounting for diurnal and seasonal variations. According to the analysis shown in Figures 3(a)(b)(c), the total charging demand increases roughly 250% in winter, and there is an increase in both charging instances and demand per charging instance. Possible explanations include increased energy consumption from air conditioning and battery thermal management during charging and driving. Figure 3(b) depicts the daily average demand of a generated profile normalized to the number of chargers (12). The generated profile shows good correlation with the original data, which validates the extrapolation method.

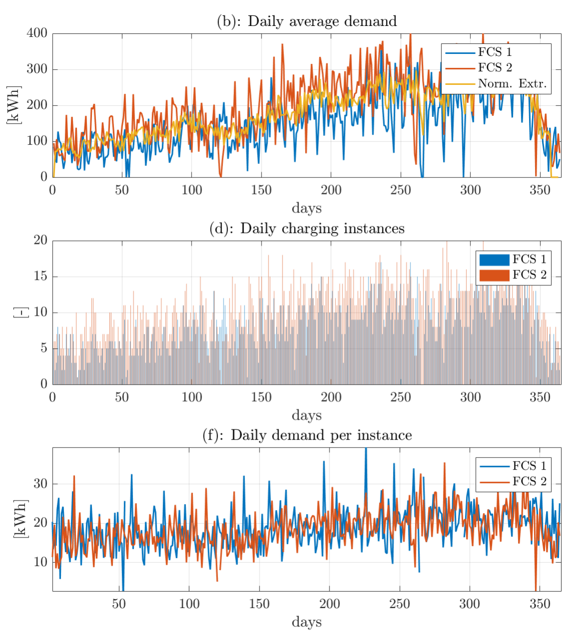

Fig. 3: (a) Total daily charging demand, (b) daily charging instances (c) daily average demand per instance

IV. Multi-Objective Optimization

A multi-objective, pareto-optimal, particle swarm optimization method is used to find the optimal trade-off between lifetime Net Present Value (NPV), C02-emission reduction, and grid power reduction, for the proposed PV-BES assisted charging station. To achieve these objectives the following variables are optimized:

- Battery rated capacity [0-5MWh]
- PV rated capacity [0-5MWp]
- grid connection size [0-5MW]
- maximum C-rate of the battery [1/h].

A schematic representation of the optimization procedure is shown in Figure 4.

1) Net Present Value: The lifetime NPV is calculated according to Eq.(1). Here, R_t is the yearly revenue, r a discount rate r of 5%, L the BES lifetime in years, and C_{inv} the total investment costs comprised of EV chargers, PV and BES system, and a summation of other one-time fees such as distribution system operator (DSO) costs. The DSO costs are based on a dutch operator [9]. Next R_t is calculated based on the revenue from EV charging, PV energy feed-in, and operational costs such as, energy costs and DSO costs. Finally, the system lifetime is assumed to be limited by the BES, and its lifetime and available capacity is calculated using a degradation model with rainflow counting method according to the approach presented in [10].

$$\mathrm{NPV} = \sum_{t=1}^{L} \frac{R_t}{(1+r)^t} - C_{inv} i \tag{1}$$

2) Energy Independence: The second objective is the energy independence Δ_{CE}, and is also an indication on the emission reduction. Δ_{CE} is calculated as the ratio of grid power drawn using a PV-BES system $E_{PV-BES}(t)$, with respect to the total EV demand $E_{EV}(t)$, according to Eq.(2).

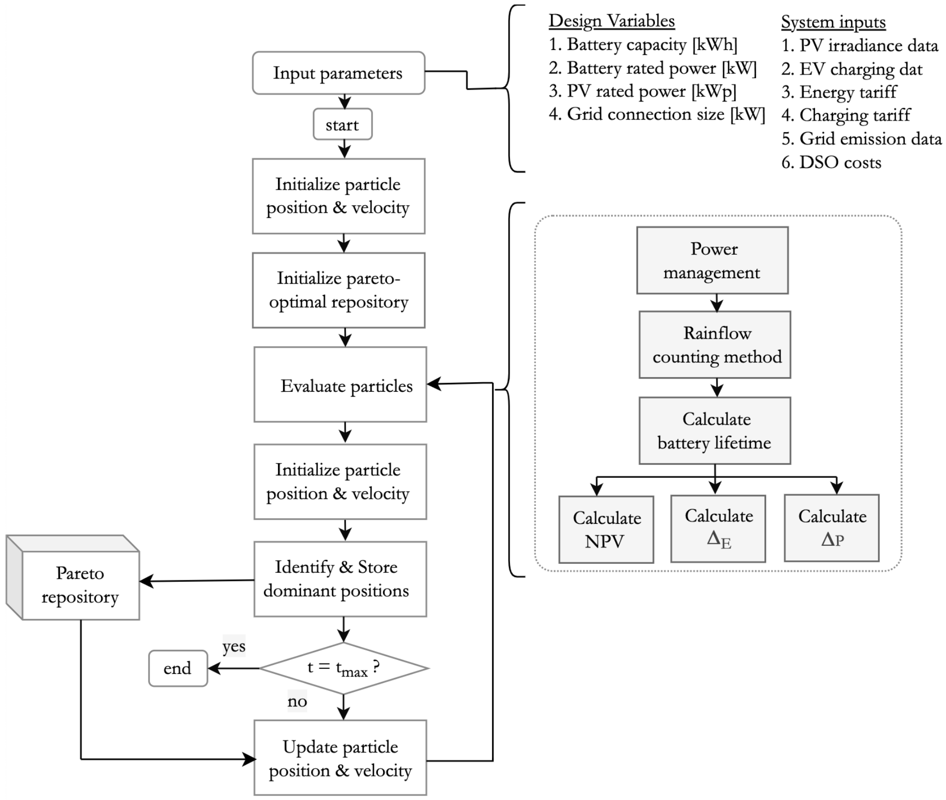

Fig. 4: Multi-objective particle swarm optimization flow including pareto-optimal solutions.

TABLE I: Capital cost parameters

Quantity	Value
50kW EV charger	75k euro
Battery energy storage	250 euro/kWh
PV system	700 euro/kWp
Cable per meter	150 euro/m
DSO one-time fee	

TABLE II: Operational cost parameters

Quantity	Value
Electricity tariff	0.1 euro/kWh
Feed in tariff	0.05 euro/kWh
Charging tariff	0.6 euro/kWh
interest	5%

$$\Delta_E = 1 - \frac{\sum_{t=1}^{L} E_{PV-BES}(t)}{\sum_{t=1}^{L} E_{EV}(t)} \tag{2}$$

3) Peak Grid Power Reduction: Finally, to create a system which is also attractive for distribution/transmission system operators, the peak grid power is also minimized to create a more flat demand profile. This is done using the power management scheme as discussed in Section 2. The total amount of peak power reduction Δ_P is calculated according to Eq.(3). P_{grid}^{PV-BES} is the resulting grid power when using the proposed PV-BES system, compared to the peak power of the EV demand $P_{EV}(t)$.

$$\Delta_P = \frac{\max(P_{grid}^{PV-BES}(t))}{\max(P_{EV}(t))} \tag{3}$$

V. Results

The pareto-fronts for the three objectives are shown in Figure 5. The four chosen solution, and their corresponding variables are given in Table III. Finally, the distribution of variables within the obtained pareto-fronts are shown in Figure 6. Based on these results, the main conclusions are:

1) The highest NPV is obtained without a battery, a PV system rated at 634kW, and a grid reduction of 3%.
2) the highest energy independence Δ_E and peak power reduction Δ_P is obtained at maximum PV-battery size. This, however, results in significant loss of NPV as the PV system is curtailed a lot due to the small grid connection size. Therefore it is concluded that the revenue from PV power feed-in is smaller than the costs of a higher grid power connection.
3) With only an 8% decrease in profit the we can achieve up to 62% of the maximum energy independence and 46% of the maximum peak power demand reduction.

TABLE III: Four chosen solutions, one for each objective and the best trade-off.

	NPV [euro]	Δ_E [%]	Δ_P [%]	E_{bat} [MWh]	P_{PV} [kW]	P_{Grid} [MW]	C_{rate} [1/h]
max NPV	2.88M	24%	3%	0	634	1.6	-
max Δ_E	-5.1M	64%	91.3%	4904	5	0.14	4
max Δ_P	-5.08M	64%	91.3%	4904	5	0.14	4
best trade-off	2.66M	40%	42%	472	1826	0.95	1.7

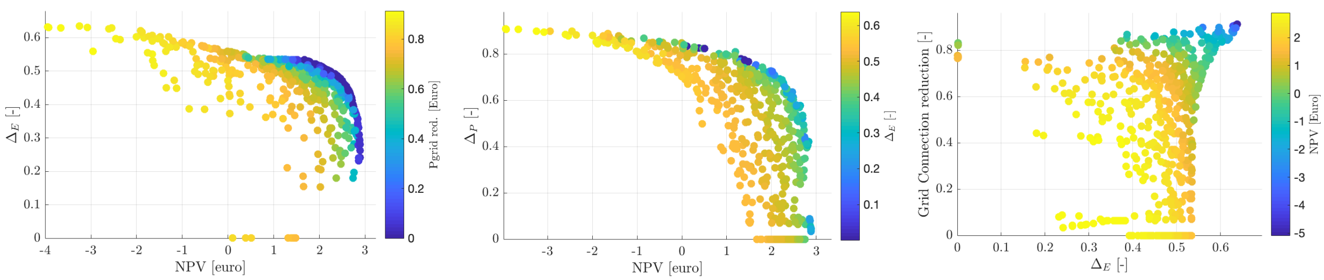

Fig. 5: Pareto-fronts for the objectives: NPV, Δ_E, and Δ_P

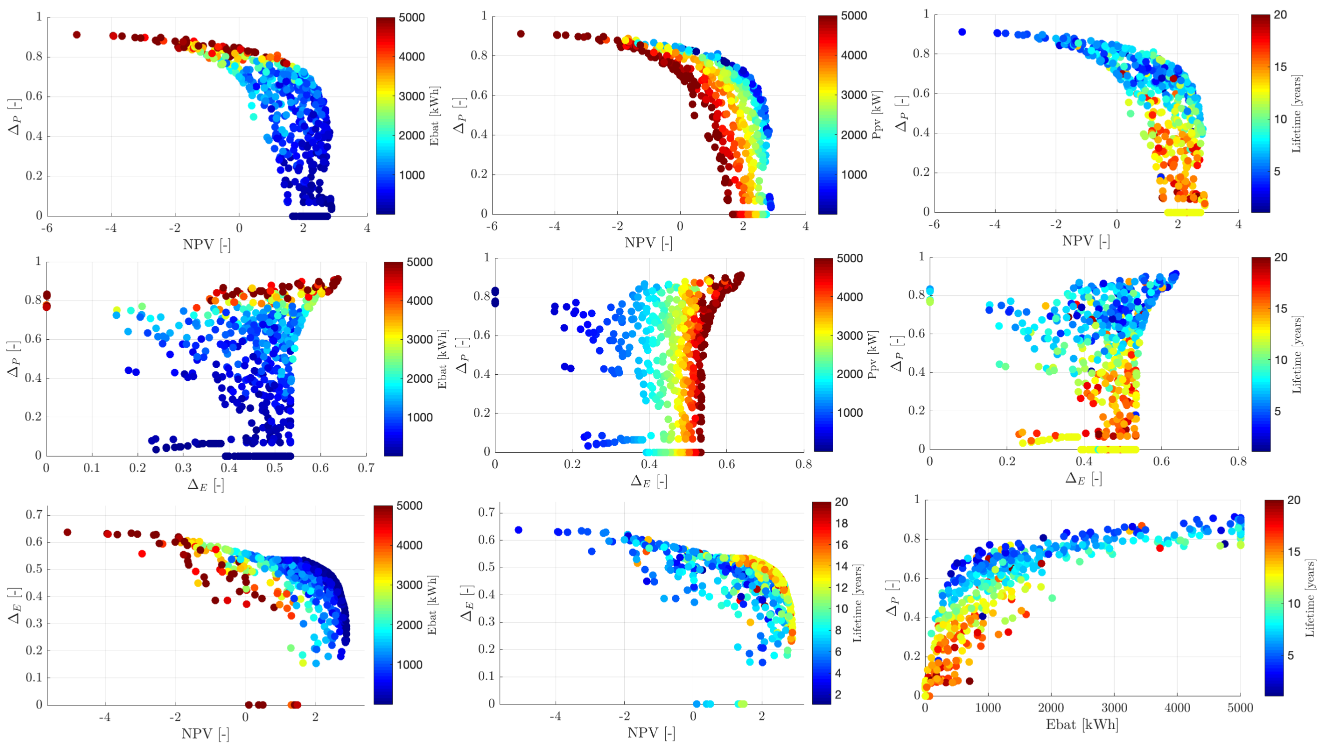

Fig. 6: Pareto-optimal solutions for a combination of variables and objectives .

Resulting in a profitable investment, with significantly reduced emissions and demand fluctuations.

4) Up to 50% grid reduction - 50% emission reduction there does not seem to be a trade-off between Δ_E and Δ_P.

VI. Conclusion

Our analysis shows of the EV demand shows a significant seasonal variation in EV charging demand, in both charging instances as well as energy demand per charging instance. Furthermore, using the provided multi-objective optimization it is shown that with only an 8% decrease in profit, a significantly more sustainable and less fluctuating EV charging demand can be achieved.

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