Techno-Economic Optimization of Electric Vehicle Charging Station with Virtual Power Plant – a University Campus Use Case

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Abstract—**Electric Vehicles (EVs) are crucial for decarbonizing the transport sector, which accounts for about one-quarter of the EU's total Greenhouse Gas (GHG) emissions. However, most EV Charging Stations (EVCS) still rely on fossil fuel-based energy generation, contributing to grid-related emissions. Integrating Renewable Energy Sources (RES) with EVCS is a key strategy to lower the emissions intensity of the EV supply chain, though its techno-economic benefits remain largely underexplored. This study addresses this gap by conducting a techno-economic feasibility analysis of RES-powered EVCS at NOVA University Lisbon, either through on-site RES integration or via a Virtual Power Plant (VPP). Two datasets were combined—including parking hours, building energy demand, and economic variables—to evaluate three scenarios using HOMER and a genetic algorithm: (i) Grid-to-Vehicle (base), (ii) EVCS with on-site RES, and (iii) EVCS with VPP. The VPP scenario is most optimal, achieving the lowest cost of energy (0.111 €/kWh), the highest RES fraction (34.6%), and a 16.15% reduction in energy bills relative to the base scenario.**

Keywords—Electric vehicle charging station, Virtual power plant, Genetic algorithm, G2V, Cost of energy

I. INTRODUCTION

Transportation is a major contributor to global energy consumption and Greenhouse Gas (GHG) emissions due to its reliance on fossil fuel-powered vehicles. In the EU, passenger vehicles and vans together account for 14.5% of CO_2 emissions [1]. To address this, the EU fleet-wide CO_2 emission target set for both cars and vans is 0 g CO_2/km from 2035 onwards, corresponding to achieve a 100% reduction [2]. Therefore, Electric Vehicle's (EV's) can be a great solution to achieve the target as EV's emit 17–30% lower than emissions of petrol and diesel cars [3]. Although EVs produce fewer emissions, their overall environmental benefits are diminished because most are charged from electricity grids that remain heavily dependent on fossil fuels. Many EV Charging Stations (EVCS) operate on carbon-intensive energy sources, limiting potential emissions reductions. To mitigate this issue, integrating EVCS with Renewable Energy Sources (RES), either on-site or through Virtual Power Plant (VPP[1]), is a promising approach to reducing GHG emissions and improving overall energy sustainability in the transport sector. However, the intermittent nature of RES, along with challenges related to energy storage and the spatial requirements for RES installations, complicates the implementation of EVCS powered by RES [4]. Therefore, the techno-economic feasibility of such solutions remains an area that needs to be examined.

Some studies attempted to analyze EVCSs from a techno-economic point of view, taking into account different techno-economic parameters. Arslan and Karasan examined the economic and emission impacts of VPP development in networks with plug-in hybrid EVs [5]. Moreover, Alabi et al. suggested a unique hybrid robust-stochastic approach to facilitate the optimum scheduling of a Zero-Carbon Multi-Energy System (ZCMES) using a VPP, taking into account EV adaptability while calculating Operational Expenditure (OPEX) and revenue [6]. Furthermore, Wang et al. developed a Deep Reinforcement Learning (DRL) approach for a VPP including EVCSs. The findings indicate that the VPP agent is capable of acquiring the strategy for selling energy to EVs, optimizing the scheduling of Distributed Energy Resources (DERs), and formulating a bidding strategy for engagement in the electricity market [7]. Besides, González-Romera et al. proposed an Energy Management System (EMS) for a residential VPP by incorporating PVs, Battery Energy Storage System (BESS), and EVs. They employed a Genetic Algorithm (GA)[2] to optimize energy costs and improve technical aspects by changing their scheduling [8]. Moreover, Alabi et al. proposed a deep learning approach (GRU-BiLSTM) and optimization model for multi-energy systems by the inclusion of EV's and carbon capture systems [9].

Although the above-mentioned studies have boosted research in this area, they still present some limitations, as a comprehensive assessment of economic viability has not yet been fully addressed. For example, Wang et al. considered

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[1] A Virtual Power Plant (VPP) is described identically to an autonomous microgrid [25]. VPP can work as a distant energy storage and energy generation plant. Also, VPP is an aggregation of decentralized units whose operations for the power grid are managed by a unified control system [26]. These units could encompass electricity producing systems such as biogas, wind, and photovoltaic energy conversion systems, cogeneration hydroelectric power plants, electricity consumers, and electricity storage facilities [26]. A VPP can play a vital role in energy export and import to the grid [27]. Also, it can work as an aggregator [28]. The energy generator and grid operator formalize an agreement that may include net metering or virtual accounting, ensuring hourly alignment between energy supplied to the grid and withdrawn by the EVCS. These agreements may also consider EVs as storage or assume full generation capacity of the RES facility.

[2] GA was introduced by John Holland in 1975. It is a "search algorithm" founded on Darwin's principles of natural selection and genetics. GA is a metaheuristic algorithm which solve mainly non-linear problems. GA encodes an organism's genetic info in mixes of binary digits. The outcome consists of sequences of two digits: 0s and 1s. GA guarantees the generation of superior offspring by randomly selecting the most advantageous digits and segments from the parental entities [29].

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profit, EVCS cost, and penalty cost. However, they did not calculate the overall economic feasibility [7]. Similarly, Alabi et al. did not considered key economic aspects such as Cost of Energy (COE) and Capital Expenditure (CAPEX) [9], while González-Romera et al. did not perform a detailed economic analysis [8]. Therefore, a gap exists in academic literature due to the lack of robust techno-economic analysis that encompass both key economic parameters and technical comparisons between on-site RES production and storage and VPP. Hence, to address this gap, the goal of this work is to perform a techno-economic feasibility analysis of combining an EVCS with a VPP or on-site RES at the NOVA University Lisbon and considered residential-load[3]. This study seeks to provide insight into both the economic and environmental benefits of using RES or VPP-supported EVCS infrastructure.

The main contribution of this study is performing one-layer technical optimization and two-layer economic optimization for energy systems serving an EVCS and residential load. In addition, key economic indicators were evaluated, namely the Net Present Cost (NPC), COE, Capital Expenditure (CAPEX), and OPEX, to support investors and decision-makers in assessing the system's feasibility. These parameters were selected based on a review of existing optimization studies in the literature [10], [11], [12]. Specifically, NPC facilitates comparison between different system configurations; COE provides insight into potential energy cost savings; CAPEX and OPEX allow for evaluation of initial investment requirements and long-term operational costs, respectively. Also, energy sales to grid and purchases from the grid were analyzed to assess the overall economic profitability of the proposed EVCS energy system. This paper is structured as following sections: the second part is dedicated to the developed methodology, the third part is devoted to results and discussion, and the last part is the conclusion.

II. METHODOLOGY

To conduct this work, first, data were collected from a specific location to perform the analysis, which is NOVA University Lisbon. Later, for the residential load, a building dataset was utilized [13]. By combining these two datasets a load profile[4] was developed. This load profile, technical and economic data was entered into the Hybrid Optimization Model for Multiple Energy Resources (HOMER)[5] (HOMER is a simulation program that aids users in performing techno-economic optimization with renewable energy [14]) software to perform a first layer technical and economic optimization. After performing the first layer optimization, the CAPEX, OPEX, COE, NPC, and CO_2 emissions rate were obtained. Then, the techno-economic output of HOMER was given as input to MATLAB. In MATLAB, GA was used to perform the second layer of economic optimization. In Fig. 1, displays the two-layer optimization methodology for EVCS.

A. Scenarios Defintion and Energy Resources

In techno-economic feasibility studies, a few scenarios are considered to analyze and check which one is better for the developed energy system. Overall, three scenarios were considered to conduct our analysis: (1) First Scenario-FS (Base scenario-BS) is a G2V infrastructure, (2) Second Scenario-SS is EVCS with RES on-site including BESS technologies, and (3) Third Scenario-TS is EVCS powered by VPP. Fig. 2 displays three considered cases in this work.

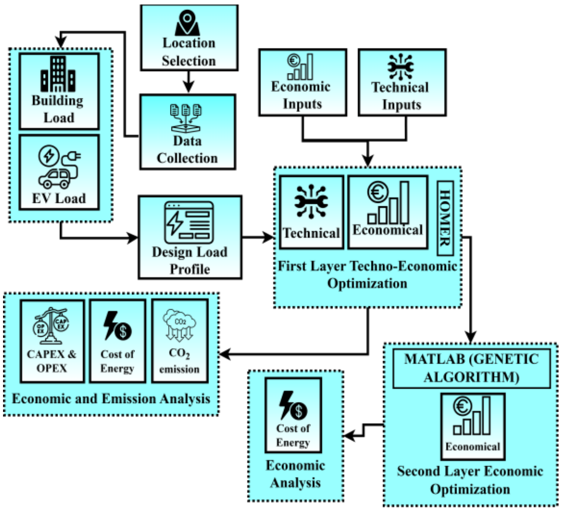

Fig. 1. Methodology of two layer optimizations for EVCS.

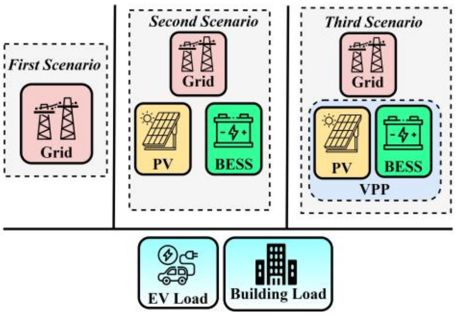

Fig. 2. Scenario Analysis.

The FS serves as the baseline, where EV's are charged solely from the grid without any direct integration of on-site RES generation. This scenario provides a reference point for evaluating the performance of the other two scenarios. In the SS, energy is supplied through on-site RES generation combined with a BESS, reducing reliance on the conventional grid. TS incorporates a VPP for remote energy storage and a DER-based PV generation facility. Both are located at the same site, which is physically separated from the university and residential loads. While the first two scenarios are primarily simulated using the HOMER tool. Afterward, the output of HOMER was extracted and manually gave techno-economic input (technical: PV generation, battery capacity, energy loads, amount of energy sold, and amount of energy bought at different hours; economic: cost of energy in different hours) in the MATLAB which is the TS for 2nd stage economic optimization. The TS is analyzed using GA in MATLAB (GA has been utilized in this work to compare algorithm-based optimization with HOMER software-based optimization). This study integrates GA to automate load scheduling through an optimization approach. Conversely, HOMER necessitates manual hourly scheduling, which requires additional effort. GA simplifies the scheduling process by increasing efficiency, flexibility, and the ability to

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[3] A dataset of 89 household's load was included in this study from reference [13]. This dataset was chosen because of scarcity of building datasets near NOVA University Lisbon. The dataset originates from Denmark and comprises measurements and statistical data that correspond with the annual energy load profile of buildings which is required for our case study. Specifically, to make the case study more realistic, how our optimization performs with residential loads using this dataset was evaluated [13].

[4] A load profile is a graph depicting power consumption over time, whereas load profile diagram illustrates accumulated power consumption in relation to operating period [30].

[5] HOMER is utilized to model the performance of an energy supply system, along with its lifecycle cost, CAPEX, and OPEX. HOMER has a built-in optimization algorithm to perform techno-economic optimization [14].

manage complex optimization scenarios without direct user involvement.

Meteorological data were analyzed to understand the potential of resources such as solar radiation and wind speed of the location. The PV system can be the most useful for operating our proposed energy system. Also, solar irradiance was quite consistent around the year, which is better for energy generation in Portugal. Also, the space required for PV could be divided into different buildings, and PV panels could be mounted on top of the EVCS. On the other hand, Wind Turbine's (WT's) can still be mounted. However, WT's were avoided for this study because of the short spaces in urban areas and the high cost of WT's. Fig. 3 illustrates the selected location's monthly solar radiation and clearness index.

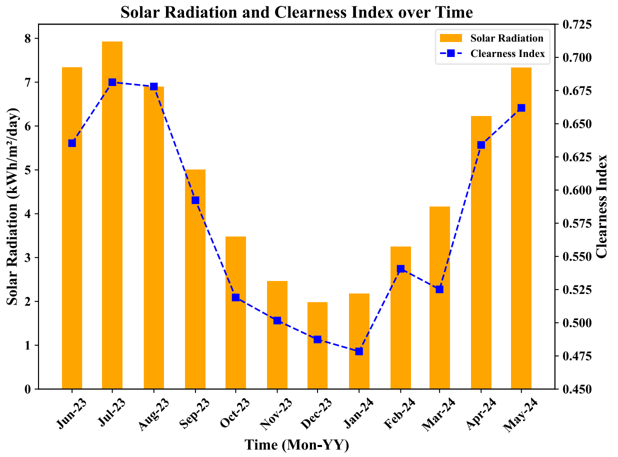

Fig. 3. Monthly solar radiation and clearness index to assess the location.

B. *Battery Energy Storage System (BESS) Modelling and EV's State of Charge (SOC)*

The storage system is a crucial element of energy systems. The charging mode occurs when solar output surpasses load demand, $E_{PV}(t)>E_{Charge}(t)$ [15], [16]. The charging mode is represented by equation (eqn.) (1). Where $E_{Batt}(t-1)$ and $E_{load}(t)$ denote the state of the battery and load demand at the time t, σ denotes the hourly discharge rate of the battery, η_{Batt} and η_{inv} denote the battery's and inverter's efficiency, respectively [15], [16]. The discharge mode during solar energy generation is less than load demand, $E_{PV}(t)<E_{Charge}(t)$. The discharging mode represents using an eqn. (2).

$$E_{Batt}(t) = E_{Batt}(t-1) * (1-\sigma) + [E_{PV}(t) * \eta_{inv} - (E_{load}(t)/\eta_{inv})] * \eta_{Batt};\ \forall\Delta t \tag{1}$$

$$E_{Batt}(t) = E_{Batt}(t-1) * (1-\sigma) - [((E_{load}(t)/\eta_{inv}) - E_{PV}(t) * \eta_{inv})/\eta_{Batt}];\ \forall\Delta t \tag{2}$$

The EV's SOC can be calculated by using eqn. (3), where Q_0 (mAh) denotes as the initial charge of the battery, Q (mAh) is the amount of electricity produced by or absorbed by the battery. Q_{max} (mAh) represents the maximum capacity of charge that the battery can maintain [17].

$$SOC\% = 100 * ((Q_0 + Q)/Q_{max});\ \forall\Delta t \tag{3}$$

C. *Techno-Economic Mathematical Modelling and Input*

NPC is the present value of all expenses and investments of the EVCS and the proposed energy system for EVCS during its lifetime. C_{NP} is the NPC in € and C_{NP} can be calculated with eqn. (4). Where C_{T_Ann} is the total annualized cost in €, n is the number of years, and i is the real interest rate. Moreover, COE is considered one of the crucial aspects of the EVCS energy system and COE can be calculated using the following eqn. (5) [11]. In eqn. (5) E_{T_Gen} denotes the total energy generation.

$$C_{NP} = C_{T\_Ann}/\left(\frac{i(1+i)^n}{1-(1+i)^n}\right);\ \forall\Delta t \tag{4}$$

$$COE = C_{NP}/E_{T\_Gen};\ \forall\Delta t \tag{5}$$

The renewable energy fraction denotes as RES_{Fr}, which is important to understand the ratio of energy supplied to EVCS from RES. RES_{Fr} can be calculated with the eqn. (6), where E_{nonRES} denotes as total energy served from non-renewable energy resources, and E_{L_EVCS} is total load served for EVCS.

$$RES_{Fr} = 1 - (E_{non_{RES}}/E_{L\_EVCS});\ \forall\Delta t \tag{6}$$

Techno-economic-environmental inputs were collected from different sources to conduct the feasibility study. Various inputs are taken into consideration to conduct techno-economic-environmental analysis, including technical specifications (required as inputs for optimization tool-HOMER) of PV panels, converters, grid, electric load, and environmental specifications (grid emissions), and economic parameters such as PV panels cost, converters cost, and grid's energy price (the pricing of buying from the grid and selling to the grid). Therefore, several economic parameters (required as inputs for optimization tool) have been considered for the proposed energy system of EVCS, including CAPEX, OPEX, replacement cost, discount rate, and inflation rate. The technical component specification is shown in Table I [11], [18]. Also, the Economic assessment's input parameter is shown in Table II [11], [18], [19]. Specifically, the data of Table I and Table II were collected from earlier research papers, published reports, and websites.

TABLE I. TECHNICAL COMPONENT SPECIFICATION

Components	Parameter	Value	Unit	Reference
Converter	Efficiency	95.00	%	[11]
	Lifetime	15	Years	
PV	Efficiency	20.40	%	[18]
	Lifetime	25	Years	

TABLE II. ECONOMIC ASSESSMENT INPUT PARAMETER

Components	Type of Cost	Value	Unit	Reference
Converter	CAPEX	277	€/kW	[11]
	Replacement	277		[11]
	OPEX	25	€/kW/year	[11]
PV	CAPEX	891	€/kW	[18]
	Replacement	891		[18]
	OPEX	26	€/kW/year	[19]

In 2020, according to [20], Portugal's total electricity consumption was 49.5 TWh, and RES utilized 62% of the total electricity. Consequently, the grid emission factor was 228.00 gCO₂/kWh [20]. Although the FS scenario does not include any on-site RES generation within the DER system, this share of RES in the national energy mix, and its contribution to lowering CO_2-related grid emissions, was still considered in the FS scenario. For HOMER optimization software, the discount rate and inflation rate are required to conduct economic analysis. In 2022, Portugal's inflation rate was 7.83% [21], and Portugal's discount rate was 4.75% [22]. Also, the project lifetime considered is 25 years for our analysis. Furthermore, the Energy Services Regulatory Authority (ERSE) values were utilized for buying electricity from the grid and sales to grid expense values [23] by using 3 different values: rush, empty, and full hours shown in Fig. 4.

D. VPP Modelling with Genetic Algorithm (GA)

In our work economic optimization of the EVCS powered by VPP is performed using GA with an objective function and constraints. Furthermore, in eqn. (7), the VPP power balance is defined. The objective functions, commencing with eqn. (7), are displayed in eqn. (8) [8], [24].

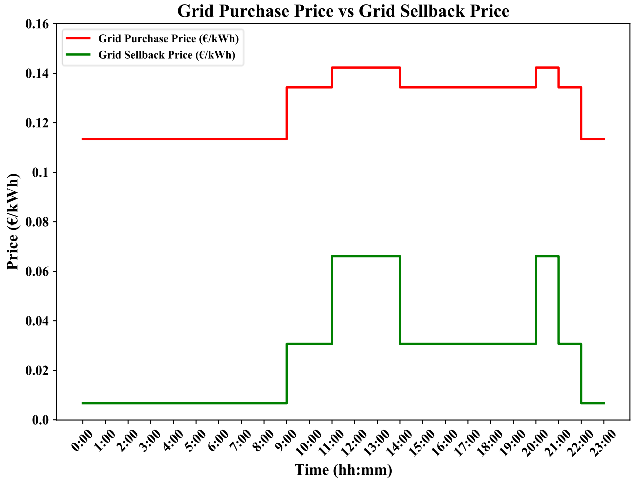

Fig. 4. Grid Purchase Price versus Grid Sellback Price.

$$P_{grid}(t) = P_{PV}(t) - P_{Load}(t) - P_{BESS}(t) - P_{EV}(t) \tag{7}$$

$$f_1 = \sum_{t=1}^{24} \left[(I_{grid-pu}(t).p_{grid-pu}(t) - I_{grid-se}(t).p_{grid-se}(t).|P_{grid}(t)| \right] \tag{8}$$

In eqn. (7), $P_{grid}(t)$ represents power interchanged with the grid at time t, P_{PV} indicates PV generation's power, P_{Load} represents power of load demand, P_{BESS} indicates BESS's power, and P_{EV} represents EV's power. In eqn. (8), $p_{(grid\text{-}pu)}$ represents energy purchase pricing from the grid, $p_{(grid\text{-}se)}$ indicates energy sellback pricing to the grid, $I_{(grid\text{-}pu)}$ represents binary index '1' when $P_{grid}(t) \leq 0$, and $I_{(grid\text{-}se)}$ binary index '1' when $P_{grid}(t) > 0$. In eqn. (8), objective function f_1 aims to minimize both the VPP electricity bill and the power exchanged with the grid. Constraints for the BESS are displayed in eqn. (9) to eqn. (11) [8], [24].

$$-P_{BESSmaximum} \leq P_{BESS}(t) \leq P_{BESSmaximum} \tag{9}$$

$$SOC_{low} \leq SOC(t) \leq SOC_{high} \tag{10}$$

$$|SOC_{in} - SOC(24)| \leq 20\% \tag{11}$$

$$SOC = SOC_{in} + (100/C_{nom}) \sum_{i=1}^{t} \begin{pmatrix} I_{BESSchur(i)}.P_{BESS}(i).\eta_{chur} \\ +I_{BESSdi(i)}.(P_{BESS}(i)/\eta_{dis}) \end{pmatrix} \tag{12}$$

$$P_{EV}(t_{EV}) \leq P_{EVmax}.n_{EV}(t_{EV}), t_{EV} \in nt_{EV} \tag{13}$$

$$\sum_{h_{EV}} P_{EV}(t) = E_{EVtotal} \tag{14}$$

The admissible range of power for the BESS is defined by the constraint in eqn. (9). In eqn. (9) $P_{BESSmaximum}$ represents the maximum BESS power. Furthermore, eqn. (10) establishes the allowable range for SOC, where, SOC_{low} denotes the lowest value of SOC, SOC_{high} represents highest value of SOC, and SOC_{in} indicates the initial value of SOC. Eqn. (11) ensures that the SOC variance between the start and end of the day is less than 20%. Both charge and discharge efficiency rates are taken into account when calculating the BESS SOC, as shown in eqn. (12). Furthermore, C_{nom} denotes BESS's nominal capacity, $I_{BESSchur(i)}$ represents binary index '1' when $P_{BESS}(t) > 0$, $I_{BESSdi(i)}$ denotes binary index '1' when $P_{BESS}(t) \leq 0$, η_{chur} and η_{dis} indicates charging and discharging efficiency of BESS in eqn. (12). Additionally, the EV power constraints are displayed in eqn. (13) through (14) [8], [24].

P_{EVmax} indicates the maximum power required by an individual EV charger, nt_{EV} denotes number of EVs connected to the EVCS at time t, t_{EV} represents the hour at which any EV is EVCS-connected powered by grid or developed RES onsite/VPP, and $E_{EVtotal}$ represents energy required for full EV charge. EV's are subject to a time constraint, meaning that they can only be charged while they are linked to the grid or PV plant to be readily accessible for charging. Also, the maximum power is restricted during these hours to the sum of the power of each charger and the number of EV's connected, as shown in (8). Every EV's SOC must be 90% at the end of the time slot during which the EV's are connected to the grid, ensuring that all of the energy required to fully charge all the EV's has been used.

E. Information of Load, Generation, and Storage Profile

89 household's load was included in this study [13]. The average load was 46.26 kW, and the peak load of those buildings was 83.67 kW. Additionally, a maximum of 42 EV's (where EV's considered as load of the energy system) can be charged at the same time with a rating of 7 kW chargers, with a total battery capacity of 288 kWh. Charger plugs could only be used in homes with a standard single-phase rating of 220-230 V, 32 A. So, these chargers can charge EV's from 09:00 to 17:00 in the parking lot. A 250-kW communitarian photovoltaic power plant was used to meet the energy needs from distant as a VPP. This power sizing can be viable for a small Portuguese community for their self-consumption. Furthermore, the 36 kWh BESS was constructed with Li-ion batteries managed by central power electronic converters.

III. RESULTS AND DISCUSSION

A. First Scenario (FS) with a Grid-to-Vehicle (G2V)

The FS has the highest COE at 0.172 €/kWh among the three scenarios. Also, it has the lowest CAPEX at 0.193 million €, as no on-site RES generation is integrated for the developed system. However, it has the highest OPEX of 0.136 million €/year and produces the highest emissions, amounting to 565.294 tons/yr. Furthermore, energy sales to the grid are absent, since the system does not produce any RES, so energy flows directly to the EV from the grid. Indeed, 894.453 MWh of energy is bought from the grid. However, this scenario has the highest NPC 5.57 million €, among the 3 scenarios.

B. Second Scenario (SS) EVCS with RES

The SS has the lowest NPC, 4.82 million €, among the 3 scenarios. Also, it has a COE of 0.114 €/kWh and CAPEX of 0.454 million €. However, this SS's OPEX is 0.11 million €/year, which is comparatively lower than the FS. SS presents a strategic advantage as it integrates RES, enhancing the profitability and sustainability of the EVCS. A total of 231.645 MWh of energy is sold to the grid with a RES_{Fr} of 34.6%. Consequently, energy purchases are reduced to 726.024 MWh. Moreover, CO_2 emissions are lower than in the FS, amounting to 458.847 tons/yr.

C. Third Scenario (TS) EVCS powered by VPP

Using the SS output from HOMER, we provided inputs to TS for cost optimization. In TS, our focus was on reducing COE and overall energy bills through GA within a VPP framework. Fig. 5 shows the accumulated energy demand and generation within the VPP. In the initial EV charging configuration, EVs were assumed to charge at maximum power starting at 09:00 until fully charged. Fig. 6 illustrates the power exchanged between the VPP (before and after GA optimization) and grid during this period, with peak demand occurring at 09:00 and moderate demand thereafter. An objective function (8), incorporating pricing data from Fig. 4, was used to optimize GA. Under FS, the daily energy bill is 41.703 €/day. GA then rescheduled the EV load across various hours to reduce energy bill and COE.

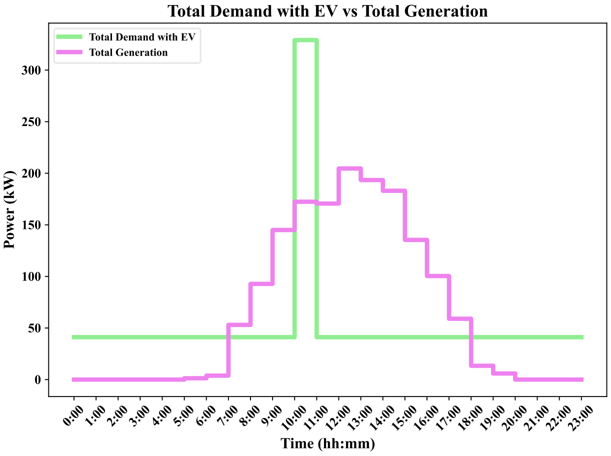

Fig. 5. Total Demand with EV vs Total Generation.

Fig. 7 presents the hourly scheduled power levels for EVs and BESS. Charging during the office period (09:00–17:00) minimizes grid stress by aligning EV charging with peak RES generation, reducing peak demand and grid dependency, and thereby enhancing grid stability encouraging the use of RES. From an economic perspective, this strategy facilitates energy cost optimization. Fig. 8 displays the adjusted demand profile for households and EVs. Post-optimization, the maximum load shifts to 13:00–14:00 a period of lower prices and higher generation. BESS further reduces costs by limiting electricity purchases during peak-priced hours, favoring acquisition during the valley period (09:00–15:00). Indeed, BESS can be used to avoid buying large amounts of electricity during the most expensive hours. After completing the simulation by GA, a final energy bill was obtained of 34.967 €/day (16.15% reduction from the FS). The COE of the 3rd case is 0.111 €/kWh, which is lower than the other two cases, 35.46% lower than the FS and 2.46% lower than COE of the SS.

IV. CONCLUSION

This study aimed to conduct a techno-economic feasibility analysis of integrating an EVCS and residential load with a VPP or on-site RES in a real-case: the NOVA University Lisbon. Two approaches were utilized, HOMER and GA, to perform this feasibility analysis of EVCS and residential load by combining dataset. HOMER performs first-layer techno-economic optimization. Later, MATLAB used output of HOMER including generation, grid sales, and purchase to complete the second layer of economic optimization, by lowering EV consumers energy bills. Overall, three scenarios were considered to conduct our analysis: (1) FS with a G2V infrastructure, (2) SS where EVCS with RES on-site including BESS, and (3) TS where EVCS powered by VPP. In this study, technical and economic aspects were considered, including energy generation, consumption, RES_{Fr}, energy sales and purchases, COE, NPC, CAPEX, and OPEX. The best outcome is found in the TS, where the lowest COE is 0.111 €/kWh, and the highest RES_{Fr} is 34.6%. Also, COE is 35.46% lower, and energy bill is reduced to 16.15% than the BS. Our results demonstrate that EVCS with VPP is better for consumers. The findings demonstrate how such an integrated system can offer sustainable and cost-effective charging solutions, thereby supporting the broader adoption of EV's while contributing to GHG reduction goals. Also, investing in EVCS will facilitate the EV transition and attract investors to invest in EVCS. It will also open new opportunities for decision-makers and investors to make sustainable investments. In the future, AI algorithms can be integrated to predict load profiles for the EVCS. Besides, a sustainable service will be proposed for the university's users as a cloud-based energy management system. Moreover, which types of actors can collaborate with the proposed service for investments and offer a sustainable service. Also, a toolchain will be prepared for further research where users can check with their techno-economic parameters, along with hourly load profile. Then it will conduct optimization and give users results within a short period.

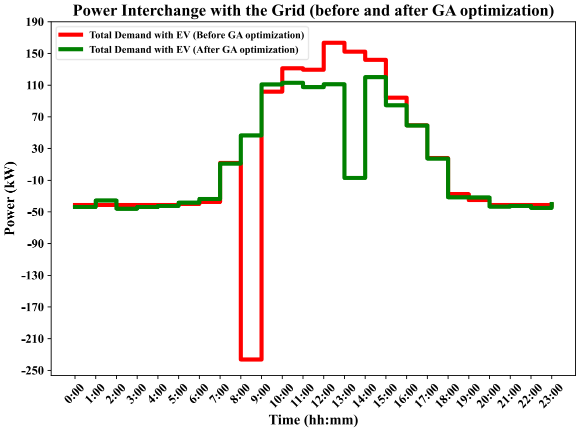

Fig. 6. Power Interchange with the Grid (before & after GA optimization).

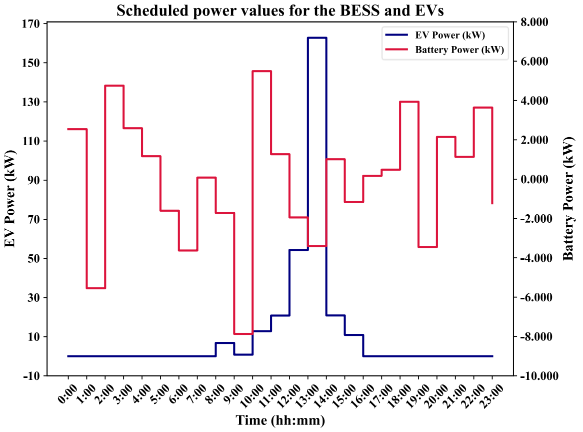

Fig. 7. Scheduled power values for the BESS and EVs.

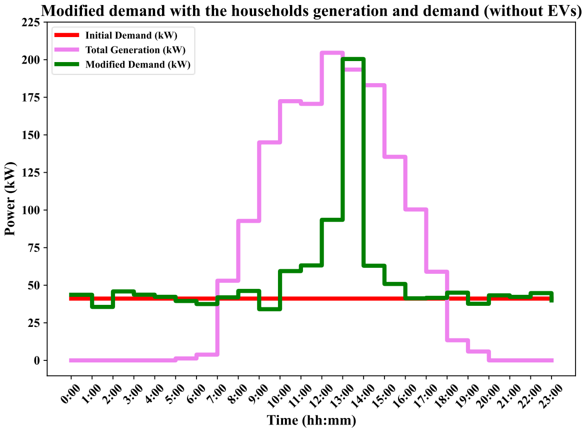

Fig. 8. Modified demand of households (without EVs).

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