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RESEARCH ARTICLE

An Optimal Distributed RES Sizing Strategy in Hybrid Low Voltage Networks Focused on EVs' Integration

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ABSTRACT The new era of the energy sector has already begun, and therefore, new challenges need to be tackled. A major challenge that residential distribution grids are going to encounter with the integration of photovoltaic (PV) panels and electric vehicles (EVs) is the unsynchronized new demand and the time-limited production of distributed generation, in combination with space limitations. Therefore, the necessity of energy storage systems (ESSs) is more than evident. ESSs have excessive manufacturing costs, implying that the purchase cost for residential users can be prohibitive. In the present work, a distributed optimal small-scale PV energy system sizing strategy is proposed, by considering the individual energy needs of each residence and their EVs. The strategy is formulated based on the demand of the households and EVs' charging. By enabling the fuzzy cognitive maps theory, a graph is designed, aiming to establish the correlation among the individual energy parameters and the characteristics of the renewable energy sources (RES). The optimization results reveal that the adopted hybrid approach can reduce the energy cost significantly, up to almost 40%, while enabling distribution system operators (DSOs) to incorporate additional loads, without the need for network expansion. Finally, based on the extracted results, a short discussion about the concept of EVs' charging by residential RES is presented.

INDEX TERMS Distributed energy networks, EVs, fuzzy cognitive maps, hybrid energy systems, RES sizing.

I. INTRODUCTION

Over the last decades, climate change has become one of the greatest challenges of the 21st century, due to the increased use of fossil fuels and the continuous growth of energy demand. Moreover, the global energy demand is projected to be significantly increased in the next decades. Focusing on residential structures, according to a study made by International Energy Agency (IEA), it is projected that the energy consumption will be increased by 65% till 2050, growing from 91 quadrillion BTU to 139 quadrillion BTU [1]. In addition, two of the major consumers of fossil fuels are the electricity production sector and the transportation sector [2]. Renewable energy systems (RES) and electric vehicles (EVs) are two technologies that can lead to a significant reduction of fossil fuels and consequently to a wide range of ecological benefits. However, a plethora of new problems, mainly related to the power grid, has been

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introduced with the adoption of those technologies [3], [4]. Therefore, several challenges should be faced to ensure that RES and EVs will be properly integrated into energy distribution systems.

Today's electricity grids are designed based on existing energy requirements. Therefore, the energy demand of new additional loads with high energy requirements, such as EVs, has not been considered. In this context, several studies have been carried out on the impact of EVs on power distribution systems. Regarding the stability of the grid, which defines its capability of restoring steady-state operation after the occurrence of a disturbance, studies such those in [5] and [6] have been carried out focusing on the effect of EVs penetration on voltage stability. The results from [5] indicate that EVs' fast charging reduces the steady state voltage stability, mainly due to the reason that the EV load behavior is represented as a constant power and negative exponential component respectively. The same results are also supported by [6], presenting that the adoption of charging stations, at buses far away from the network's transformer, increase the voltage drops and the system's power losses. A probabilistic analysis on the effects of EVs on low voltage distribution networks carried out on 2 UK underground low voltage networks showed that transformers can experience overload problems for EV integration rates above 40% [7]. A similar study examining the impact of EVs on different types of distribution networks (residential, commercial, industrial) concluded that networks supplying residential consumers are expected to experience significant line overloading issues from the integration of EVs [8]. At the same time, voltage deviation is expected to be highly increased, while unbalances in residential single phase distribution networks are expected to occur. An EVs' impact analysis on a case study Tunisian low voltage network demonstrated that the integration of EVs can lead to voltage drop, bellow its acceptable limits [9]. Finally, the integration of EVs into electricity grids is expected to significantly increase power losses, reaching over 50%, compared to the case in which there are no EVs [10].

According to the literature, the challenges of distribution networks, with respect to EVs' charging, can be addressed through designing and implementing charging management systems, expanding existing network structures, or integrating energy storage systems into energy distribution networks [11], [12]. Apart from the main objective of charging EVs, which is to meet their energy needs, the most usual objectives that can be achieved by enabling EVs' charging management systems are: (i) to reduce the cost of charging EVs; (ii) to reduce or eliminate the upgrade cost on the part of DSOs; (iii) to maximize the utilization of the power generated by RES for charging EVs; (iv) to avoid delays in charging EVs due to high demand from power systems; and (v) to ensure the smooth operation of the power systems [13].

In addition, the integration of RES may tackle adverse impacts of EVs on the energy systems [14]. In this context, EVs' charging from RES and especially the synergy between PVs and EVs has been studied in the literature [15], [16]. The installation of distributed residential small-scale RES may lead to avoiding the use of EVs' charging management systems, as the power transferred from the grid to consumers is relatively small and is not expected to pose power quality issues [17].

However, the installation of photovoltaic systems (PV), including the essential energy storage system (ESS), may as well, cause issues regarding the grids stability and power quality [18]. In [19], the uncontrolled installation can result in voltage unbalance and fluctuations. In addition, most of the users arrive at their residence during evening hours [20]. Assuming that most of the chargers around the globe are residential [21], this affect grid stability since the potential energy production from PVs is very limited. Therefore, the power quality can be affected by the combination of PV and ESS, causing impacts on network, and hence power quality studies are essential in RES' integration studies [22].

One major problem associated with the installation of RES is the high cost of ESS. It is widely accepted that the integration of ESS may lead to unaffordable investment costs. However, the integration of ESSs may pose significant advantages, providing additional benefits to both residential users and distribution networks. The use of RES systems, consisting of residential PV systems and battery ESSs (BESSs), was extensively examined in [23]. Among others, the contribution of BESSs to residential RES is examined, aiming to meet the energy requirements of heat pumps. According to the results of the study, the PV-BESS combination is more valuable than using PVs alone, since the use of BESS increases the self-consumption of residences, providing additional flexibility to the heat pumps. Furthermore, in the process of optimizing RES systems, which considers the costs of PVs and BESSs as well as the cost of purchasing energy from the grid, the optimal installed capacity of PVs is significantly increased when BESSs are integrated. The installed capacity of PV systems is increased by more than 1 kW when BESSs are considered. Finally, heat pumps, like EVs, are unfavorable loads for the distribution grid. However, it is implied that the use of BESS can also contribute significantly to this part (through increased self-consumption). According to a study presented by SolarPower Europe [24], the use of residential energy storage technologies is projected to increase significantly in the coming years. Under the best-case scenario, the total capacity of residential BESSs across Europe is estimated to increase to 14.6 GWh in 2025, up from 3 GWh in 2020. Even in the worst-case scenario, this increase would exceed 10 GWh.

Moreover, this problem has been studied in the literature through the design of optimal ESSs sizing strategies, with one of the main objectives being to reduce energy costs. In [25], an optimal methodology for distributed BESS's sizing in residences is presented. The proposed methodology calculates the BESS's capacity and the charging/discharging profiles of each residence, based on its individual energy purchase cost and its energy consumption profile. The optimization is achieved by minimizing the payback period of the BESSs' investment costs. An investigation about the feasibility of residential BESS's sizing, including EVs' charging demands, has been studied in [26]. The residential consumption profiles and the EVs' charging profiles are added for the calculation of total energy consumption. Eight different residential loads with defined BESS's capacities are examined. According to the results of the presented economic analysis, the integration of residential RES with PVs and batteries can significantly reduce energy purchase costs. In the same context, an optimal sizing methodology for PV and energy storage systems in EV charging stations has been proposed in [27]. Through the combination of multi-agent systems theory and the PSO meta-heuristic optimization algorithm, the charging cost of EVs was minimized. It is noted that the peak charging of EVs occurs during the morning and midday hours, during which there is energy production from PV systems. The importance of the cost factor of the essential ESS component in a system of PVs has also been made clear in [28]. In this study, an algorithm is proposed, aiming to maximize the amount of power that can flow from the ESS to the grid while minimizing the total cost of the component. The research concludes that, while designing the optimal capacity of the ESS, net present value (NPV) cost (construction and operation & maintenance, O&M) and other economic factors that are related to PV's production and its market value, should not be ignored. To reduce the energy cost of PV powered charging stations, a novel classification of EVs' scheme is introduced in [29]. The individual's charging behavior separates the drivers into premium, conservative and green. The total energy cost of the grid is calculated for the abovementioned categorization based on real-time pricing provided by the grid during each day.

Bearing in mind the behavior of EVs in relation to the energy production of the residential small scale solar panels, it is concluded from the literature that these systems are unable to meet the energy needs of charging on their own, due to the lack of synchronization of production with the energy demand (overnight charging). Hence, to be able to maximize the exploitation of the power generated by PV systems for residential EVs' charging, the use of ESSs appears as an attractive solution, despite the high investment cost they present.

Aiming to resolve this limitation, the present study presents a novel optimization strategy that encourages the hybridization of distribution systems, resulting in a rather remarkable reduction in energy costs. In the present concept, residential ESSs and PV panels are combined to achieve this goal, focusing on the specific needs of each individual residence and the integration of EVs. A distributed optimal strategy, based on multi-agent systems and fuzzy cognitive maps theory is designed, including a management system for ESSs discharge, to reach the objective. The PSO optimization algorithm has been employed to calculate the optimal values of the strategy. Through an optimization strategy, correlations are also created between the residential loads, EVs, and RES sizes, so that, depending on the energy needs of each user, the optimum economic solution is proposed. Two different objective functions are examined. Those are the sum and the average energy costs of the residences. The IEEE European Low Voltage feeder, including a set of residences, is used as a case study to evaluate the effectiveness of the proposed methodology and to investigate how the different characteristics of the residences and the EVs affect the optimal RES sizing. The evaluation of the proposed strategy proved that the energy can be significantly reduced, up to almost 40%, compared to two base scenarios. According to the authors best knowledge, it is the first time that the individual characteristics of the EVs are taken into consideration, through the enablement of the FCMs, for the distributed sizing of residential RES, including PVs and ESSs. At the same time, the positive impact of the integration of residential RES in the electricity distribution systems is also examined, through the evaluation of the behavior of different parameters related to their power quality.

The rest of the paper is organized as follows. In Section II, the configuration of the under-study systems is presented, including the modelling procedure of the EVs and the RES, and the energy management system. Section III presents the structure of the RES sizing strategy, together with the formulation of the optimization problem. In Section IV, the parameters of the case study system, along with the characteristics of the EVs and the costs of the different components are defined. The results and the evaluation of the optimization strategy are presented and discussed in Section V. Based on the results the outcomes of the present study are summarized and concluded in Section VI. In addition, the details of EVs' model characteristics are depicted in an Appendix section.

II. PROPOSED ENERGY DISTRIBUTION SYSTEM ARCHITECTURE AND OPTIMIZATION METHODOLOGY

A. SYSTEM DESCRIPTION

The emerging global transformation in the energy sector is forging a shift towards autonomous or hybrid systems, with the adoption of distributed energy sources, improved ESSs and the newly established technology of EVs. Targeting the users of Low Voltage Distribution Systems, the integration of EVs and distributed dedicated renewable energy small scale systems, including solar panels and energy storage, is being considered, attempting to integrate them into the transformation in an optimal way. The architecture of the target systems is presented in Fig. 1. The basic modules of the system are as follows:

- EVs;
- residential loads;
- distributed residential RES modules, which includes photovoltaic arrays of monocrystalline silicon panels and battery banks;
- the distributed radial low-voltage network.

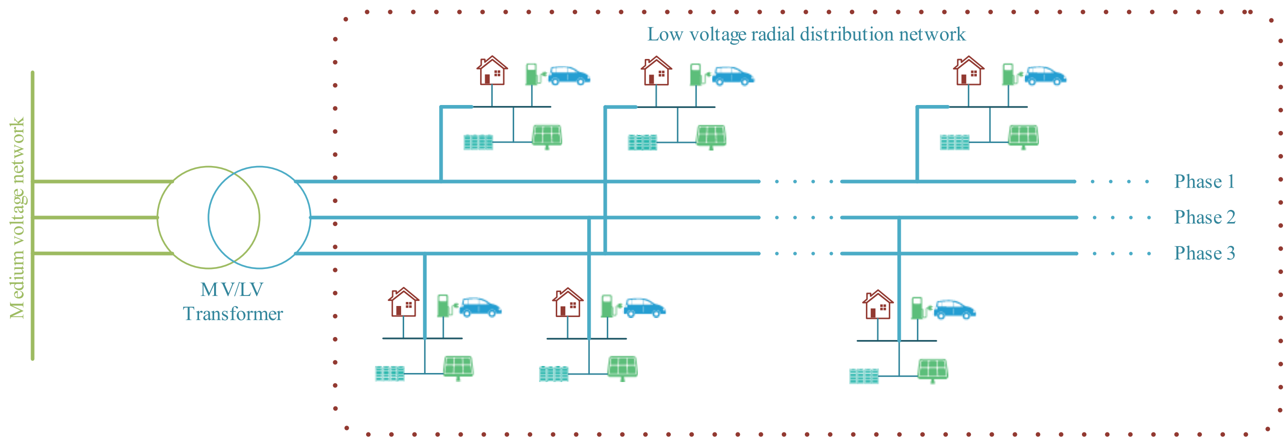

FIGURE 1. Configuration of the under-study systems.

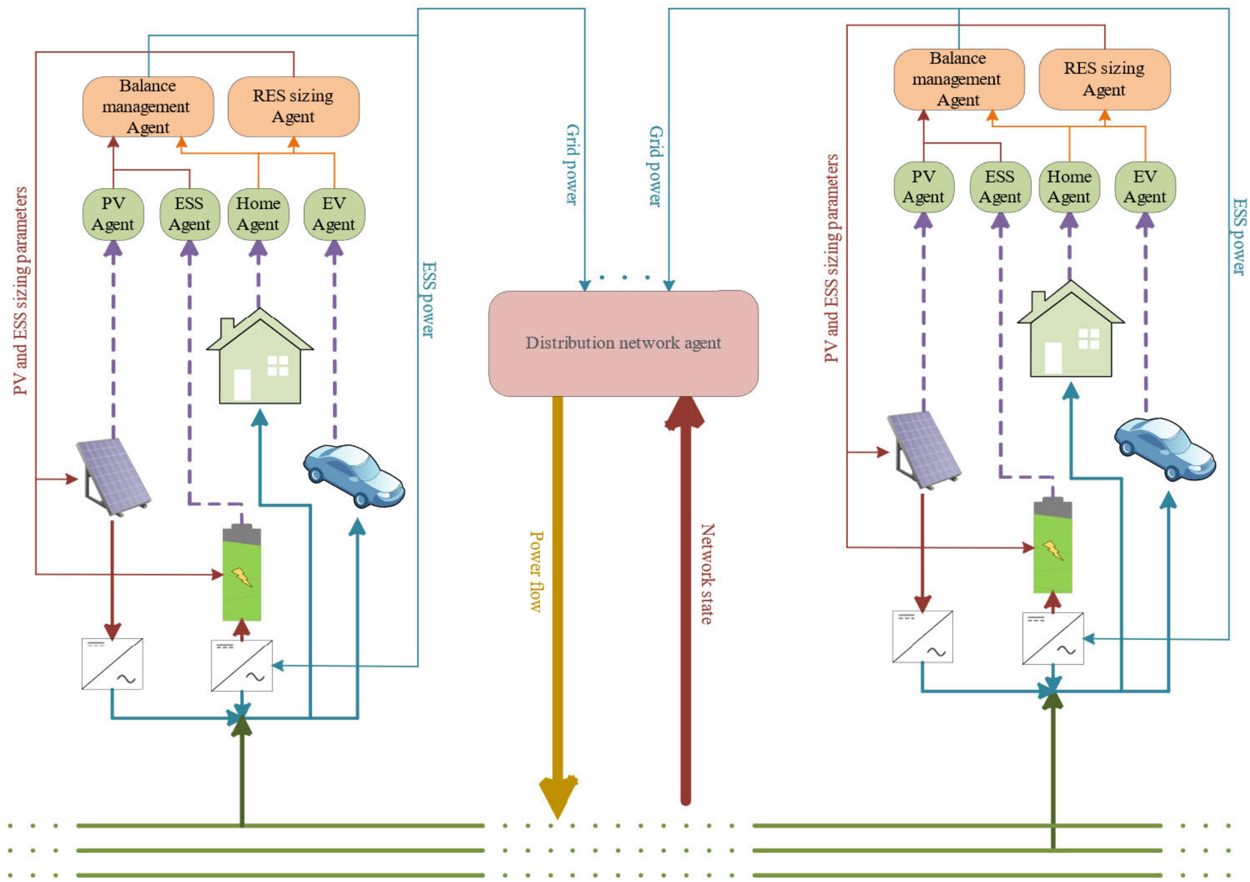

FIGURE 2. Structure of the proposed multi agent system.

As can be deduced from Fig. 1, the problem consists of different heterogeneous elements, combined in a common environment, which is the electricity distribution network. Hence, the modelling of the proposed optimization strategy is achieved by deploying a multi-agent system (MAS). The aim of the MAS system is to minimize the energy cost of the considered consumers, by optimizing the size of the PVs and the ESSs for each consumer, based on their individual energy needs, considering the specific characteristics of EVs, as an additional high consumption load.

B. MULTI-AGENT SYSTEM STRUCTURE

The MAS structure consists of several agents that interact in a common environment. Through their perception of the environment in which they are located and their actions, the agents achieve specific goals.

Based on the different elements that comprise the energy distribution network and the consumers connected to it, the proposed MAS consists of 7 different types of agents, as depicted in Fig. 2. The role of the agents is to monitor and control the different distributed elements of the considered energy distribution system. Therefore, the types of the considered agents are as follows: (i) the home agents, (ii) the EV agents, (iii) the PV agents, (iv) the ESSs agents, (v) the RES sizing agents, (vi) the balance management agents and (vii) the distribution network agent. Each residence is equipped with each one of the agents, except for the distribution network agent, which represents the low voltage energy distribution network. A detailed description of the structure and operation of each type of agent follows.

C. DISTRIBUTION NETWORK AGENT

Typically, low voltage energy distribution networks consist of many distributed customers, each of whom has different energy requirements and needs, depending on their individual energy behavior. When adding high consumption supplemental loads, such as EVs, a reduction in the power quality, offered by the distribution systems, is expected. The role of the present agent is to perform power flow analysis, based on the power required by each residence from the grid, to monitor the power quality of the distribution network, and to inform the system about the state of the network.

To define the quality of those networks, three main characteristics are taken into consideration: (i) voltage deviations (1) [7], (ii) lines' ampacity violations (2), arising from the continuous overcharging of conductors and transformers [30], and (iii) occurrence of unbalances between the three phases of the networks due to imbalanced single-phase loads (3) [31].

$$V_{\min} \leq V_{i,j} \leq V_{\max} \tag{1}$$

$$I_{i,j} \leq I_{i,\max} \tag{2}$$

$$\mathrm{VUF} = (V_2/V_1) \times 100\% \tag{3}$$

where V_{min} and V_{max} are the voltage operational limits of the distribution network, $V_{i,j}$ is the voltage of the bus i at phase j, $I_{i,j}$ is the current that flows through the phase j of the feeder i, $I_{i,\max}$ is the ampacity of the feeder i, VUF is the voltage unbalance factor and, V_1 and V_2, are the voltages of the positive and the negative sequential circuits respectively. Since an increased number of buses is included in such networks, an overview about the voltage deviation, can be extracted, using the Average Voltage Deviation Index (AVDI), as defined in (4) [32].

$$\mathrm{AVDI_i(t)} = \frac{1}{N}\sum_{j=1}^{N} \mathrm{sqrt}\left(\left|(V_{ref}^2 - V_{i,j}^2(t))\right|\right) \tag{4}$$

where N is the number of buses and V_{ref} is the system's reference voltage. Keeping those parameters within their operational limits ensures the normal operation of the network and the electrical loads that are supplied. Therefore, the agent calculates the parameters of (1)-(4), through performing sequential power flow analysis, for a given time period, with a pre-defined timestep and informs the overall system about the state of the network, at each time step. The algorithm of the present agent is defined as follows (1).

TABLE 1. Pseudocode of the distribution network agent.

Algorithm: Pseudocode of the distribution network agent
Data: $V_{i,j}$, $I_{i,j}$, VUF, $\mathrm{AVDI_i}$
Initialization
Begin
For each time step, t, do
Gather the power demanded by each system load, as calculated by the balance management system of each residence.
Perform power flow analysis.
Calculate the power quality parameters, based on (1)-(4).
Check if any of the parameters are beyond the allowable limits
End
return

It is noted that the considered low voltage networks are connected to an interconnected medium voltage feeder and thus, the voltages and the currents at the buses and the feeders of the network are calculated at a selected nominal frequency. The frequency is 50 Hz (typical European distribution networks) [33], [34]. The slack bus of the network is located on the side of the medium voltage network and represents the interconnected power system that supplies, among others, the low voltage network. Therefore, the medium voltage slack bus will provide the loads with the requested power and hence, it is assumed that there will be a power balance between generation and load consumption. Finally, is it assumed that the inverters of the small-scale RES are grid-following [35].

D. HOME AGENTS

The role of the home agent is to measure the power that is consumed by its corresponding residence. At each time step, the home agent informs the balance management agent about the power required to cover the residential loads, defined as P^i_{HH} for a given residence i. Moreover, home agents inform the RES sizing agent about the mean daily energy consumption of the corresponding residence ($\bar{E}^i_{HH}$), which is used by the RES sizing agent to size the RES of the respective house. The algorithm by which the present agent operates is shown in 2.

E. PV AGENTS

The role of the PV agent is to monitor the power generated by the PV system and to inform the balance management agent, respectively, about the amount of the available PV power. The power that is produced by a PV system is related to the incident irradiance (I^i_{PV}) and the area A^i_{PV} of the PV panel. Those features are multiplied by a coefficient (η_{PV}), which depicts the capability of a PV system to transform the

TABLE 2. Pseudocode of the home agent.

```
Algorithm: Pseudocode of the home agent
Data: P^i_HH, Ē^i_HH
Initialization
Begin
Inform the RES sizing agent about the mean daily energy consumption.
For each time step, t, do
        For each residence, i, do
                Measure the power required by the residence.
                Inform the energy balance agent about the required
                power.
        End
End
return
```

irradiance energy into electrical power [29]. Moreover, power electronics are needed to integrate the solar panels of a PV system into an energy distribution system. Typical electronic devices that are used are a DC/DC converter and an AC/DC inverter. State-of-the-art PV technologies adopt power factor correction devices, and hence it is assumed that PV systems inject only active power. Therefore, the power produced by a PV can be expressed by (5).

$$P^i_{PV}(t) = A^i_{PV} I_{PV}(t) \eta_{PV} \eta_{inv} \tag{5}$$

where η_{inv} is the efficiency of electronic devices. The algorithm of the PV agent is as follows (3).

TABLE 3. Pseudocode of the PV agent.

```
Algorithm: Pseudocode of the PV Agent
Data: P^i_PV, A^i_PV, I_PV, η_PV, η_inv
Initialization
Begin
For each time step, t, do
        For each residence, i, do
                Compute the produced power from the
                PV system, based on (5).
                Inform the energy balance agent about
                the produced power.
        End
End
return
```

F. EV AGENTS

The role of the EV agent is to model the behavior of the EVs, to inform the RES sizing and the balance management agents about the technical characteristics of the corresponding EV - for the purposes of sizing the RES system - and to inform the balance management agent about the power that is required by the EV, in order to be charged.

In the present work, only the battery of the EVs is modelled since it is the component that secures the main interface with the network. Furthermore, the efficiency of their chargers (η_{EV}) is considered. The states that express the operation of an EV are: (i) the charging state, in which power is delivered to its battery, (ii) the travel state, where the energy stored is reduced and (iii) the parking state, in which the EV is parked and the stored energy in its battery remains constant. The parameters considered in the modelling process of EVs are depicted in Fig. 3.

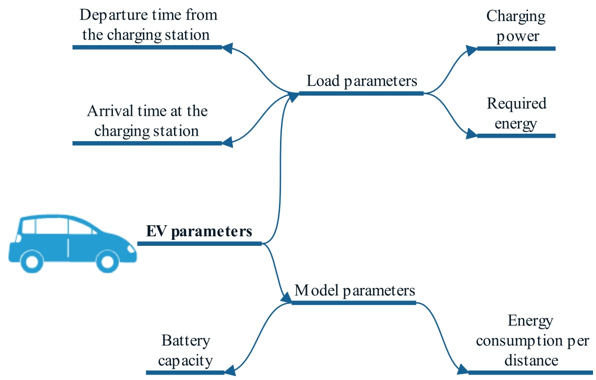

FIGURE 3. Key features of EVs.

When EV is charging the stored energy of the EV battery increases, according to (6) [36].

$$E^i_{EV}(t) = E^i_{EV}(t-1) + (\mathrm{SoC}^i_{\mathrm{EV}}/100)(P^i_{EV} \eta_{EV} \Delta \mathrm{t}) \tag{6}$$

where, $E^i_{EV}(t)$, is the stored energy at timestep t, P^i_{EV} is the EVs' charging power and SoC^i_{EV} is the battery state-of-charge, defining the percentage of stored energy during a period of Δt.

When EVs are on the second state, the consumed power is calculated based on the distance travelled [37], given by (7).

$$E^i_{EV}(t) = E^i_{EV}(t-1) - (E^i_{EV,CON}/E^i_{EV,MAX}) D^i_{EV} \Delta \mathrm{t} \tag{7}$$

where, $E^i_{EV,CON}$ is the vehicle's energy consumption per distance, $E^i_{EV,MAX}$ is the rated energy of the EVs' battery and D^i_{EV} is the distance travelled. Taking into consideration (6)-(7), it is assumed that each EV can be characterized by three features. Those features are the distance they travelled, the consumption rate and their battery capacity. To secure the optimal operation of EVs' battery, the state-of-charge should be limited, as given in (8) [36]. Fig. 3. presents the parameters that are considered to model the EVs.

$$20\% \leq \mathrm{SoC}^i_{\mathrm{EV}} \leq 80\% \tag{8}$$

Finally, the pseudocode of EV agent algorithm is presented in 4.

G. BALANCE MANAGEMENT AGENTS

At each time step, the overall power demand (P_D) of each residence is calculated by the residence's power, defined as P^i_{HH} and the charging power of the EV, P^i_{EV} (9).

$$P_D = P^i_{HH} + P^i_{EV} \tag{9}$$

The demand is covered by a synergy between the RES' ESS and the grid. The balance power (P^i_{BAL}) between the

TABLE 4. Pseudocode of the EV agent.

Algorithm: Pseudocode of the EV agent
Data: E^i_{EV}, $E^i_{EV,CON}$, $E^i_{EV,MAX}$, SoC^i_{EV}, P^i_{EV}, D^i_{EV}
Initialization
Begin
Inform the RES sizing agent about the distance it travelled, the consumption rate and it battery capacity
For each time step, t, **do**
For each residence, i, **do**
Compute the SoC of the EV, in accordance with its state: (i) charging state, (ii) travel state, and (iii) parking state.
Inform the balance management agent about the required charging power, if the EV is in a charging state.
End
End
return

power produced by PVs (P^i_{PV}) and the total demand is calculated by (10) [36].

$$P^i_{BAL} = P^i_{PV} - P^i_D \tag{10}$$

When $P^i_{BAL} > 0$, the demand is covered by the RES system and the surplus power is stored in the ESS. On the other side, when $P^i_{BAL} < 0$, a percentage of the demand is captured by the ESS, while the rest is supplied by the energy distribution system. The present hybrid function is formulated in (11).

$$P^i_D = a^i P^i_{BAL} + (1 - a^i) P^i_{GRID} \tag{11}$$

where, α^i is a representative variable of the percentage of power captured from the ESS and, P^i_{GRID} is the power that will be captured from the distribution network. A hybrid function focusing on the power harvested from the distribution network as well as from the residential ESS is proposed. It aims to delay the complete discharge of the residential ESS to avoid power quality issues. Moreover, by controlling the discharge rate, a preferable usage of the stored energy is achieved, thus further increasing the value of the proposed strategy.

Therefore, for a given period of Δt, the battery stored energy is calculated based on (12) [36].

$$E^i_{BAT}(t) = E^i_{BAT}(t - \Delta t) + (E^i_{BAT}(t)/E^i_{BAT,MAX}(t))(P^i_{BAL}\Delta t) \tag{12}$$

where, $E^i_{BAT,MAX}$ is the rated energy of the battery. Table 5 presents the pseudocode of the balance management agent.

Finally, it is noted that if the stored energy falls below a specified level, all the required power is supplied by the energy distribution network. The present restriction avoids the full discharge of the residents' ESSs.

H. RES SIZING AGENTS

As mentioned above, each residence has its individual energy needs, and hence, there is the necessity to examine the behavior of each customer independently, in order to ensure his profits. This is achieved by enabling the RES sizing agent, which, based on the individual energy characteristics of each corresponding residence, calculates the area of the PVs to be installed, the rated energy of the battery, and the variable a^i of the balance management system.

TABLE 5. Pseudocode of the balance management agent.

Algorithm: Pseudocode of the balance management agent
Data: P_D, P^i_{HH}, P^i_{EV}, P^i_{BAL}, P^i_{PV}, P^i_D, a^i, P^i_{GRID}, E^i_{BAT}, $E^i_{BAT,MAX}$
Initialization
Begin
For each time step, t, **do**
For each residence, i, **do**
Calculate the consumption power from the residence (9).
Calculate the balance power, based on (10).
Calculate the amount of power that will be captured from the ESS and from the distribution network (11).
Inform the distribution network agent about the required amount of power from the distribution network.
End
End
return

Considering that an energy distribution system supplies many customers, let us define them as n, and that for each customer the optimal area of the PV and the optimal battery capacity (at least) must be defined, by keeping their expenses at a minimum value, *2n* decision variables must be calculated, i.e., the size of the PVs and the rated capacity of the ESSs.

The problem's complexity, and hence, the number of the decision variables, can be reduced by enabling Fuzzy Cognitive Maps (FCMs). FCMs are defined as fuzzy structures that represent casual reasoning between the different characteristic features of a complex system. Each feature in the graph is defined as a node, and the interactions that the nodes have between each other are formulated, based on occurring weights. By adopting the view that there is a relationship between the energy characteristics of each distribution network's residence and its RES modules, the graph of Fig. 4 can be extracted. The variable net_i represents the weighted sum of the node *i*, while $f(net_i)$ represents the activation function of the corresponding node.

As depicted in Fig. 4, to achieve the optimal sizing of RES, a certain structure is followed. Firstly, specific components included in the identity of EVs, with their respective weights are connected to create the node $f(net_1)$. Those are the maximum capacity of the storage system $E^i_{EV,MAX}$, the daily traveled distance D^i_{EV}, and the energy consumption $E^i_{EV,CON}$, while w_1, w_2 and w_3 are their respective weights. The node $f(net_1)$, together with the energy demand of the household $\bar{E}^i_{HH}$, and with the additional weights (w_4-w_6 and w_5-w_7 accordingly), create two new nodes $f(net_2)$ and $f(net_3)$, related to the area of the solar panel (A^i_{PV}) and the capacity of the ESSs, $E^i_{BAT,MAX}$.

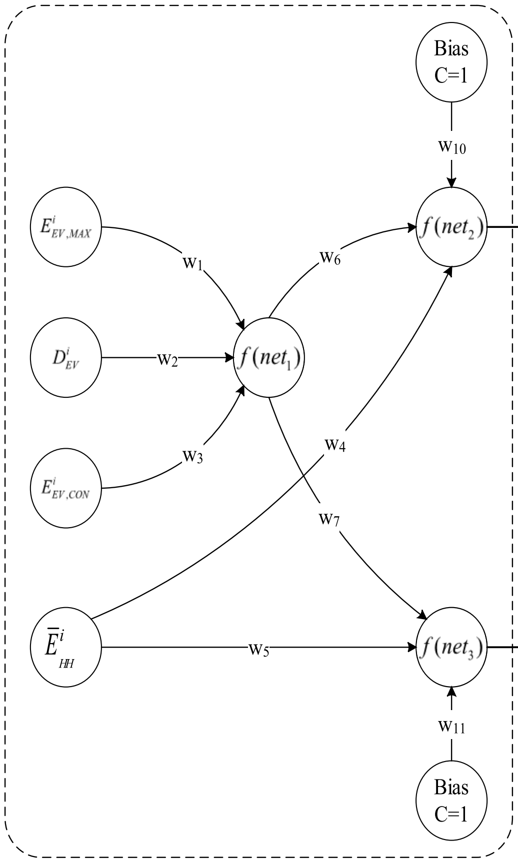

FIGURE 4. Structure of the distributed RES sizing module.

In addition to the sizing of the RES, there is a need to calculate the variable a, for each residence, as defined in (11). A control method focusing on the power harvested from the distribution network as well as from the residential ESS is proposed, as can be seen in Fig. 5. It aims to delay the complete discharge of the residential ESS to avoid power quality issues. Moreover, by controlling the discharge rate, a preferable usage of the stored energy is achieved, further increasing the value of the proposed strategy.

Therefore, the calculation of the net_i, for each feature is based on the weighted sum model (13).

$$\text{net}_i = \sum_{j=1}^{N} (C_j w_j + w_{bias,i}) \tag{13}$$

where C_j is the value of feature j, w_j is its corresponding weight and $w_{bias,i}$ is its bias weight. As for the activation function of the graph nodes, the sigmoid function is adopted (14) since it is commonly used in other FCMs [38], [39].

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{14}$$

where λ represents the steepness of the activation function in the area between zero.

Finally, as seen in Figs. 4 and 5, biases have been considered to offset the results of the nodes which calculate the surface area of the PV systems, the capacity of the ESSs and the factor a. The adoption of biases in the critical nodes of the FCMs increases the flexibility of the modules, during the optimization of the weights. The pseudocode of the RES sizing agent is presented in 6.

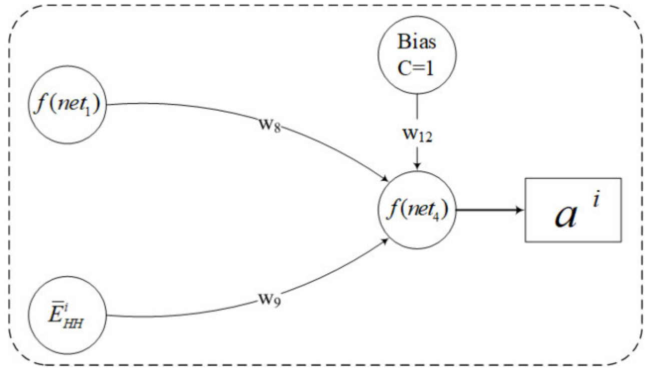

FIGURE 5. Structure of the hybrid coefficient determination submodule.

TABLE 6. Pseudocode of the RES sizing agent.

Algorithm 1: Pseudocode of the RES sizing agent
Data: $E^i_{EV,MAX}$, D^i_{EV}, $E^i_{EV,CON}$, $\bar{E}^i_{HH}$, A^i_{PV}, $E^i_{BAT,MAX}$, a^i
Initialization
Begin
For each residence, i, **do**
At the beginning of the simulation, calculate the PV area, the maximum capacity of the ESS and the variable a, based on the FCMs, as depicted in Figs. 4 and 5, and inform the corresponding PV agent and the balance management agent about the values of the variables.
End
Return

III. OPTIMAL SIZING METHODOLOGY AND OPTIMIZATION PROCESS

A. OVERVIEW

The aim of the optimization process is to minimize the energy costs of the residences that are connected to the same low voltage distribution network. According to our approach, as defined in the above section, the total energy cost (C^i_{TOTAL}), as expressed in (15), consists of the energy purchase costs from the distribution network (C^i_{EC}) and the net-present cost of the RES (C^i_{NPC}).

$$C^i_{TOTAL} = C^i_{NPC} + C^i_{EC} \tag{15}$$

The net-present cost of the RES includes the investment cost of the PV panels, the ESS, and the electronics (16). In addition to the investment cost, the operational and maintenance costs of the PV panels are also included (17).

$$C^i_{RES,INV} = A^i_{PV} C_{PV} + E^i_{BAT,MAX} C_{BAT} N_{BAT,REP} + C_{ELEC} \tag{16}$$

$$C^i_{RES,OM} = A^i_{PV} C_{PV,OM} \tag{17}$$

where C_{PV} is the price of the PV panels, $C_{PV,OM}$ is their operational and maintenance cost, C_{BAT} is the price of the

ESS, $N_{BAT.REP}$ is the number of the RES battery replacement and C_{ELEC} is the price of the electronics, including the inverter of the PVs and the ESS.

Adoption of RES is a long-term economic investment and hence, by taking into consideration the lifetime of the system in years (T), the annuity factor (R), the depreciation period (j) and the interest rate (I), the net-present-cost (C^i_{NPC}) is defined as (18):

$$C^i_{NPC} = \sum_{n=1}^{T} \left[C^i_{RES,INV} R + C^i_{RES,OM} (1+j)^{n-1} \right] \quad (18)$$

In addition to the net-present cost, the energy purchase cost from the distribution network, as a commodity, is related to the dynamics of inflation, and therefore, it is estimated to change over time, in line with inflation.

By assuming a daily mean energy consumption, E^i_{GRID}, and a yearly mean price for the energy purchase cost from the energy distribution network at the year that the consumers' RES investments will take place (C^0_{EC}) and by taking into consideration the inflation rate (IR), the C_{EC} is calculated by (19).

$$C_{EC} = \sum_{j=1}^{T} \sum_{month=1}^{12} \sum_{day=1}^{30} \left[(E^i_{GRID}) C^j_{EC} \right] \quad (19)$$

where, C^j_{EC} is defined as (20):

$$C^j_{EC} = \left(C^{j-1}_{EC} IR + C^{j-1}_{EC} \right) \quad (20)$$

B. PSO ALGORITHM

There are many optimization techniques for engineering problems. Most of them use as information the derivative of the objective function, like the Langrage multipliers method. The result that comes up from those techniques usually tends to be a local optimum. However, when the problem is complicated with probabilistic rules, but the transition doesn't follow deterministic rules, then evolutionary algorithms are used to solve those optimization problems, such as genetic algorithms, simulated annealing, particle swarm optimization (PSO), and ant colony optimization. Those algorithms explore the area where the solution is located, so the solution presents a global optimum. They do not require the objective function to be derivative or continuous.

Energy optimization problems, including distribution power systems and EVs, are characterized by a high degree of complexity [11]. Therefore, the present work makes use of the metaheuristic PSO algorithm since it is an efficient method without the requirement for multiple hyperparameters. Additionally, it has been applied to other energy optimization problems, demonstrating satisfying results [25].

PSO is based on computational intelligence and its purpose is to find the optimal solution of an objective function by performing a stochastic search based on a population [40]. The population consists of particles and each of those particles represents a potential solution. The first population is initialized randomly, and the particles move freely with velocity in the research space. To train FCM matrix, the i-th particle's position ($\mathbf{x_i}$) and its velocity ($\mathbf{v_i}$) have the following format:

$$(\mathbf{x}_i) = [x_{i,1}, x_{i,2}, \ldots, x_{i,d}]^T \quad (21)$$

$$(\mathbf{v}_i) = [v_{i,1}, v_{i,2}, \ldots, v_{i,d}]^T \quad (22)$$

where d is the number of the parameters that will be optimized.

The velocity and the position of each particle are renewed in the next generation, as presented in (23) and (24).

$$v_{i,j}(k+1) = (w * v_{i,j}(k)) + c_1 r_1 [p_{i,j} - x_{i,j}(k)] + c_2 r_2 [p_{g,j} - x_{i,j}(k)], j = 1, 2, \ldots, d \quad (23)$$

$$x_{i,j}(k+1) = x_{i,j}(k) + v_{i,j}(k+1), j = 1, 2, \ldots, d \quad (24)$$

where k is the generation number, w is the inertia weight factor, $p_{i,j}$ is the best personal position of the i-th particle (pbest), $p_{g,j}$ is the best global position of all the population (gbest), c_1 is the cognitive acceleration constant, c_2 is the social acceleration constant, while r_1 and r_2 are uniformly distributed random numbers between 0 and 1. The new velocity and position are calculated and the gbest and pbest are updated. The algorithm terminates when the conditions are satisfied, otherwise it proceeds to the next iteration.

C. PROBLEM OPTIMIZATION

The objective of the proposed optimal sizing strategy for distributed residential RES in low voltage energy distribution networks is to minimize the costs of each individual household, by optimizing the weights of the sizing module and, weights of the hybrid submodule and the biases $w \in \{w_1, \ldots, w_{12}\}$. The weights are normalized ranging between 0 and 1. To this end, two different objective functions are examined. The first approach (Opt RES - Objective 1) is defined by the sum of the total costs of each household (25), while the second one (Opt RES - Objective 2) takes into consideration the mean total costs of the households (26).

$$f_1(w) = \sum_{i=1}^{N} C^i_{TOTAL} \quad (25)$$

$$f_2(w) = \frac{1}{N} \sum_{i=1}^{N} C^i_{TOTAL} \quad (26)$$

Subject to the technical constraints of the energy distribution network and the operational constraints of the ESS, the formulation of the optimization problem is as follows:

$$\begin{aligned} &\text{Given}\mathbf{w} = \langle w_1, w_2, w_3, \ldots, w_{12} \rangle \\ &\text{minimize} f_j(w) \text{ or } f_2(w) \\ &\text{such as} \\ &lb_i \leq \mathrm{w}_i \leq ub_i, i = 1 \ldots 9 \\ &s.t. \\ &(1)\text{-}(4) \end{aligned}$$

where, $\mathrm{lb_i}$ and $\mathrm{ub_i}$ are the limitations on the decision variables and (1)-(4) are the constraints of the optimization problem.

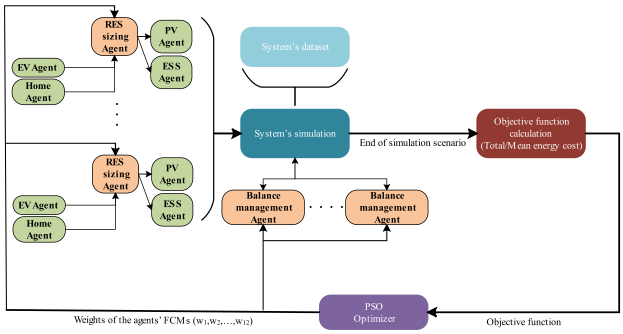

FIGURE 6. Strategy's optimization flow.

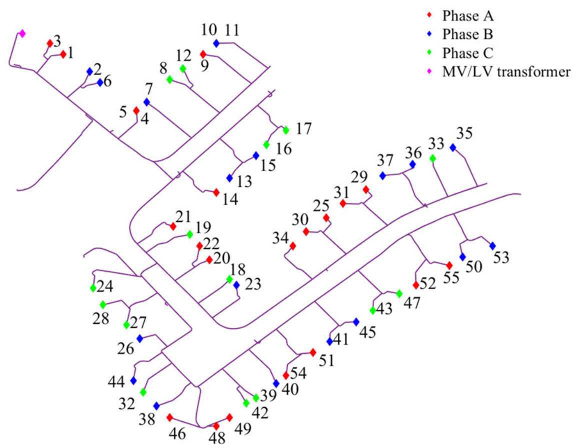

FIGURE 7. Structure of the case study distribution low voltage test feeder.

The flow of the optimization strategy is given in Fig. 6, while the hyperparameters of the PSO algorithm that has been used in the present study, are presented in 7 [36].

TABLE 7. The hyperparameters of the PSO optimization algorithm.

Parameter	Value
Topology	Global best
No. of particles	40
Iterations	200
Maximum stall iterations	20
Tolerance	10^{-6}
Self and social adjustment weights	2.05

IV. CASE STUDY NETWORK AND SIMULATION SCENARIOS

A. CASE STUDY LOW VOLTAGE DISTRIBUTION NETWORK

The evaluation of the proposed methodology was performed by using a modified structure of the IEEE European Low Voltage test feeder, as depicted in Fig. 7, including a dataset of daily representative power demand curves (1 min time-step). It is a representation of a radial European distribution feeder. Since most of the European low voltage distribution networks are designed with a neutral wire, a modification considering a 4-wire system was applied, grounded in the network's transformer, and in each household [41].

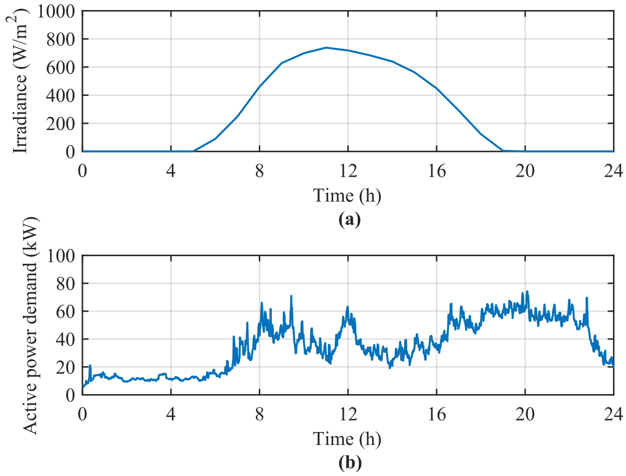

FIGURE 8. Case study production and demand curves: (a) Typical daily Irradiance Curve and (b) Typical active power demand without EVs.

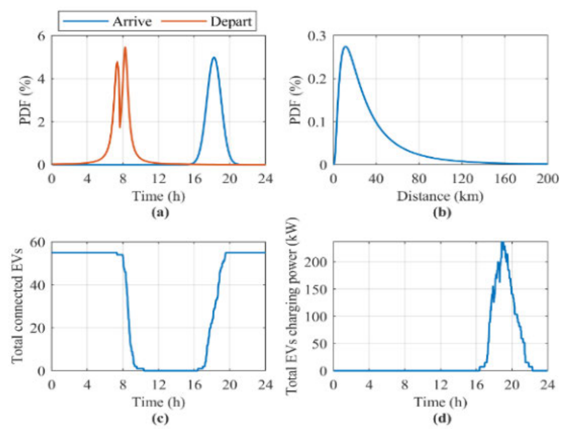

FIGURE 9. EVs' load characteristics: (a) PDFs of the departing and arriving times at the residences, (b) PDF of the distance travelled, (c) Number of connected EVs to the home chargers at each timestep and (d) Total charging power demand at each timestep.

The daily irradiance curve, that is used in the present study, is calculated by taking the mean value of each hour during a period of a year from a dataset, as a base case, collected by the DUTH Electrical Machines Laboratory, referring to the city of Xanthi, Greece, Fig. 8a. The irradiance, and therefore the power produced by solar panels, peaks between 8.00 and 14.00, in a period of the day where the demand lies between 40-50kW, without considering EVs, Fig. 8b. By the time of EV's arrival, where the load's demand increases, around 16.00, the energy production is close to zero, receiving that value at approximately 18.00.

B. EVS' PATTERNS AND CHARACTERISTICS

An evaluation of the effectiveness of the proposed method was made regarding the EV's battery capacity, the distance travelled, and its consumption rate in relation to the optimal sizing of the distributed RES. To accomplish that, ten different commercial EV models have been employed, all of which possess different characteristics as presented in

APPENDIX A. An assumption has been made that each user of the distribution network owns one EV. The departure time of each user as well as the time of arrival at the respective residence and the daily distance travelled between these periods are stochastic phenomena based on [42], as depicted in Fig. 9.

The corresponding Probability Density Factors (PDFs) are indicated in Fig. 9a&b respectively. Using the inverse transform sampling, for the 55 users of the network, the number of EVs connected to the grid during the day is calculated and portrayed in Fig. 9c. We accept that each vehicle is fully charged at the maximum allowed percentage, as is previously defined in (8), at the beginning of every day. Furthermore, by the time of its arrival, the EV is instantly plugged in the charger and connected to the grid. Given those facts, the total power needed to fulfill the charging energy needs of the fleet is given in Fig. 9d. A noteworthy aspect is that the various EV models are stochastically allocated across the system's loads according to the total sales of each model during the year of 2021 [43]. Finally, it is assumed that EVs charge daily, to avoid EVs' battery deep discharges. This consideration is made as deep discharges of electric vehicle batteries reduce battery lifecycles, leading to an acceleration of their aging mechanisms [44]. Moreover, as there is a range anxiety and an imperfect knowledge of the next day's driving cycle EVs' technical constraint for the SOC was set at the end of the day, so that the SOC cannot be below the upper limit of (8) [45].

C. CASE STUDY SIMULATION SCENARIOS AND PARAMETERS

The parameters used for the simulation of the case study system are presented in 8. Regarding the solar panels, the maximum area covered in each residence is taken as 35 m^2 based on the experience of solar energy experts [46]. The maximum allowable capacity of the essential residential ESSs ($E_{BAT.ALL}$) is considered 40 kWh, by considering the regulations, as defined in the NFPA 855 standard, where it is assumed that every residence can install utility closets, storage, or utility spaces [47]. Finally, according to calculations that have been made by the European Commission and the European Central Bank, based on the harmonized index of consumer prices, it is projected that the mean inflation rate in the European Union will be 3.00% until 2050 [48]. As for the EVs' charging power, the maximum allowed power for single phase charging is assumed to be 7.40 kW [36]. The rest of the parameters have been gathered based on recent literature.

The proposed optimization case studies have been appraised based on the examination of four scenarios, with the following details:

Scenario 1 - No RES – In this specific scenario the assumption that RES have not been adopted in the case-study distribution network was made. Therefore, to supply the residential households and the EVs, energy is provided by the distribution network.

TABLE 8. Case study parameters.

Parameter	Symbol	Value
Annuity factor (%)	R	8%
Average battery cost (€/kWh) [49]	$C_{BAT,AVG}$	130
Electronics cost (€) [49]	C_{ELEC}	2500
EVs' charging power (kW)	P_{EV}	7.4
Inflation Rate (%/year)	IR	3.00
Initial energy price (€/kWh)	C_{EC}^{0}	0.2192
Interest rate (%)	I	5%
Lifetime period Years	T	20
Maximum permitted ESS (kWh)	$E_{BAT.ALL}$	40
Maximum PVs (m^2)	$A_{PV.MAX}$	35
Number of battery replacement [49]	$N_{BAT.REP}$	3 (Every seven years)
PV efficiency	η_{PV}	0.135
PV inverter efficiency	η_{inv}	0.96
EV charger efficiency [50]	η_{EV}	0.87
PV investment cost (€/W) [49]	C_{PV}	1
PV operational and maintenance cost (€/kW) [51]	$C_{PV,OM}$	0.015 €/kW
Voltage operational limits (pu)	V_{min}, V_{max}	5 %
Voltage unbalance factor (%)	VUF	≤ 2%

Scenario io 2 - Max RES – A worst case scenario has been employed, resulting in the installation of maximum capacity PVs and ESSs at each residence. It is noted, that due to the limited space of the RES, in this scenario, a small amount of power is supplied from the energy distribution network.

Scenario 3.A - Opt RES (Objective 1) – In this scenario the adoption of the proposed optimization algorithm is made, aiming to minimize the total energy cost (25), while the energy needs of the users are fully covered.

Scenario 3.B - Opt RES (Objective 2) – In the last scenario, the adoption of the proposed optimization algorithm is made, aiming to minimize the mean energy cost (26), while the energy needs of the users are fully covered.

The simulations were carried out for a period of one representative day at one-minute intervals by using the data, which represent a typical behavior of the system components. Consequently, the calculations were made based on the daily results.

V. CASE STUDY OPTIMIZATION RESULTS AND DISCUSSION

A. OPTIMIZATION RESULTS

Considering the formulation of the optimization problem, the objective is to reach the optimal weights in both

Scenarios 3.A and 3.B of the distributed RES sizing modules and the hybrid coefficient determination submodule. Table 9 presents the values of the resultant weights for both optimization Scenarios. It is recalled that the first objective function concerns the cumulative energy costs of the residents (25), while the second objective function calculates their average energy costs (26).

TABLE 9. Optimized weights.

Optimized system's weight	Objective 1	Objective 2
W_1	0.05	0.05
W_2	0.98	0.99
W_3	0.01	0.02
W_4	0.52	0.52
W_5	0.02	0.01
W_6	0.77	0.77
W_7	0.12	0.12
W_8	0.01	0.01
W_9	0.01	0.01
W_{10}	0.98	0.97
W_{11}	0.14	0.14
W_{12}	0.99	0.98

The weights w_1, w_2 and w_3 are related to the EVs of each household. A comparison between w_1, w_2 and w_3 proves that the optimal sizing cost is achieved when there is a strong correlation with the travelled distance, which corresponds to the weight w_2. As is proven, the capacity of the vehicle's ESS and the consumption rate have a minor role, determining them to be insignificant parameters.

The subsequent weight pairs, w_4-w_6 and w_5-w_7, define the significance of the household components and EVs, in the sizing of the PVs and the ESS respectively. A side-by-side comparison of these pairs can lead to the conclusion that the EVs are having a more influential and critical role in the sizing of the parameters, whereas the consumed energy of the residential units is quite reduced, especially in the sizing of the PVs. Focusing on the differences between the weights w_4 and w_5, those have a significant and substantial difference. This can be explained by the fact that the PV costs are relatively smaller than the ESS costs.

As for w_8 and w_9, they represent the decision coefficient, which specifies the percentage of power to be captured by the system's ESS and is determined by the EV and household components. The weights converge at their minimum value, which underlines the weak correlation between the energy needed for the charging process and the supply of it from ESS, aiming to achieve the minimum consumption from the grid.

The weights w_{10}, w_{11} and w_{12} represent the biases of the FCMs, regarding the sizing of the PVs, the sizing of the ESSs, and the factor of the hybrid controller. The weights of w_{10} and w_{11} tend to reach their upper limits. As for w_{10}, this is due to the fact that PV systems are a low-cost investment, and therefore do not significantly increase the investment cost of RES. Therefore, the high weight of the bias leads the sizing strategy to decide to cover almost all the available surface with PV, regardless of the characteristics of the EVs and the energy needs of each residence. Regarding the bias weight w_{12}, its high value indicates that most of the power consumption should be covered by the batteries of the houses to serve their loads. On the other hand, the bias weight associated with the battery sizing, w_{11}, is relatively low. This is because it is the ESSs that have a significant impact on the increase in energy costs, and therefore their size should be directly dependent on the energy characteristics of the houses.

Comparing the changes in the weights for the two objective functions examined, these are negligible. Hence, it is concluded that both functions achieve the objective of the proposed strategy, which is the optimal sizing of the distributed RES system, for each individual residence.

TABLE 10. Energy costs for each examined scenario.

Scenario	Energy purchase cost (network) (€)	Total RES cost (€)	Total Cost (€)	Total PV(m^2)/ ESS (kWh)
1 (No RES)	2,382,350.14	0	2,382,350.14	0/0
2 (Max RES)	139,019.01	2,259,328.13	2,398,347.14	1925/ 2200
3.A (25)	297,535.59	1,152,964.56	1,450,500,15	1459/ 917
3.B (26)	299,922.61	1,154,698.74	1,454,621.35	1464/ 918

The lifetime total energy cost of every scenario is presented in 10. The proposed optimal strategies achieved a significant reduction in the total energy cost, compared to the stress scenarios. The maximum reduction is noted following Scenario 2, in which the maximum available size of RES is adopted. The optimization of objective 1 reduces the total cost by 39.52%, while objective 2 reduces it by 39.35%. Compared to the scenario without the adoption of RES, a decrease of 39.11% and 38.94% is achieved, by using objectives 1 and 2, respectively.

Therefore, the adoption of RES seems to be a beneficial solution for the charging demands of EVs, despite the unsynchronized behavior of PVs and EVs. However, the opportunities of RES, and especially the investment in ESSs, are directly associated with the needs of each residence. There are such households that do not consume much power. In this case, the adoption of the maximum allowable RES is not a beneficial investment. Therefore, the minimum cost is achieved by combining the energy from distribution energy networks and from local RES. Finally, while in Scenario 2, the maximum allowable size of the RES units is adopted, there is still an amount of energy that needs to be harvested from the distribution network, due to the limitations of RES installation.

A more comprehensive evaluation of the performance of the strategy in terms of cost reduction is carried out by dividing the residents into 5 clusters, according to their daily energy needs, including their residential energy demand and their EVs' charging demand. The k-means clustering method

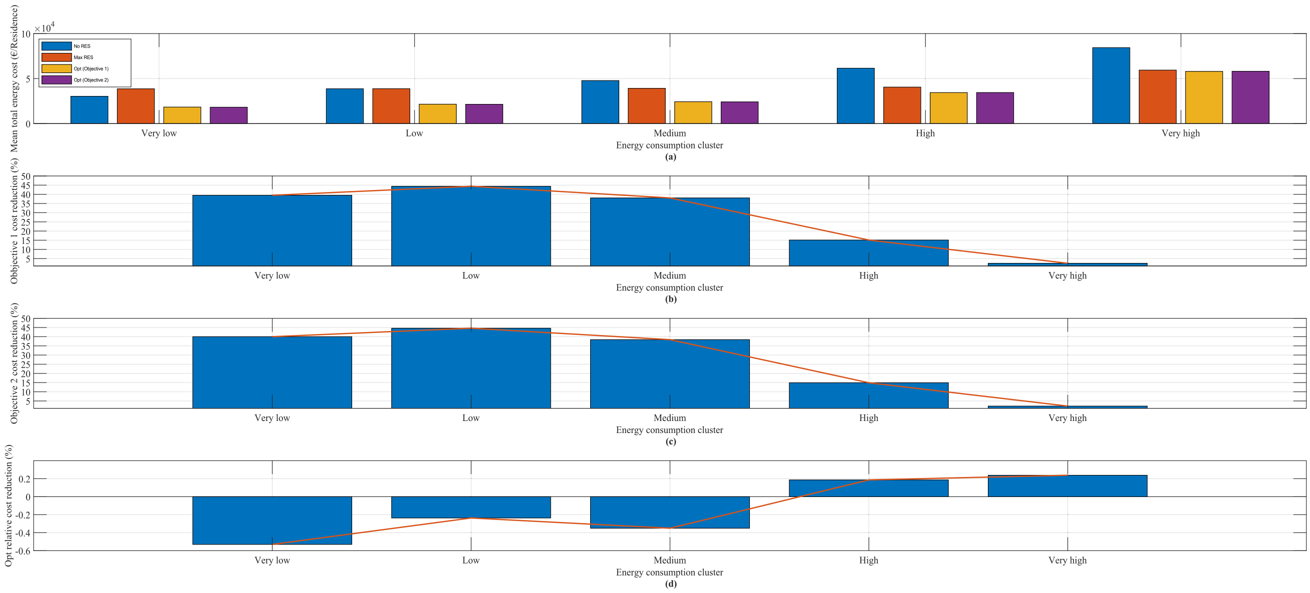

FIGURE 10. (a) Clusters' mean total energy cost, (b&c) Percentage of cost reduction by enabling objectives 1 and 2 respectively, (d) Percentage of difference between objective 2 and objective 1.

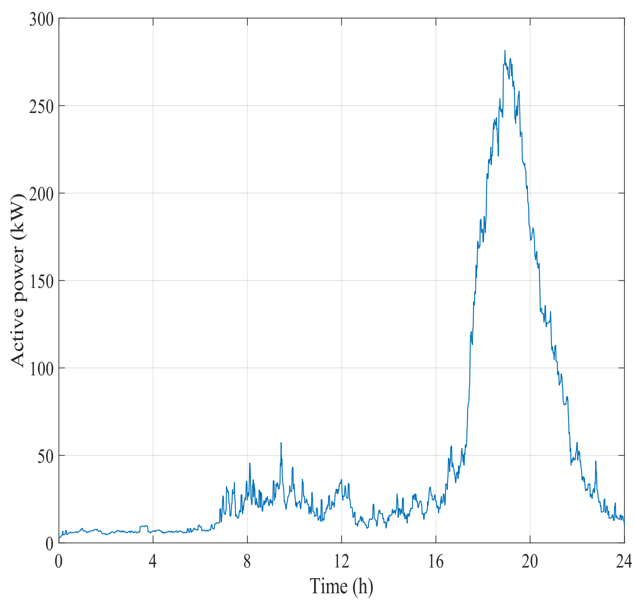

FIGURE 11. Power demand at the substation of the case study distribution energy network, according to scenario 1.

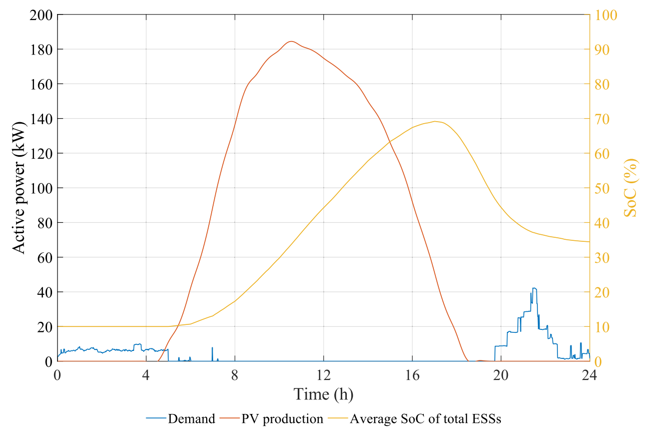

FIGURE 12. Power demand at the substation of the case study distribution energy and total PV produced power, according to scenario 2.

is used for the classification process [32]. The cluster, where each residence of the case study distribution system, belongs is presented in 9. Fig. 10a depicts the mean total cost for each cluster and for each case study scenario. Fig. 10b&c present the reduction percentage of the total cost that is achieved by enabling Objective 1 and Objective 2 respectively, compared to Scenarios 1 and 2. Fig. 10d depicts the percentage of difference between the optimization results for objective 1 and objective 2.

By comparing very-low and low-class consumers, it can be noted that the maximum installation of RES is not cost-effective; on the contrary, for medium, high, and very-high class consumers, a reduction in overall costs is achieved. By implementing the optimization strategy, cost reduction is achieved, regardless of the class of each consumer, for both objective functions. It is noticeable that low to medium consumers have a higher cost reduction compared to the rest. This is due to the correlation between high energy consumption, overall energy cost and high adoption of RES units. The power demand for scenarios 1, 2, 3.A and 3.B, that is required from the distribution network, as well as the respective total power produced from the PVs and the average SoC of the ESSs that are installed in the overall residences are presented in Fig. 11-14.

The power demand, without the existence of the RES, is higher, compared to the other scenarios. An important reduction of the peak load was achieved by the adoption

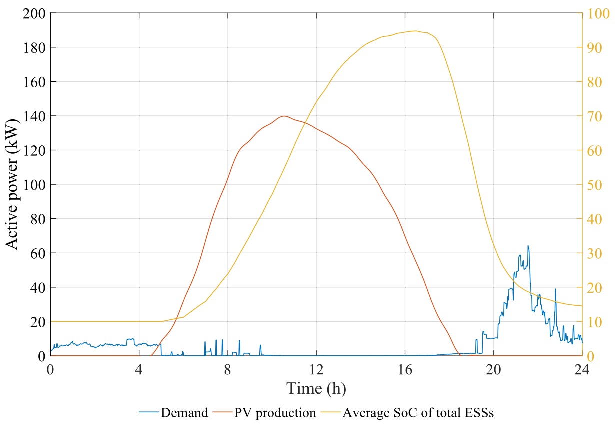

FIGURE 13. Power demand at the substation of the case study distribution energy and total PV produced power, according to scenario 3.A.

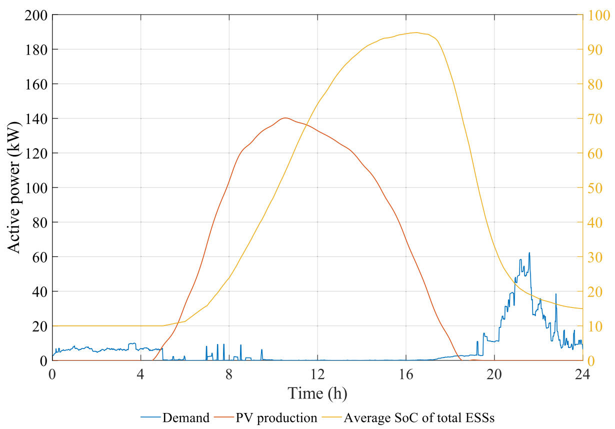

FIGURE 14. Power demand at the substation of the case study distribution energy and total PV produced power, according to scenario 3.B.

of RES. As expected, the demand power is strongly related to the size of the RES systems. Hence, the peak load in scenarios 3.A and 3.B, is higher than in scenario 2. However, in scenarios 3.A and 3.B the variation of the load demand is smoother than in scenario 2. This is achieved by the usage of the battery power controller, which shares the requested power from the loads, between the distribution network and the RES' ESS. Finally, as can be deduced from the results of optimizing the weights of the FCMs, the behavior of scenarios 3.A and 3.B is identical, as both objective functions converged to almost the same solution.

To carry out a further analysis of the application of the proposed optimization strategy, five residences, one from each cluster, are selected to be discussed. Table 12 presents the energy characteristics of the selected residences. The ID of each residence corresponds to its position in the low voltage energy distribution network, as shown in Fig. 7, while Fig. 15-19 depict the behavior of the power and ESSs of the above residences, according to the category to which they belong.

TABLE 11. Clusters of the case study residences.

Cluster	k-mean value (kWh)	Residences
Very low	12.49	4,7,13,21,22,25,27,31,37,40,51,52
Low	15.72	15,17,20,28,36,38,39,42,43,44,48,54
Medium	19.75	2,5,6,10,11,12,16,18,29,32,35,41,49,53
High	25.48	3,9,14,24,30,34,45,46,47,50
Very high	37.46	1,8,19,23,26,33,55

TABLE 12. Energy characteristics of selected residences.

Cluster	ID	Residence daily energy demand	EV's daily energy demand	Total energy demand	RES size PV area/ ESS storage
Very low	**51**	8.30	4.19	12.49	24/9.9
Low	**17**	5.34	9.62	14.96	26/13.6
Medium	**49**	8.02	12.46	20.48	27/17.2
High	**30**	6.81	17.02	23.83	29/21.4
Very high	**55**	7.21	29.48	36.69	34/33.8

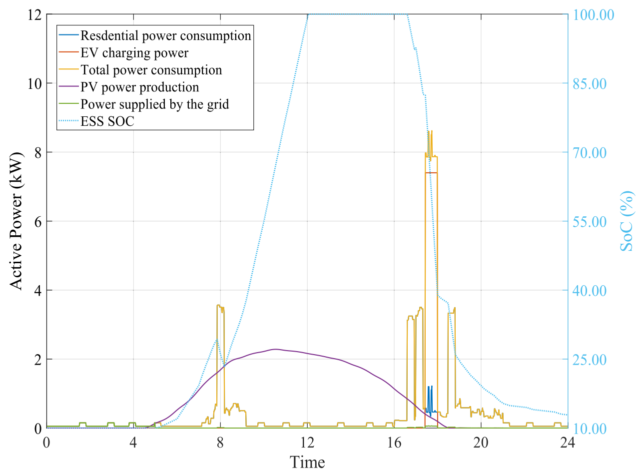

FIGURE 15. Power curves and ESS' So variation of an indicative very low energy consumption residence (Residence 51).

It is noted that the energy consumption of each residence, as well as the energy costs, as calculated in Scenario 3.A, are presented in detail in Appendix B. Observing the ESS SoC in all five residence-classes, the most significant change occurs during the charging period of the EVs. Even in the case of the residence with the lowest consumption, where the vehicle consumes a small amount of energy compared to the other EVs, the SoC changes by almost 40%. Therefore, most of the power received by EVs during charging comes from RES.

As for the power coming from the electricity grid, in all cases, it remains relatively low. Only in the case of vehicles with very high consumption there is an increased power from the grid towards the end of the charging process. This is since

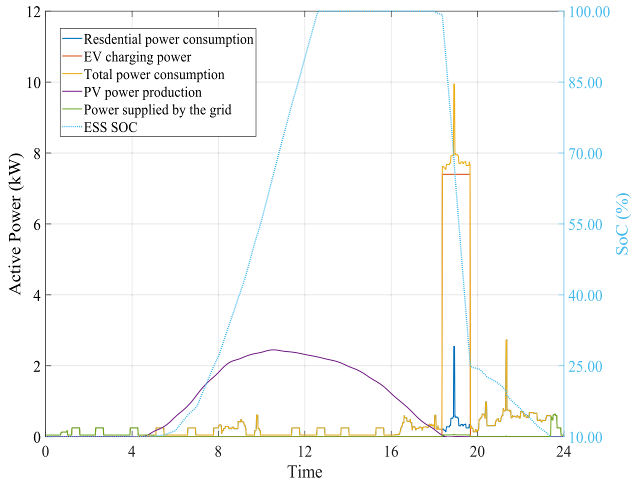

FIGURE 16. **Power curves and ESS' So variation of an indicative low energy consumption residence (Residence 17).**

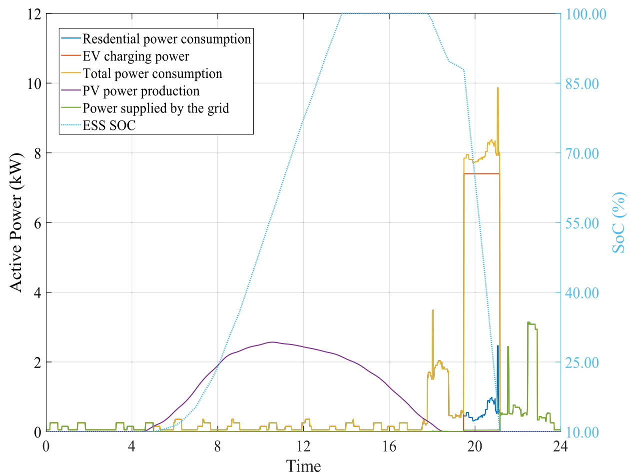

FIGURE 17. **Power curves and ESS' So variation of an indicative medium energy consumption residence (Residence 49).**

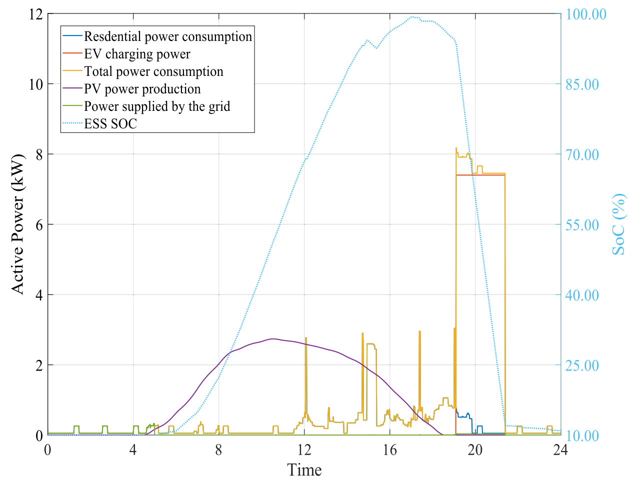

FIGURE 18. **Power curves and ESS' So variation of an indicative high energy consumption residence (Residence 30).**

the ESS SoC drops to its lower limit before the charging process is completed, thus stopping the supply to the loads.

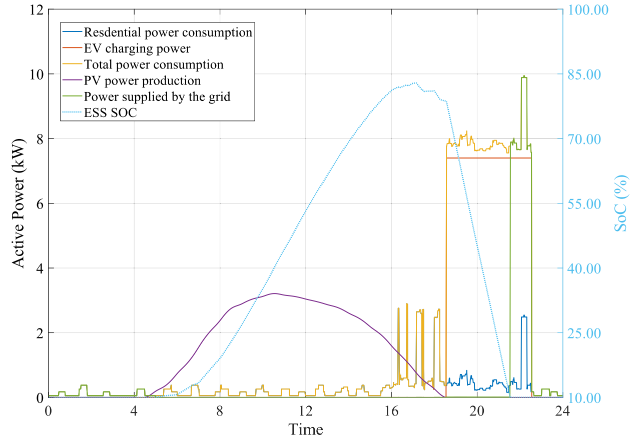

FIGURE 19. **Power curves and ESS' So variation of an indicative very high energy consumption residence (Residence 55).**

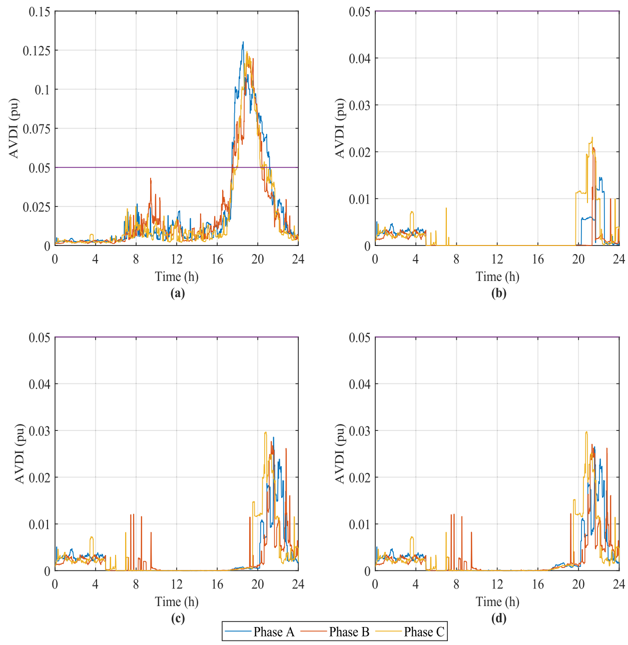

FIGURE 20. **Average voltage deviation index of the case study energy distribution network for each scenario: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3.A and (d) Scenario 3.B.**

Finally, in the cases where very low, low, and medium energy consumption exists, it is observed that the batteries of the respective houses remain fully charged for a significant period (Fig. 15-17).

B. FEASIBILITY OF THE DIFFERENT SCENARIOS BASED ON THE NETWORK OPERATIONAL CONSTRAINTS

The technical constraints evaluated in the present study are: (i) voltage drop of the buses, evaluated through the average voltage deviation index (Fig. 20), (ii) the feeders charging state (Fig. 21), (iii) and the unbalance of the network (Fig. 22). The transformer's rated power is not considered, since according to the dataset of the case study feeder, is relatively high, compared to the power demands, even with

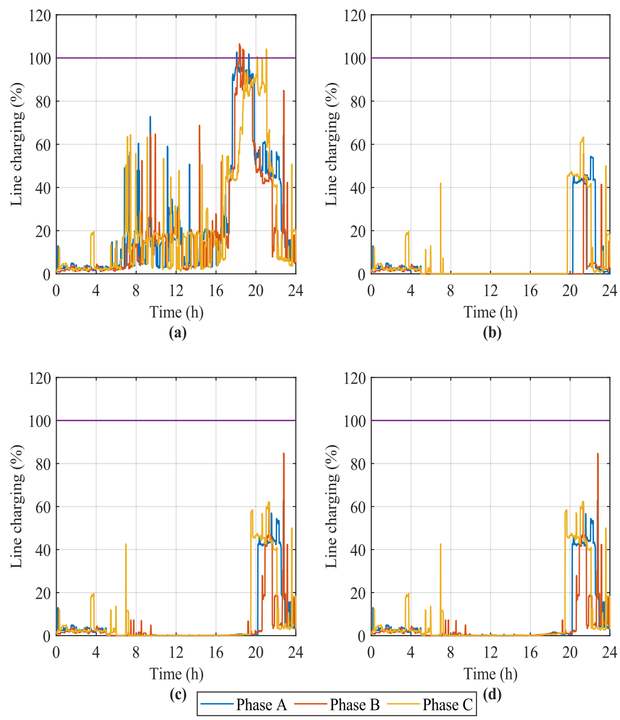

FIGURE 21. Maximum line loading across the energy distribution network for each scenario: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3.A and (d) Scenario 3.B.

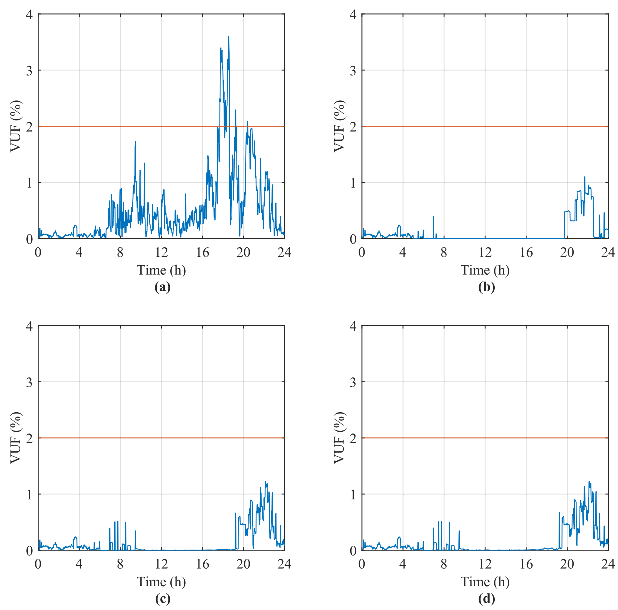

FIGURE 22. Voltage unbalance factor of the case study energy distribution network for each scenario: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3.A and (d) Scenario 3.B.

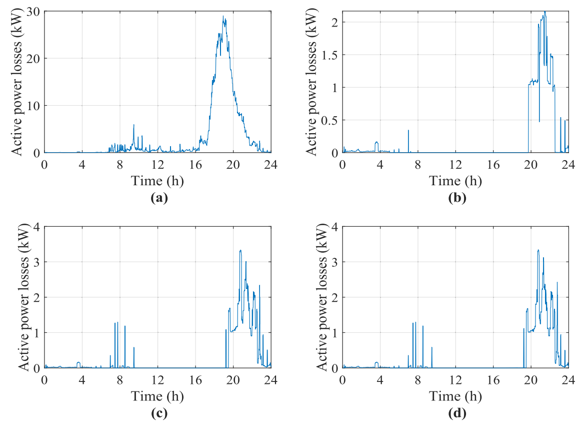

FIGURE 23. Total active power losses of the energy distribution network for each scenario: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3.A and (d) Scenario 3.B.

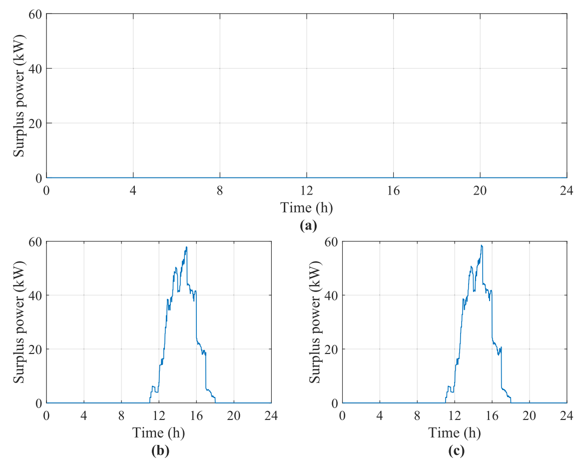

FIGURE 24. Total power that PVs can produce and is not being used for each scenario: (a) Scenario 2, (b) Scenario 3.A and (c) Scenario 3.B.

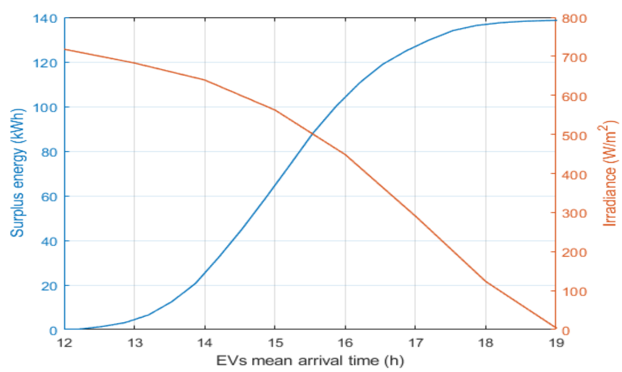

FIGURE 25. Variation of surplus power production from PVs in accordance with the EVs mean arrival time at the home chargers.

the existence of the EVs. According to Fig. 20a, in reference to the 1st scenario, during the charging period of the most EVs, several voltages drop exist, leading to unacceptable values. Based on the EVs' behavior, they return to their residential chargers during the afternoon. By considering that the charging process is done with the maximum allowable charging power of 7.4kW, peak loads are created to the distribution system. In contrast to scenario 1, in scenarios 2, 3.A and 3.B the maximum average voltage deviation does not exceed the operational limit since the power consumption from the energy distribution system is limited.

In addition to the AVDI parameter in scenario 1, a similar limit violation occurs in the voltage imbalance factor.

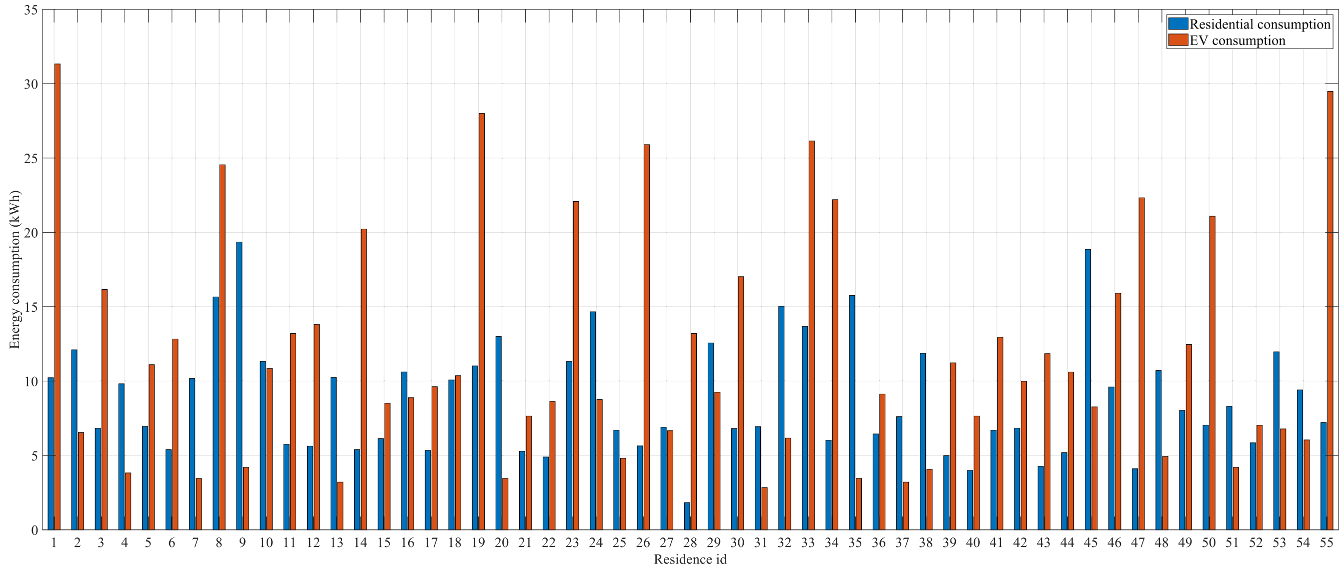

FIGURE 26. Daily energy profiles of the case study residences.

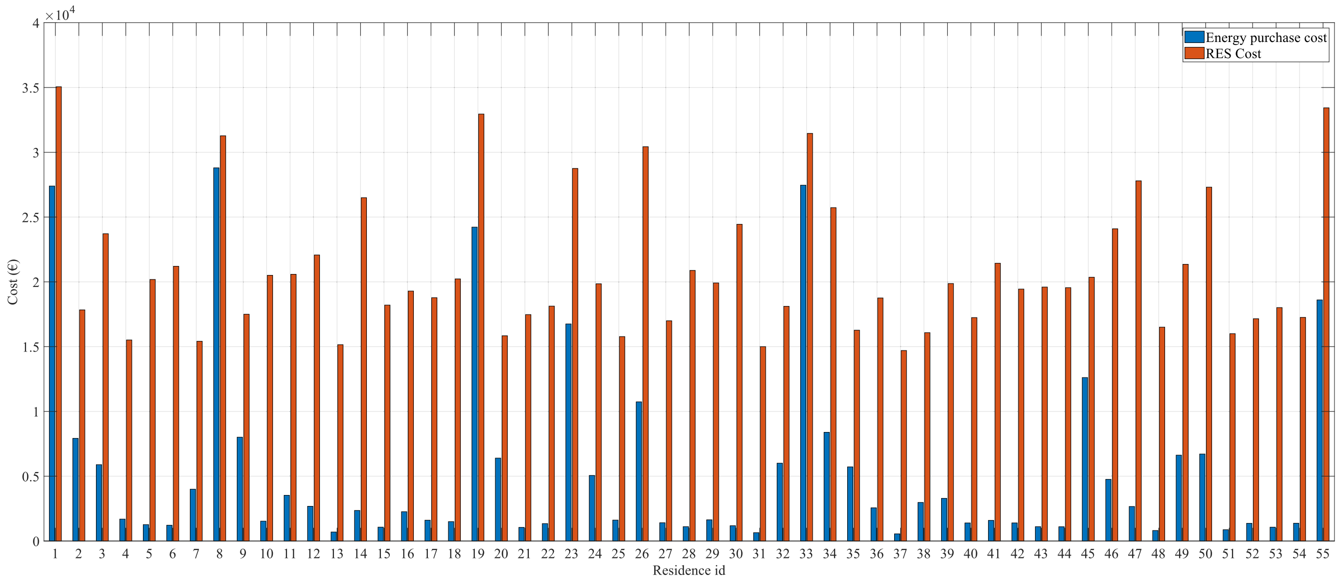

FIGURE 27. Energy purchase cost from the distribution network and NPC cost of the small-scale RES for each residence. The results refer to scenario 3.A.

In general, low voltage distribution systems are unbalanced, due to the single-phase loads' behavior, and hence, adoption of EVs, further worsens those unbalances. The adoption of the distributed residential RES systems and the reduction of the energy dependence from the distribution networks reduces the unbalanced state of them significantly, as depicted in Fig. 21. Furthermore, the behavior of the VUF in scenarios 2, 3.A and 3.B demonstrates that its reduction is linked to the size of the adopted RES. This can be inferred since in scenario 2, the VUF is found to be lower than in scenarios 3.A and 3.B. As can be concluded, the lines of the test feeder (Fig. 22) cannot serve the required power in scenario 1, during the charging process. Whereas the maximum charging of the feeders in scenario 2, 3.A and 3.B, is significantly reduced, by almost 50%. Therefore, the adoption of distributed residential RES can also benefit the distribution system operators (DSOs), by avoiding overloading the feeder, due to EVs' charge, providing the ability to serve additional loads.

Finally, the integration of residential RES systems can significantly contribute to reducing the power losses that occur when loads are fed from the electricity distribution system. According to the results of the present study, in the scenario where no residential RES systems are installed (Scenario 1), daily energy losses reach 74.58 kWh. In contrast to Scenario 1, in Scenario 2, in which the sizes of residential RES are the maximum possible, losses tend to be minimal

(4.10 kWh). In scenarios 3.A and 3.B the daily energy losses are slightly higher, compared to scenario 2. More specifically, in scenario 3.A it is 5.90 kWh while in scenario 3.B it is 5.81 kWh. However, the reductions in energy losses compared to scenario 1 are significant with a reduction rate of almost 92%. The active power losses for each of the four examined scenarios are presented in Fig. 23.

C. SURPLUS POWER OF RES

Considering the optimization scenario, the total losses of the RES surplus power are examined. As the ESSs are sized to provide the best economic benefit to the consumers, there are times when the PV can produce power, but the batteries are fully charged, preventing the energy from being stored (Fig. 24).

The surplus power in scenario 2, in which it has been assumed that RES in all residences is sized to the maximum allowable sizes, is zero. This implies that the batteries never fully charge, so they have the ability to store all the energy generated by the RES. In contrast to scenario 2, in scenarios 3.A and 3.B excess power occurs. This is due to the fact that PV systems are much cheaper than energy storage systems, so that the installed PV systems, as extracted by the optimization strategy, produce a larger amount of energy than the ESS can store. This power can be further utilized by the electricity distribution networks and redirected to loads in need within the distribution network through net-metering technology. It should be noted that this study has not considered this technology, which may bring additional benefits to consumers, as there is a lack of regulations for power injection into distribution networks in most countries. Furthermore, the distribution networks are required to be equipped with additional electrical devices.

A second investigation of the surplus power is done in accordance to mean EVs' arrival time. Herein, this is intended to determine how a potential shortening of the arrival time can lead to a reduction in losses of the generated PV power due to the limited capacity of the ESS, and how these two parameters are linked to each other. Fig. 25 depicts the results of the examination by varying the mean arrival time of the EVs at the charging stations.

The presented results show that there is an exponential relationship between the mean arrival time of the EVs and the power losses of the RES system. As soon as EVs' arrive to their home charger, they can capture more energy from the PVs of the RES system, and hence, less power needs to be stored in the system's ESS.

VI. CONCLUSION

As EVs are widely spread around the world, their high demand is expected to have an impact on current perceptions of the structure of distribution energy systems. The adoption of distributed residential small-scale RES seems to be an attractive solution for EVs' adoption. In addition to the widely known benefits of RES, a strong motivation for small-scale investments can lead to a significant energy cost reduction, directly affecting the consumers.

To this end, in the present paper, an optimal strategy for distributed RES sizing in residential energy networks was implemented, focusing on EVs' adoption. According to the results, the energy costs of the residences can be reduced in a significant manner, by adopting a hybridization approach rather than an autonomous one, and hence, it is shown that a simultaneously supply of the loads by the distribution network and the small-scale RES is more beneficial, resulting to cost decrement, up to almost 40%. The objective functions, that is the summarization of the energy cost and the mean energy cost, seems to be both effective and to convergence to the same optimal solution. Furthermore, it is important to be noted that the adoption of residential small- scale RES, can ensure the normal operation of the distribution networks, without requiring the upgrading of network infrastructure or the integration of algorithms to control the charging of EVs. Consequently, the study of the results suggests that the integration of RES can be a feasible solution for DSOs.

Moreover, focusing on residential charging, the results show that EVs' arrival time plays a vital role in RES energy losses due to insufficient ESS capacity. It came up that there is an exponential relationship between the reduction of the EVs' arrival time and the RES power losses. To avoid the oversizing of the ESS, leading to increased RES investment costs and possible avoidance by the consumers to turn to green energy technologies, different policies can be examined, such as the adoption of residential ESS, managed by the distribution system operators or policies, related with the work hours, since the examined EVs' scenario is a typical daily scenario.

Future work will concentrate on the implementation of EVs' charging management systems in addition to the present methodology and the adoption of additional technologies for net-metering support and V2G technology, aiming to a further reduction of the energy cost for each individual actor and present additional benefits to DSOs. Finally, more detailed battery models will be considered which will take into consideration the degradation of EVs' and RES' batteries.

APPENDIX A

Table 13 presents the basic characteristics of the EVs, that are integrated in the present study.

TABLE 13. Model characteristics of the considered EVs.

Model	E_{rated} (kWh)	$E_{EV,CON}$ (kWh/km)	No. of EVs
Volkswagen E-Golf	35.80	0.1650	3
Nissan Leaf	40.00	0.1640	1
Peugot 208 EV	50.00	0.1640	6
Renault Zoe	54.70	0.1650	5
Volkswagen ID3	62.00	0.1660	14
Kia Niro EV	64.00	0.1730	3
Mercedes A250 e	66.50	0.1870	1
Hyundai Kona EV	67.50	0.1620	2
Tesla Model 3	79.00	0.1670	14
Audi E-Tron	93.40	0.2100	6

APPENDIX B

Fig. 26 shows the daily energy demand of each residence, as well as the daily energy consumption of the corresponding EVs.

Fig. 27 shows the energy costs for each residence as calculated by the optimization strategy, which are divided into the NPC cost and the costs of purchasing energy from the grid.

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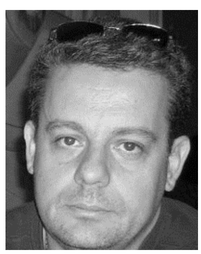

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