Multi Agent Control Based Energy Optimisation of a Prosumer Household and a Community with Bidirectional Electric Vehicles

Aliqyaan Sakarwala(✉), Nauman Beg, Karen Derendorf, and Frank Schuldt

Institute of Networked Energy Systems, German Aerospace Center (DLR), Oldenburg, Germany
aliqyaan.sakarwala@gmail.com

Abstract. Prosumer households with photovoltaic systems face the problem of occasionally generating electricity that cannot be used within the house but must be fed into the electricity grid. This is not desired since with changing policies in Germany, the feed-in tariff has been reduced considerably and the cost of power consumed from the grid has increased significantly. To consume more solar power instead of feeding it into the grid the excess solar power can be consumed by a bidirectional electric vehicle present at the household. Additionally, this system can supply power to the household if solar power is insufficient. **This study presents how bidirectional electric vehicles can optimise the self-consumption of solar photovoltaic energy and increase the self-sufficiency of the loads in a household and a community (i.e. group of households) by a hierarchical structure of control systems: car, household and community.** They are optimising power flow locally and additionally consider information from the over- and underlying controllers. The car controller is a bidirectional charging station where the electric vehicle is connected. It takes user preferences that are used by the household controller to perform power optimisation by handling the mismatch between generation and demand. The community level controller performs an on-the-top optimisation which reduces the power flow between the community and the electricity grid. The effect of the proposed system is investigated on a reference distribution grid simulated in the software package DIgSILENT PowerFactory whereas the control framework is developed in Python. Real load and irradiation profiles are used to execute the simulations. The results show that there is a 31% and 48% increase in the self-consumption and self-sufficiency on a household level whereas a 30% and 50% increase on a community level when the coordinated control system is implemented.

Keywords: Vehicle-to-Grid · Self-Sufficiency · Self-Consumption · Prosumer Household · Electric Vehicles

1 Introduction

The United Nations Climate Change conference held at Glasgow in 2021 made targets to limit the global temperature rise to 1.5 °C [1]. Such targets are only possible if there is a change in social habits by integrating distributed renewable energy sources, adopting

P. Schossig et al. (Eds.): IRES 2022, AHE 16, pp. 434–450, 2023.
https://doi.org/10.2991/978-94-6463-156-2_28

zero-emission electric vehicles (EV), along with the right political framework to support these changes. The number of solar photovoltaic (PV) installations have increased since the year 2000 after the German Renewable Energy Act was introduced [2]. The feed-in-tariff for a PV system was 51 EUR cents/kWh in 2000 [2] which has been reducing over the years to a value of 8.56 EUR cents/kWh in 2021 for a 10kW system [3]. With the energy cost of 32.16 EUR cents/kWh [4] in 2021 it is desirable for a household prosumer to consume most of its generated energy rather than feeding it into the grid.

A mismatch between the time of generation and consumption of PV is observed which leads to a feed-in of excess PV into the grid. This excess PV can be consumed by introducing a battery backup to the system. With increased self-consumption (SC) of PV due to the batteries, the self-sufficiency (SS), a factor indicating the amount of consumption being sufficed by the generation, also increases. A study by the Fraunhofer Society shows that a PV system with a lithium-ion battery increased the SC by 82% as compared to the conventional system without batteries [5].

EVs can substitute stationary batteries since a car on average is parked 22 h at home or at the office with 16 h of uninterrupted parking as per a mobility survey in six European countries [6]. The number of new battery EVs has increased by 83% in 2021 as compared to 2020 in the year-end report of the German Federal Motor Transport Authority [7]. German ministries are targeting to have between seven to ten million EVs on road by 2030 [8].

Unidirectional EV as a replacement of a stationary battery storage has been investigated in [9–11] on a household level. Comparing a system with EV as a storage to a system without storage, an improvement was seen in the SC of the system but not by a great amount due the mismatch between the availability of the EV at home and the time of PV generation. The SS had reduced in [9] as the household consumption had increased due to an addition of an EV in the house. In [10], SS and SC were found to be lower with an EV in the house as compared to when it was not present. To increase the SC, the EV will have to charge during the day which will require a change in social habits or an increase in charging stations near the workplace as PV is produced normally when people are at work [11]. Smart charging techniques have to be implemented to see better results of EVs being used as battery storage systems for a household. SC and SS are higher with a controlled smart charging strategy by 8.7% and 6.9% respectively when comparing with an uncontrolled strategy in [12].

Controlled strategies which incorporate not only charging the EV with excess PV but also discharging when consumption is greater in the house will further increase the SS of the system which is only possible if the EV has capabilities of bidirectional power flow. The concept of Vehicle-to-Grid (V2G) where the EV can charge as well as discharge, has been used in [13–15] for a household. There is a 13% increase in SC with bi-directional charging strategies as compared to unidirectional in [13]. Techno-economic analysis for a span of ten years is shown in [14], where a bi-directional EV can reduce the operational expense with respect to the electricity cost by 37% but has effects on the EV's battery lifetime which is reduced by 12%. It is found that same level of SC and SS can be achieved when a battery storage is replaced by a bidirectional EV but can vary based on the EV battery capacity, the driving profile and number of hours an EV is parked at home [15].

Studies on a community level i.e. on a group of households are conducted in [9] and [10]. The results show a decrease in the SS of the community when adding an EV to each household without any optimisation or V2G capabilities, because they act as additional load in the household. Centralized charging, a central unit which decides on the charging power of the EV, and decentralized smart charging strategies are used in [12] without V2G capabilities on a community level. A complex algorithm and an advance communication infrastructure are required in centralized smart charging, whereas the decentralized or distributed charging of EV is conducted on a user level which is less complex and has low privacy violations. Centralized strategies outperformed decentralized strategies which was indicated with an increase in the SC value of the community.

Research on bi-directional charging is only performed on a household level, none of the papers presented in the literature discusses V2G capable EVs used in optimising the community's SC or SS. In this study, a controller based hierarchical model was developed to improve the SC and SS of a household and a community using bi-directional EVs connected to each household. Agent based modelling was performed to optimise the household and the community to make it less dependent on the grid. Real load and PV irradiation profiles from *Hochschule für Technik und Wirtschaft (HTW)*, Berlin database were used to calculate the household consumption and generation [16, 17]. The model was implemented on a reference grid form the project MONA 2030 and the simulations were carried out for one week in the summer and winters to examine the seasonal performance of the controllers.

2 Methodology

In this section, basic grid element models used for energy optimisation are described. The controller architecture using these models is also illustrated.

2.1 Model Elements

2.1.1 Grid

Project MONA 2030 [18], an open source reference grid is used for the simulation. It focused on optimisation of transmission and distribution grids with high renewable energy feed-in. In total there are 9 representative grids categorizing various city sizes, population and if it's in a rural or urban location. Grid type 5 has been selected for this study based on the number of houses in the model and has features similar to a small town as per [18]. The grid has 14 households which were modified in DIgSILENT PowerFactory to include a PV system and an EV to each household as seen in Fig. 1.

2.1.2 Solar Photovoltaic

The time series power output of a solar PV system was modelled using the PVLIB library for each of the households in the community. PVLIB is a library written for Python. It is a toolbox developed by the Sandia National Laboratories which is used to design and model all aspects related to PV systems [19]. The ModelChain class method of PVLIB was used, that required inputs like system size, inverter data, PV panel data and

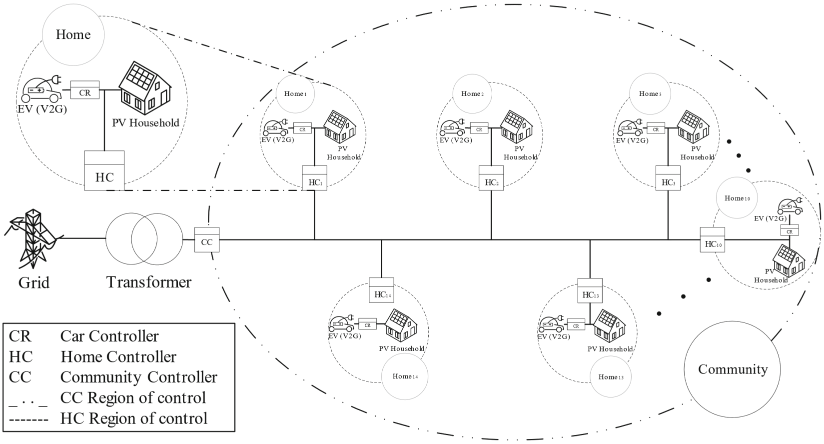

Fig. 1. Grid structure with grid elements and controllers

a time series weather data that gives a time series power data as an output. One minute resolution time series weather data was taken from the HTW Berlin database [16].

2.1.3 Loads

Representative electrical load profiles for residential households taken from the HTW Berlin database are used [17]. It is an open-source data of 74 German single-family households accounting all the electrical loads including cooking stove, washing machine, refrigeration and lighting loads. The average annual consumption of all the 74 profiles is 4.7 MWh which is a good estimate of a household of 4 members in a family [20].

2.1.4 Electric Vehicle

Honda e, an EV manufactured by Honda Motor Company Ltd. Was selected to be modelled as an EV for the study. It has bidirectional charging capabilities with charge/discharge power of 6.6 kW and a battery capacity of 35.5 kWh.

2.2 Indicators

The results of the simulations will be quantified and examined based the following indicators:

2.2.1 Self-consumption

SC is defined as the fraction of self-consumed PV energy to the total PV energy generated [21], it can be represented by Eq. 1.

$$SC = \int_{t=t_1}^{t=t_2} \frac{P_{PVconsumed}}{P_{PVgeneration}} \cdot dt * 100\,[\%] \quad (1)$$

where $P_{PVconsumed}$ is the self-consumed PV power and $P_{PVgeneration}$ is the generated PV power between the times t_1 and t_2.

2.2.2 Self-sufficiency

SS is defined as the fraction of loads supplied by the total consumed generation i.e. the consumed generation ($P_{consumed\ generation}$) to the total loads of the entity (in this case a household or a community) ($P_{total\ consumption}$) [21], it can be represented by Eq. 2.

$$SS = \int_{t=t_1}^{t=t_2} \frac{P_{consumed\ generation}}{P_{total\ consumption}} \cdot dt * 100\,[\%] \tag{2}$$

2.2.3 Dependency on the Grid

Dependency on the grid (DotG) is a self-defined factor that indicates how much energy is being exchanged between an entity and the electricity grid. It is a time invariant function, which is calculated at the end of the simulation period based on the amount of energy consumed form the grid ($E_{grid\ consumed}$) and the amount of energy feed into the grid ($E_{grid\ feed-in}$) as seen in Eq. 3. It is additionally calculated as a percentage by comparing the value with a predefined base case as seen in Eq. 4.

$$DotG = E_{grid\ consumed} + E_{grid\ feed-in}\,[kwh] \tag{3}$$

$$DotG_{Percentage} = \frac{DotG}{DotG_{base\ case}} * 100\,[\%] \tag{4}$$

2.3 Energy Optimisation Model

The model aims to optimise the power flows to increase the SS and SC, and reduce the DotG by using controllers connected to the car, household and the community namely Car Controller (CR), Home Controller (HC) and Community Controller (CC) respectively. Hierarchal architecture was used to design them so they can interconnect with its lower and/or higher-level controller. They were tailored to be scalable so that the model can be implemented on any grid structure. Such controller layout as shown in Fig. 2 is called a multi agent control [22]. The higher priority controller(s) are independent of the lower one, for example, if the CC is not functional, it doesn't affect the functioning of the HC and CR. The region of interest of the controllers defines the working boundaries of their control actions as shown in in Fig. 1.

For a discrete time step (T) of simulation, the controllers in Python set and communicate the values of the model elements to PowerFactory that performs load flow calculation. The results of the load flow calculations are retrieved in Python where the controllers perform their analysis. Based on the results of the analysis, the new control actions for the model elements are set for the next time step. The simulations were of one minute time step ($T = 60$ s) as all the data i.e. load profiles and PV irradiation data were in one minute resolution. The controllers set their target actions based only on the calculations in the current time step. The controllers do not integrate any prognosis algorithms.

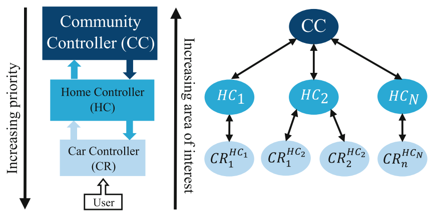

Fig. 2. Controller hierarchal architecture

2.3.1 Car Controller

The CR is like a bi-directional charging station connecting the EV with the household as seen in Fig. 1. It takes input from the user when the EV is connected to it. The inputs include the time when the EV will leave the house ($Time_{leave}$), the desired state of charge (SoC) the vehicle should have when it leaves the house (SoC_{target}) and the charging mode. The user has an option to choose from two charging modes, i) Normal Charging (NC) mode and ii) Optimised Charging (OC) mode. The NC mode resembles a unidirectional, traditional charging mode which charges the EV once it is connected to the CR whereas the OC mode is the bi-directional charging mode which charges or discharges the EV based on the algorithm of the HC. If the HC is not present, the EV falls back to the NC mode.

The main function of the CR is to physically charge or discharge the car based on power setpoints calculated by itself (NC mode) or given by HC (OC mode). Other features include protecting the EV from charging with a power greater than the allowed charging limits, as well as protecting the EV's battery from overcharging or deep discharging.

2.3.2 Home Controller

The HC optimises SS at individual household level by regulating charge/discharge behaviour of EVs in OC mode (OC EVs). The residual power flow regulation at household-grid interface is achieved through monitoring, logging and controlling individual OC EV powers at each time step considering the following aspects:

- Residential loads ($P^{household}$)
- Loads of EVs in NC mode ($P^{NC,EV}$)
- Photovoltaic infeed (P^{PV})
- Departure times of individual OC EVs
- Target SoC limits of individual OC EVs
- Battery capacity (E^{batt}) of individual OC EVs

The residual power ($P^{residual}$) between monitoring intervals is proportionally distributed among OC EVs under the target SoC constraints and their availability. The new power set-point ($P^{OC,EV}$) for an OC EV between the two simulation time steps (t, $t+T$) is governed by the following relationship:

$$P_{k,t+T}^{OC,EV} = -P_t^{residual} \cdot \frac{E_k^{batt}}{\sum_{i=1}^{i=\alpha} E_i^{batt}} \tag{5}$$

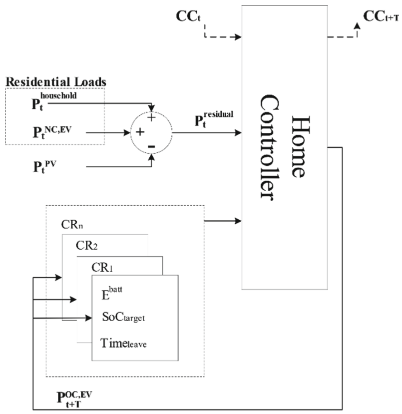

Fig. 3. Overview of the Home Controller

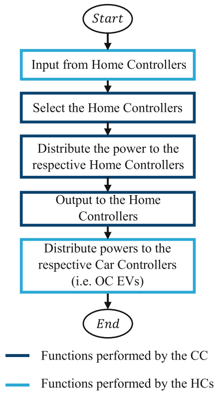

Fig. 4. Flow of events for the Community Controller's functioning

where, α is the number of OC EVs connected to the HC, $k\epsilon\mathbb{N}$; $1 \leq k \leq \alpha$ and $t\epsilon mT$; $m\epsilon\mathbb{N}$

The $P^{residual}$ at household-grid interface is calculated by aggregating all power inflows (+ve) and outflows (-ve) on the interface at monitoring intervals. A generic structure of the HC is depicted in Fig. 3.

2.3.3 Community Controller

The CC optimises power flow based on the community-grid interaction considering the total in/out flow of power. It performs an on-the-top optimisation using the OC EVs to reduce the DotG of the community and making it as self-sufficient as possible. The CC receives information from the HCs and performs its control algorithm. The results from the CC are power values assigned to each HC which they have to consume or generate additionally using their OC EV(s). As the CC has lower priority than the HC and the CR, the commands from the CC can be overwritten by the higher priority controllers if charging power and/or storage conditions are violated. The CC performs its optimisation in the following situations:

- When there is power outflow to the grid, it instructs the HCs to consume the excess generation, which leads to an increase in the SC
- When there is power inflow from the grid, it instructs the HCs to generate power to suffice the loads resulting an increase in the SS

Not all HCs are instructed by the CC to consume or generate excess power. They are selected based on inputs from the HC, which are, the amount of power exchange with the grid and the charging or discharging power of the EV(s) present at that respective HC. If there is no OC EV present at the HC, it is not selected by the CC for its optimisation as it cannot control any aspect of that HC. The selection of HC is done so as to not alter the state of the HCs which are already well-optimised by its OC mode algorithm. The distribution of power to the selected HCs is done using a weighted distributed model. This model distributes a value (M) to Z number of receivers, where each receiver has a weight (x) and based on the weight, the value M is distributed to them. The same model is used by the HCs to distribute the power value received from the CC to its CRs (i.e. the OC EVs). Figure 4 shows the flow of events concerning the CC at each time step of the simulation.

2.4 Simulation Setup

Two scenarios will be simulated A) single household and B) community (group of 14 households). In each of these scenarios, three sub scenarios will be simulated i) with only CR connected i.e. EV will be in NC mode, ii) with CR and HC connected i.e. EV will be in OC mode and iii) with all the controllers (only for scenario B as A is just a single household). Each scenario (A and B) and sub scenarios (i, ii, iii) will be simulated for a duration of one week (Monday - Sunday) once in summer (15^{th} – 21^{st} June 2020) and once in winter (21^{st} – 27^{th} December 2020). The EV parameters ($SoC_{initial}$, SoC_{target}, $SoC_{reduction}$, $Time_{leave}$, $Time_{return}$), load and PV values set for the simulation are given in Table 1 of Appendix A.

3 Results and Discussion

Note: A scenario or system addressed by '*with CR*' implies that the system neither has the HC nor the CC connected and the EV is in NC mode. Similarly, '*with HC*' means that the system has the CR and the HC connected but the CC is not connected and the EV is in OC mode. On the same lines, '*with CC*' has all the three controllers i.e. CR, HC and CC connected in the system and all the EVs are in OC mode.

3.1 Single Household

3.1.1 Functionality of the Home Controller

The functionality of the HC is explained with the help of Fig. 5 which compares the deficit of the household (i.e. the amount of power being consumed or generated from/to

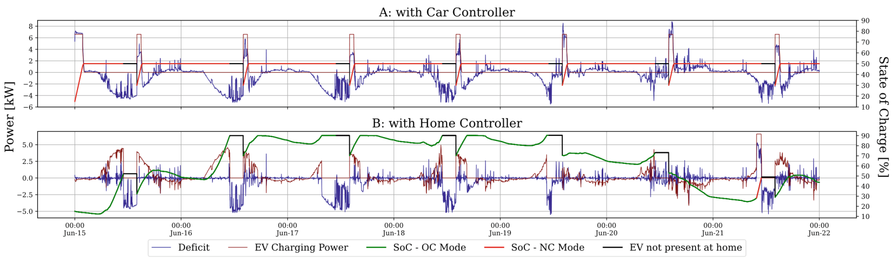

Fig. 5. Deficit, EV charging power and its state of charge in a single household scenario with car controller (A) and with home controller (B)

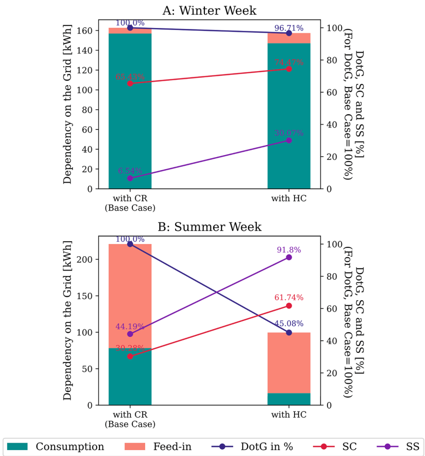

Fig. 6. Dependency on the grid, self-consumption and self-sufficiency of the household in a winter week (A) and in a summer week (B)

the grid), the charging power of the EV and its SoC under the variation *with CR* and *with HC*. Different colours in the SoC line represent the current EV operation mode, red being NC mode and green is the OC mode. The black colour in the SoC line represents unavailability of the EV i.e. not present at home. Once the EV returns back, the drop seen in the black line of the SoC graph is the reduction in its SoC as it has travelled some distance when it was away. For all the simulations, the drop was set to 20% which is equivalent to 50 km of travel.

In Fig. 5 (A), by seeing the deficit, it can be said that the household is always consuming power or feeding in the excess PV power into the grid. On the other hand, in the *with HC* case (graph B), it stays close to zero. Only if the EV is not present at home or the EV has reached its maximum SoC limit (90% in this case) as seen on 16th to the 19th of June it differs significantly from zero. The OC EV plays a major role in balancing the deficit. When there is no PV generation, the SoC of the OC EV reduces as it discharges to the loads and once the PV starts generating power, the OC EV is charged with the excess PV in the household which can be seen with an increase in the SoC value. The instruction of charging and discharging of the OC EVs are given by the

HC. Between times 11:00 to 14:00, the deficit values of (A) and (B) are same as there is no EV present to perform the optimisation. Deviations from zero in the deficit values in (B) appear since control actions are lagging by a single time step.

3.1.2 Performance of the Home Controller

Controllers are benchmarked using three performance indicators (i.e. DotG, SC and SS) described in the methodology. These indicators are shown in Fig. 6, to compare the outcomes of the *with CR* and *with HC* case in a winter week (graph A) and a summer week (graph B). The green bar represents the total amount of energy that has been consumed by the household from the grid and the peach bar is the total feed-in of energy from the household to the grid. The total bar represents the DotG in kWh. On the secondary y-axis, the DotG percentage is shown which is calculated by keeping the *with CR* scenario as a base case (i.e. 100%). It can be read as the DotG of the *with HC* case is 45% of the *with CR* case in (B). The red and purple lines represent the SC and SS respectively.

The DotG in the summer week (Fig. 6 (B)) reduces by 55%. The reduction in feed-in to the grid is because of the increase in the SC. On the other hand, the reduction in consumption from the grid is because of OC EV's bi-directional capability of discharging to the loads in the household. The SS also increases as more loads are being sufficed by the consumed generation (i.e. the generation that has been consumed by the loads or by the EV) in the household. There is still a large amount of feed-in in the summer week which is due to i) the EV reaches its maximum SoC limit so it cannot consume any more PV power, ii) the absent time - when the EV is not available, the excess PV during the absent time is fed into the grid.

In the winter week (Fig. 6 (A)), the total PV generation is only 10% of the total PV generation of the summer week. Hence there is more consumption from the grid as compared to the summer week which results in a lower decrease in the DotG value. In the winter week, a higher feed-in can be noticed in the *with HC* case as compared to the *with CR* case which is due to the design limitation of the controller. The controller makes decisions based on time (t) for the next time step ($t + T$). If there are high loads at time t, then the EV discharges at time $t + T$ to suffice those high loads. At $t + T$, if the loads reduce, the EV still discharges based on the decision made at time t. As the

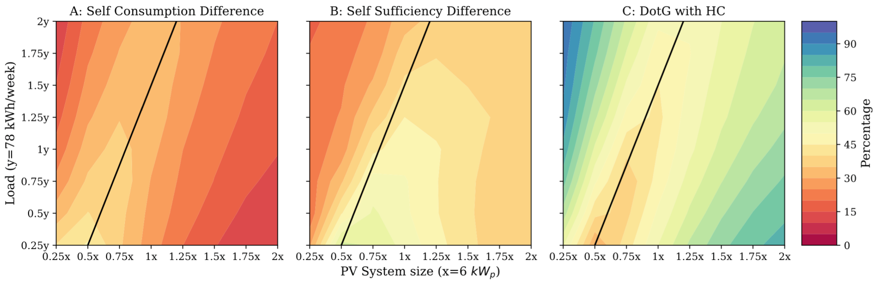

Fig. 7. Sensitivity analysis of loads and PV system size of a household by comparing the *with CR* and *with HC* case using the indicators

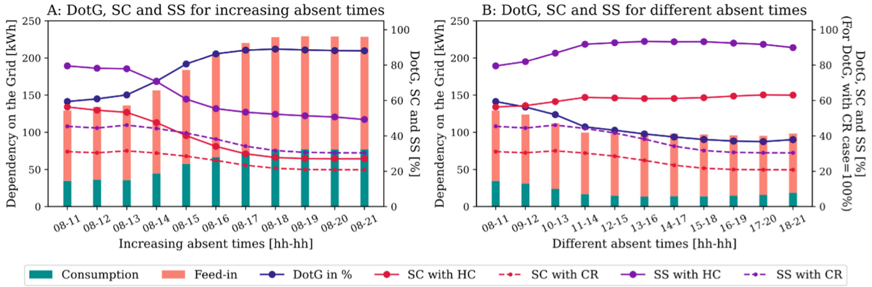

Fig. 8. Sensitivity analysis by varying the absent time of the EV

EV discharges more than the loads in the household, there is feed-in of power by the EV into the grid.

3.1.3 Sensitivity Analysis of the Home Controller

Figure 7 shows a graph of sensitivity analysis by varying the PV system size and the loads in the household. By varying the system size, one can get an idea how the controllers behave throughout the year, as PV and load output do not remain the same. As well as it gives an idea how system design plays a role in reducing the DotG. In Fig. 7, on the x-axis are the different PV system sizes, whereas on the y-axis are the different loads of the household. Graph (A) is the difference of SC values between the *with HC* and *with CR* case ($SC_{withHC} - SC_{withCR}$), same is for graph (B) with the SS values. Graph C is the DotG values of the *with HC* case keeping the *with CR* case as 100%.

The highest SC can be achieved at 0.25x + 2y (1.5 kW_p of PV system (51 kWh/week) and 156 kWh/week of load) of 89% but has the lowest value of SS of 37%. Similarly, at 2x + 0.25y (12 kW_p of PV system (409 kWh/week) and 20 kWh/week of load) the highest SS can be achieved with 97% but has the lowest SC of 22%. Having a larger PV system for fewer loads or having a smaller PV system for larger loads is not practically and economically feasible for a consumer or a grid operator. A perfect match of the system design can be made by seeing DotG value where the black line represents the best fit system design ratio between the loads and the PV system size. This leads to the conclusion that system design plays an important role to get the best outcome of the controllers. With low loads and high PV, one cannot expect to consume all the PV due to the EV's battery storage constraints. Nevertheless, since all the differences are positive and the DotG values are less than 100%, the system with controllers always perform better than the traditional system (*with CR* case).

Not always will an EV be present at home, results of SC, SS and DotG for different absent times can be seen in Fig. 8. The PV irradiation used for this sensitivity analysis is the same which is used in the summer week. DotG bar plots are shown only for the *with HC* case, solid lines are SS and SC values *with HC*, whereas the dashed lines are of the *with CR case*. The DotG percentage is calculated taking *with CR* case as base case (i.e. set to 100%) for each respective sensitivity analysis simulation.

In Fig. 8 (A), with longer absence times of the car the value of DotG is increasing which means it's getting closer to the *with CR* case value (100%). This is because there

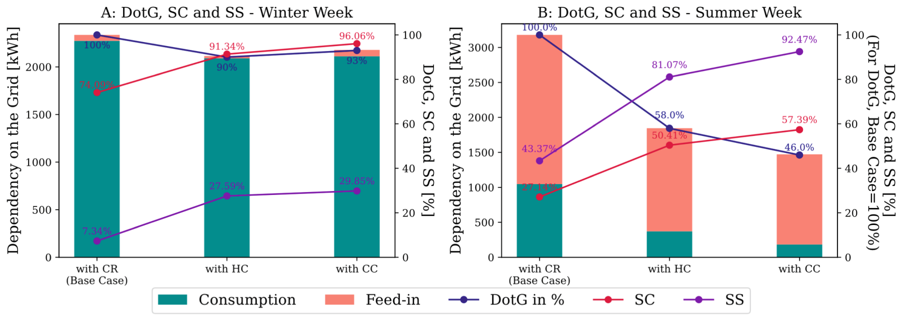

Fig. 9. DotG, SC and SS of a community for a winter week (A) and for a summer week (B)

is no storage available as the EV is not present for a long time, which results in lower consumption of PV and fewer loads being sufficed by the OC EV. The value of SC and SS in the *with HC* case decrease with increasing absent times, but always remain higher than *with CR* case.

In Fig. 8 (B), with later departure times of the car the value of DotG is seen with a decreasing trend as the EV charges with the PV power when it leaves later during the day rather than charging from the grid when it leaves before the PV starts generating. The high feed-in in all the cases is due to i) EV reaching its SoC maximum limit and ii) the EV's absent times. The difference of the SC and SS values between the *with HC* and *with CR* case keep on increasing when moving from left to right. The *with CR* case only performs better if the EV arrives home when the PV system is generating power as it can consume the excess power during its charging. On the other hand, in the *with HC* case, the EV's charging power is always optimised based on the PV generation in the household.

3.2 Community

Simulation results for the community based on the system setup and scenarios described in Sect. 2.4 are shown in this section. Figure 9 shows a graph of DotG, SC and SS for a community in a winter week (A) and a summer week (B). The simulations were performed comparing three scenarios *with CR*, *with HC* and *with CC*.

The DotG reduces in both the graphs when a HC is introduced to the system. A larger decrease can be observed in the summer week than in the winter week. This is due to the higher PV generation in summer which is consumed by the EV because of its OC mode and thereby reducing the feed-in. When a CC is added to the community, the DotG further reduces in the summer week as the excess PV in one household can be consumed by EV(s) in other households in the community. Similarly, the excess loads in one household can be sufficed by the EV(s) in another household. In the winter week, the DotG increases a little in the *with CC* case due to the design limitation of the controller as explained in the previous section. SS and SC increase with the integration of each level of controller. High values of SC can be achieved in a winter week in all the cases as compared to a summer week due to high loads and low amount of PV generation. More loads are being sufficed by the consumed PV in the summer week than the winter week so the SS values are higher in the summer.

3.2.1 Sensitivity Analysis of the Community Controller

Sensitivity analysis of different PV sizes is performed on the community as seen in Fig. 10. The irradiation values used are the same which are used in the summer week simulation. The DotG magnitude (in kWh) is plotted against DotG percentage where the *with CR* case is used as a base case i.e. 100%. The markers on the graph represent the configuration of the system with respect to the controllers. PV 100% is the PV system size used in Fig. 9. PV75%, PV50% and PV25% represents 75%, 50% and 25% of the PV system size used in PV100% respectively.

With reduction in the PV system size, the magnitude of DotG (kWh) in the *with CR* case reduces, but it's not the same in the *with HC* and *with CC* case. If the PV size reduces considerably (from PV50% to PV25%), the system cannot suffice itself with the amount of self-consumed PV, so the energy has to be consumed from the grid, which results in a high DotG value. Similar effect can be seen in Fig. 9 (A), where a winter week is simulated.

In Fig. 10, the difference between the DotG percentage in the *with HC* and *with CC* case are 12%, 15%, 17% and 1% in the PV100%, PV75%, PV50% and PV25% respectively. The difference reduces drastically after a certain point which can be seen in the PV25% case. Hardly any change can be seen between the *with HC* and *with CC* case in PV25% because of the low PV generation. The amount of PV which is generated is self-consumed by the loads in the house so the EV has to charge from the grid where as in the other cases (PV 100%, 75% & 50%) the EV is charged by the excess PV in the household, or by the excess PV which is available in the community. In conclusion, in the PV25% case, the HC optimises the households by consuming all the PV, which leads to a small margin left for the CC to optimise the community.

Figure 11 shows the probability distribution of the deficit in the community (i.e. the amount of power being exchanged between the community and the grid) when the summer week is simulated. X-axis shows the absolute deficit in bins of 2 kW and y-axis indicates the relative frequency which states how often the deficit in a particular bin occurs. 100% on the y-axis equals to total number of time steps of the simulation (10,080 time steps). Figure A, B and C show simulations of the community *with CR*, *with HC* and *with CC* respectively.

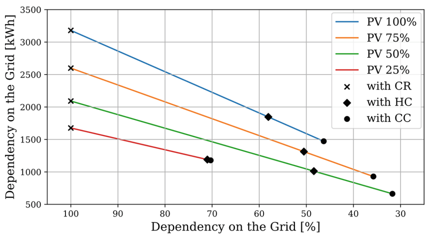

Fig. 10. Sensitivity analysis of the community controller with different PV system sizes

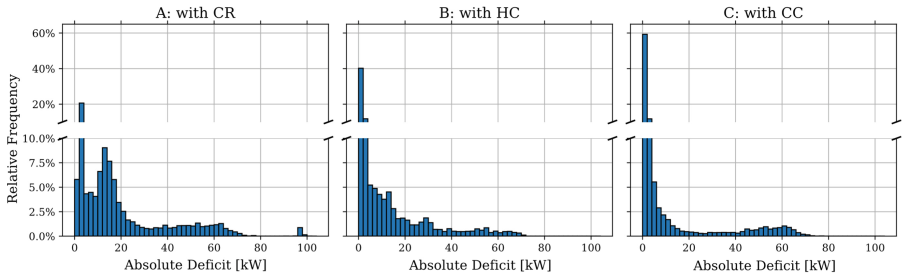

Fig. 11. Probability distribution curve of the deficit value of the community

The highest relative frequency in Fig. 11 (A) is of the bin 2–4 kW. It shifts to the first bin 0–2 kW in the *with HC* and *with CC* case. By comparing the relative frequency of the 0–2 kW bin in the three plots, the relative frequency increased by 24% in *with CR* to *with HC* plot and by 20% when moving from *with HC* to *with CC* plot. The largest bin observed in graph (A) is 98–100 kW. This reduces in the *with HC* (graph B) and *with CC* (graph C) case to a value between 70–76 kW. The reason for a high deficit in graph (A) is because of the EVs (which are all in NC mode) charging once they are connected to the CR. At the start of the simulation all EVs have an $SoC_{initial}$ of 15% and they charge themselves till they reach SoC_{target} which is 50%. 14 EVs charging themselves together with a power of 6.6 kW each results in a total of 92 kW plus the loads of the 14 houses which makes it such a high value of deficit. This situation is not very realistic as same arrival times of all EVs in the community is not very likely. Similar situation can be seen at the start of the simulation in Fig. 5 (A) where the EV charges at 00:00 on the 16^{th} of July with a power of 6.6 kW until it reaches its SoC_{target}. Between 40–80 kW, the graph shows high power exchange from the grid. This is due to the charging of those EVs from the grid which leave early in the morning and arrive late in the evening (EVs of house 2, 3, 4, 5, 6 and 7 in Table 1 found in the appendix).

Reduction in the magnitude of deficit and increase in the frequency of the lower deficit values indicate that there is more power transfer within the community than between the community and the grid which results in a lower DotG.

4 Conclusion

In this study, a hierarchical power (energy) optimisation model was built. The first level optimises the household and the second level optimises the community by using bidirectional EVs as controllable elements to increase the consumption of solar PV and reduce the dependency on the electricity grid. The results show that a bidirectional EV with controlled charging strategies improves the SC and SS of a household by 31% and 48% whereas of the community by 30% and 50% respectively in comparison to an uncontrolled unidirectional charging strategy.

System design, i.e. combination of loads and PV system size, plays a major role in obtaining the best performance of the controller. With optimum sizing of the system, the reduction in DotG can range from 50% to 30%. In addition, higher values of SC (63%) and SS (93%) can be achieved if the EV stays home for a long period of time and leaves the home late in the evening. The combination of CR, HC and CC benefits not only the consumer but also the grid operator. For consumers, there is less energy consumption which results in financial savings. The grid operators can benefit from reduced grid stresses since balancing generation with consumption locally reduces power import/export requirements from/to the grid.

Real loads and PV irradiation profiles were used in the simulations for realistic analysis. Future work could include using real mobility profiles to perform the simulations and compare the results. Economic analysis, to find out how much a consumer can save when she/he adopts a HC in her/his household, can be done to quantify the profitability of the system. The effect of this control strategy on the grid stability and ancillary grid support needs further investigations.

All the results obtained by the simulations are system design specific. Any change in the system size (loads or PV) and EV parameters ($SoC_{initial}$, SoC_{target}, battery capacity, maximum charging/discharging power) and availability will change the outcome of the simulation results but the trends of decrease in the DotG and increase in the SC and SS are still correlated. It is concluded that the improvements in performance indicators of the proposed controller strategy are significant with high PV penetration during summers over uncontrolled charging strategy. The benefits are limited during winter weeks or with low PV penetration.

Acknowledgments. All the authors would like to thank the Federal Ministry for Economic Affairs and Energy (BMWi) for the funding of the research project ROLLEN.

Authors' Contributions. **Aliqyaan Sakarwala–** Conceptualization, Methodology, Software, Validation, Investigation, Data Curation, Visualization, Writing - original draft; **Nauman Beg –** Conceptualization, Methodology, Software, Writing - reviewing & editing; **Karen Derendorf –** Project administration, Funding acquisition, Supervision, Conceptualization, Writing - reviewing & editing; **Frank Schuldt –** Funding acquisition, Writing - reviewing & editing.

Appendix A

In Table 1, $Time_{return}$ - Time when the EV returns after it leaves the house; $SoC_{reduction}$ - The amount of SoC that reduces when an EV returns back home, it is equivalent to 50 km of driving distance. For scenario A, the parameters of column $Home_{\text{Single Household}}$ are used and for scenario B (community), the parameters of column Home1 to Home14 are used.

Table 1. PV, load and EV parameters for simulation

Household	Solar PV		Household Loads		Electric Vehicle				
	Winter Week Generation [kWh/week]	Summer Week Generation [kWh/week]	Winter Week Consumption [kWh/week]	Summer Week Consumption [kWh/week]	$SoC_{initial}$ [in %]	SoC_{target} [in %]	$Time_{leave}$ [hh:mm]	$Time_{return}$ [hh:mm]	$SoC_{reduction}$ [in %]
$Home_{Single\ Household}$	16.79	204.65	105.73	78.02	15	50	11:00	14:00	20
Home1	14.35	178.38	100.37	81.08	15	50	19:00	22:00	20
Home2	16.79	204.65	137.18	55.24	15	50	18:00	20:00	20
Home3	16.79	204.65	84.92	73.90	15	50	07:00	16:00	20
Home4	26.57	309.40	189.15	125.54	15	50	08:00	17:00	20
Home5	19.23	230.89	126.08	80.18	15	50	09:00	18:00	20
Home6	21.68	257.09	139.50	90.42	15	50	09:00	18:00	20
Home7	16.79	204.65	105.73	78.02	15	50	08:00	17:00	20
Home8	19.23	230.89	126.99	60.98	15	50	07:00	16:00	20
Home9	14.35	178.38	94.87	46.48	15	50	13:00	16:00	20
Home10	14.35	178.38	91.05	51.53	15	50	19:00	00:00	20
Home11	16.79	204.65	102.85	68.91	15	50	17:00	19:00	20
Home12	9.50	125.76	25.44	40.25	15	50	20:00	23:00	20
Home13	19.23	230.89	156.59	56.48	15	50	19:00	21:00	20
Home14	16.79	204.65	108.59	75.85	15	50	21:00	00:00	20

References

1. United Nations, *What do we need to achieve at cop26?: Secure global net zero and keep 1.5 degrees within reach* (accessed: Oct. 1 2021).
2. J. Hoppmann, J. Huenteler, and B. Girod, "Compulsive policy-making—The evolution of the German feed-in tariff system for solar photovoltaic power," *Research Policy*, vol. 43, no. 8, pp. 1422–1441, 2014, doi: https://doi.org/10.1016/j.respol.2014.01.014.
3. Bundesministerium für Wirtschaft und Klimaschutz (BMWK), "Renewable Energy Sources Act (EEG 2021)," § 48 (2). [Online]. Available: https://climate-laws.org/geographies/germany/laws/renewable-energy-sources-act-eeg-latest-version-eeg-2021
4. E. Thalman and B. Wehrmann, *What German households pay for power.* [Online]. Available: https://www.cleanenergywire.org/factsheets/what-german-households-pay-power (accessed: Jun. 9 2022).
5. M. Braun, K. Büdenbender, D. Magnor, and A. Jossen, "Photovoltaic self-consumption in Germany: using lithium-ion storage to increase self-consumed photovoltaic energy," in *24th European photovoltaic solar energy conference (PVSEC), Hamburg, Germany*, 2009.
6. G. Pasaoglu, D. Fiorello, A. Martino, L. Zani, A. Zubaryeva, and C. Thiel, "Travel patterns and the potential use of electric cars – Results from a direct survey in six European countries," *Technological Forecasting and Social Change*, vol. 87, 2013, doi: https://doi.org/10.1016/j.techfore.2013.10.018.
7. S. Immen and D.-C. Thomsen, *Fahrzeugzulassungen im Dezember 2021 - Jahresbilanz.* [Online]. Available: https://www.kba.de/DE/Presse/Pressemitteilungen/Fahrzeugzulassungen/2022/pm01_2022_n_12_21_pm_komplett.html (accessed: Jun. 9 2022).
8. Die Bundesregierung, *Klimaschutz - Verkehr: uUstieg auf Elektromobilität Fördern.* [Online]. Available: https://www.bundesregierung.de/breg-de/themen/klimaschutz/verkehr-1672896 (accessed: Jun. 10 2022).
9. R. Luthander, D. Lingfors, J. Munkhammar, and J. Widén, "Self-consumption enhancement of residential photovoltaics with battery storage and electric vehicles in communities," *Proceedings of the ECEEE Summer Study on Energy Efficiency, Hyères, France*, pp. 991–1002, 2015.
10. J. Munkhammar, P. Grahn, and J. Widén, "Quantifying self-consumption of on-site photovoltaic power generation in households with electric vehicle home charging," *Solar energy*, vol. 97, pp. 208–216, 2013.

11. P. Nunes, T. Farias, and M. C. Brito, “Day charging electric vehicles with excess solar electricity for a sustainable energy system,” *Energy*, vol. 80, pp. 263–274, 2015.
12. R. Fachrizal and J. Munkhammar, “Improved photovoltaic self-consumption in residential buildings with distributed and centralized smart charging of electric vehicles,” *Energies*, vol. 13, no. 5, p. 1153, 2020.
13. M. Mueller and Y. Schulze, “Future grid load with bidirectional electric vehicles at home,” in *ETG Congress 2021*, 2021, pp. 1–6.
14. S. Englberger, H. Hesse, D. Kucevic, and A. Jossen, “A techno-economic analysis of vehicle-to-building: Battery degradation and efficiency analysis in the context of coordinated electric vehicle charging,” *Energies*, vol. 12, no. 5, p. 955, 2019.
15. D. Gudmunds, E. Nyholm, M. Taljegard, and M. Odenberger, “Self-consumption and self-sufficiency for household solar producers when introducing an electric vehicle,” *Renewable Energy*, vol. 148, pp. 1200–1215, 2020.
16. Hochschule für Technik und Wirtschaft, *Weather data.* [Online]. Available: https://wetter.htw-berlin.de/home/info (accessed: Sep. 1 2021).
17. T. Tjaden, J. Bergner, J. Weniger, and V. Quaschning, “Repräsentative elektrische Lastprofile für Wohngebäude in Deutschland auf 1-sekündiger Datenbasis,” *Hochschule für Technik und Wirtschaft HTW Berlin*, 2015.
18. F. Samweber, S. Koeppl, A. Bogensperger, M. Müller, and T. Estermann, *Projekt MONA 2030: Ganzheitliche Bewertung Netzoptimierender Maßnahmen gemäß technischer, ökonomischer, ökologischer, gesellschaftlicher und rechtlicher Kriterien-MONA 2030 Abschlussbericht*: München.
19. W. F. Holmgren, C. W. Hansen, and M. A. Mikofski, “pvlib python: A python package for modeling solar energy systems,” *Journal of Open Source Software*, vol. 3, no. 29, p. 884, 2018.
20. M. Bost, B. Hirschl, and A. Aretz, “Effekte von Eigenverbrauch und Netzparität bei der Photovoltaik: Beginn der dezentralen Energierevolution oder Nischeneffekt?,” p. 26, 2011.
21. R. Luthander, J. Widén, D. Nilsson, and J. Palm, “Photovoltaic self-consumption in buildings: A review,” *Applied energy*, vol. 142, pp. 80–94, 2015.
22. Z. Wang, R. Yang, and L. Wang, “Multi-agent control system with intelligent optimization for smart and energy-efficient buildings,” in *IECON 2010–36th annual conference on IEEE industrial electronics society*, 2010, pp. 1144–1149.