Increasing Photovoltaic Self-consumption: An Approach with Game Theory and Blockchain

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Abstract. In this paper, we present a distributed approach to optimise self-consumption on a university campus grid. The grid contains photovoltaic generators, electric vehicles, loads and a battery. We propose to solve the optimisation problem with a distributed method using game theory, where each element of the grid tries to reach its own objectives. In addition to this optimisation framework, we develop a physical model of the grid. This model uses real consumption and production data. We use it to simulate the production and consumption profiles obtained from the optimisation problem in order to check if these solutions respect the grid constraints. Finally, we propose to implement concretely this distributed approach using a private blockchain, which stores production and consumption data. In addition, a smart contract is deployed on the blockchain to transcribe the game theory framework. The smart contract collects the preferences of each element of the grid and launches the optimisation process. Then the blockchain gathers the results and replaces the role of a central optimisation supervisor. We present some preliminary results to illustrate our method.

Keywords: Photovoltaic self-consumption · Game theory · Blockchain

1 Introduction

Due to environmental concerns, many countries have promoted the development of photovoltaic (PV) generators through diverse financial incentives, leading to an increase of the worldwide PV capacity from about more than 10 GWp in 2008 to more than 500 GWp at the end of 2018 [1]. PV generators differ from

Supported by the European city of Lille (MEL) and Greenbirdie under the Smart Buildings as nodes of Smart Grid (SBnodesSG) Chair.

J. L. Afonso et al. (Eds.): SESC 2019, LNICST 315, pp. 180–194, 2020.
https://doi.org/10.1007/978-3-030-45694-8_14

traditional power plants like nuclear or coal power plants: their capacity is much lower so they are spread on large geographical areas and often connected to low or medium voltage grid. For example, small PV generators of less than 4 kWp counted for 21% of the total PV capacity installed in the UK in 2016 [2]. As a result, new uses of electricity networks appear with the development of PV generators. The continuous decrease of PV installation costs encourages consumers to produce their own electricity from rooftop solar panels. This situation corresponds to self-consumption. The overall electrical grid can benefit from self-consumption behaviour with a decrease of energy flows on the lines, leading to a decrease of investments costs [3].

We define the self-consumption rate as the part of the electricity produced by the PV generators that is locally consumed over the total local consumption [4]. Increasing this self-consumption rate requires adapting the consumption to the PV production, which is highly intermittent. Generally, we consider two main options to reach this aim. First, the use of a storage system, such as electrochemical batteries, can store the PV generation during the day and deliver power to the consumer at night. Second, demand-side management (DSM) system adapts the consumption so that it fits the period of high PV production [4].

France, Sweden and the Netherlands now also allow collective self-consumption, in which a group of consumers shares the local PV production on the low voltage grid over a small area, creating a local energy community [5]. The idea is to benefit from the differences between the consumption profiles of all the consumers in order to maximise the self-consumption rate. Consumers and producers exchange the local energy production. However, collective self-consumption projects are still at an early stage and we believe that a large-scale development requires a new framework to optimise the self-consumption rate and thus to make collective self-consumption attractive for all participants.

The question this article deals with is: how to optimise energy exchanges on a local energy community in a distributed way? Indeed, to support decentralisation of the grid, we believe that a distributed method is more relevant and enables to get rid of a central agent.

In this perspective, we propose a new approach to improve the self-consumption rate between several tertiary buildings. We base our study on the grid of Lille Catholic University, France, which combines PV generators, a battery, charging stations for electric vehicles and tertiary buildings. We define a global optimisation problem to increase the self-consumption rate. In order to take into account the preferences of each participant, we decompose this global problem in several smaller local problems. Thus, we build a decentralised framework using game theory, in which each participant acts freely in order to reach its individual objectives. Game theory is gaining popularity in the literature as a distributed optimisation method for smart grid, as it reflects its distributed and heterogeneous nature [6]. In [7], the authors introduce a bargaining game to manage a micro-grid both in connected or islanded mode. Nguyen *et al.* use game theory for demand side management in a system containing storage devices [8].

The results show a decrease of energy costs for energy consumers and a peak power reduction of the overall system.

In our case, we define a specific non-cooperative game so that the self-consumption rate increases when each player tends to meet its own objectives by adjusting its consumption or production profile. We introduce parameters so that each element is able to adjust its objective function (called utility function) according to its own preferences. These preferences can represent the cost paid (or earned) for electricity consumption (or production), the users' comfort, or the will to consume the local PV production. The benefit of such an approach is that it only requires that the participants optimise locally their behaviour, without any cooperation. Thus, it does not require a central agent to coordinate all the participants.

To verify the relevance of our work, we aim to test the results of the proposed optimisation framework on a physical model of the grid, including real production and consumption data. We test the results with the model in order to guarantee that the real grid can support the energy flows between the different elements.

In addition, in order to implement concretely this framework, we propose to use blockchain technology. Blockchain consists in a distributed and secured database, supporting the execution of algorithms called smart contracts [9]. It shows promising features for collective self-consumption and energy sharing and interest for this topic is growing. One of the main applications observed in the literature is the implementation of energy markets between consumers and producers. Mengelkamp *et al.* propose to improve energy sharing by creating local markets supported by blockchain [10]. In [11] and [12] authors use blockchain to implement local markets with an auction scheme, where producers and consumers publish demand offers and sell offers with smart contracts, and blockchain automatically matches the offers. In [13], the authors present a method to solve an optimal power flow in micro-grid networks. The global problem is first divided in local problems and then blockchain aggregates all the local solutions to provide the overall optimum.

In our vision, we suggest using this technology to store in a secure way the production and consumption data. Moreover, a specific smart contract will collect each user's preferences and launches the optimisation process. Thus, blockchain is a promising tool to implement concretely the distributed optimisation framework that we introduced.

The novelty of our work consists in proposing a concrete and fully distributed method to increase self-consumption rate in a local energy community by the combination of different tools (game theory and blockchain). We exploit the distributed nature of the grid and of the blockchain to get rid of a central optimisation agent. Moreover, the test of our approach on a physical model of a real grid, provided with real production and consumption data, shows the feasibility of such an approach.

This paper is divided as follows. In the second part, we introduce the optimisation problem and the game theory framework used to solve it. In the third part, we detail how we combine the three tools (optimisation algorithm, physical model of the grid, blockchain) to implement this framework. Then, we show and analyse some preliminary results on simple scenarios.

2 Optimisation Framework Using Game Theory

In our problem, we consider a local university grid that contains loads (buildings), a storage system (an electrochemical battery), rooftop PV generators and several charging station for electric vehicles. There is a connection point to the distribution grid. We aim to increase the self-consumption rate of the local grid, by adjusting the charge and discharge schedule of the battery and the electric vehicles, and eventually by delaying the consumption of the buildings. Thus we define an optimisation problem.

Two main approaches exist for solving optimisation problems: centralised or distributed methods. In centralised methods, a supervisor agent knows the entire characteristics of the system, computes the solution of the optimisation problem with a specific algorithm and then sends the results to each element of the grid. Thus, the central agent imposes the actions to take to the entire system. However, in distributed methods, the global optimisation problem is divided in local sub-problems so that finding the local solutions for all sub-problems provides the overall solution. Distributed methods benefit from several advantages. First, the local sub-problems are simpler and therefore easier to solve than the global problem. Second, to solve a local problem, we do not need to know the situation of the entire system. Thus, they are often more robust because they are not impacted by the failure of one element [14].

Regarding electrical networks, a distributed approach is interesting because it reflects the real structure of the grid. Indeed, a grid contains many different elements (loads, generators...) connected between them, but each one has very limited information about its neighbouring environment. Moreover, each element tries to optimise individually its situation, for example the payoffs or the comfort, without considering the global situation of the grid. To reflect this reality, we choose to apply a distributed method to our optimisation problem. More specifically, we choose to use game theory, that defines a mathematical framework for distributed optimisation in which each element of the system aims to optimise its own individual situation.

Game theory is a relevant method in our case for several reasons. First, it models a situation where players are in competition. This reflect the case of a local energy community where players are in competition to reach their consumption/production objectives. Second, game theory enables to take into account not only cost objectives, but also other considerations like comfort [15]. Finally, game theory is interesting because each agent has to solve a simpler problem, in comparison to the global optimisation problem.

2.1 Problem Formulation

We define a non-cooperative game in which each element tries to reach its personal objectives, without any coordination with the other elements. As we mentioned previously, this situation reflects the reality of a local grid where participants have limited knowledge about the structure of the grid and do not necessary communicate between them to meet their goals. Thus, we consider a game with N players, which are the N elements of the grid (loads, PV generators, battery, electric vehicles charging stations). The game is defined by the set $G = \{N, (S_i)_{i \in N}, (U_i)_{i \in N}\}$, where S_i is the strategy set of the player i and U_i its utility function. Here, the strategy set is defined as $S_i = \{x_i\}$, where x_i is the energy consumption or production profile of the player.

The utility function, or objective function, mathematically translates the goals of the player and measures user's satisfaction. The players tend to maximise their utility function by adjusting their strategy, here their energy consumption or production profile. The next paragraph details the objectives and the utility function of each player. In the following, we note $c(t)$ the price function of the electrical energy in the local grid over time.

Utility Functions

EV User. For an EV user connected to the charging station, we propose the following function (we write $x_{PV}^{forecast}$ for the forecast local PV production):

$$U_{EV}(x_{EV}(t)) = \alpha_1 \ln(1 + x_{EV}(t)) - \alpha_2\, c(t)\, x_{EV}(t) - \alpha_3 \ln\left(1 + \frac{x_{PV}^{forecast}(t)}{x_{EV}(t)}\right) \quad (1)$$

The term $\alpha_1 \ln(1 + x_{EV}(t))$ represents the objective to charge the vehicle. With the term $\alpha_2 c(t) x_{EV}(t)$, the user aims to minimise the cost to pay. Then we introduce the term $\alpha_3 \ln(1 + \frac{x_{PV}^{forecast}(t)}{x_{EV}(t)})$ to represent the objective to use preferentially the local PV production. The natural logarithm function is classically used for energy buyers as it models the satiety of the users [11]. We introduce the weight coefficients α_1, α_2 and α_3 so that each user can adjust its preferences. These coefficients are commonly used in the literature for multi-objective optimisation to combine different objectives into a unique objective function. We impose $\alpha_1 + \alpha_2 + \alpha_3 = 1$ [16].

For each EV, we have to consider some constraints. We authorize only charge and the charging power is limited by the maximum power of the charging station:

$$0 \leq P_{EV}(t) \leq P_{max}^{EV} \quad (2)$$

Moreover, the state of charge (SOC) has upper and lower bounds, which are characteristics of the vehicle battery:

$$SOC_{EV}^{min} \leq SOC_{EV}(t) \leq SOC_{EV}^{max} \quad (3)$$

Battery. We consider that the battery has three objectives: first to maximise its availability, which means to keep a median SOC in order to be able to charge or discharge at any time, second to optimise its payoffs, and third to charge using local PV production. Thus, we propose the following utility function:

$$U_b(x_b(t)) = \beta_1 D(t) - \beta_2\, c(t)\, x_b(t) - \beta_3 (x_{PV}^{forecast}(t) - x_b(t))^2 \tag{4}$$

Here also we use the coefficients β_1, β_2 and β_3 to detail the player's preferences, and we impose the sum to be equal to one. The term $D(t)$ represents the availability of the battery, and models the fact that the battery aims to keep a median SOC, written SOC_{median}. This function is equal to 0 when the SOC is equal to SOC_b^{min} and SOC_b^{max}, and 1 for SOC_b^{median}.

The charging power and discharging power of the battery are limited:

$$0 \leq P_b(t) \leq P_b^{charge,max} \tag{5}$$

$$0 \geq P_b(t) \geq P_b^{discharge,max} \tag{6}$$

Moreover, similarly to the EV, the SOC has boundaries:

$$SOC_b^{min} \leq SOC_b(t) \leq SOC_b^{max} \tag{7}$$

PV Generators. PV generators simply tend to maximise their production, because their marginal production cost is equal to zero [13]. So their goals are to optimise their payoff, and to limit the production curtailment. Therefore, we write the following utility function with the two respective terms:

$$U_{PV}(x_{PV}(t)) = \gamma_1\, c(t)\, x_{PV}(t) - \gamma_2 (x_{PV}^{forecast}(t) - x_{PV}(t))^2 \tag{8}$$

The coefficients γ_1 and γ_2 model the user's choice, and we impose $\gamma_1 + \gamma_2 = 1$.

Loads. We consider that the loads have some flexibility, which means that they can decrease their consumption compared to their expected consumption $x_{load}^{expected}$. However, we impose that the total energy consumed at the end of the day is equal to the expected consumption for the entire day. In other words, loads can delay their consumption but do not globally decrease it. Then the objectives are to minimise the cost paid for electricity, to minimise the decrease of consumption, that represents a loss of comfort for the user, and to consume the local PV production. Therefore, following [7], we write the following utility equation:

$$U_l(x_l(t)) = -\delta_1\, c(t)\, x_l(t) - \delta_2 (x_l^{expected}(t) - x_l(t))^2 - \delta_3 \ln(1 + \frac{x_{PV}^{forecast}(t)}{x_l(t)}) \tag{9}$$

Each user can specify its preferences by adjusting δ_1, δ_2 and δ_3 (with $\delta_1 + \delta_2 + \delta_3 = 1$). The constraint on the flexibility f imposes:

$$x_l^{expected}(t)(1 - f) \leq x_l(t) \leq x_l^{expected}(t)(1 + f) \tag{10}$$

Nash Equilibrium. One important concept in game theory is the Nash equilibrium, a situation in which no player can increase its utility by being the only to change its strategy [6]. Mathematically, if we write $X^* = \{x_1^*, ..., x_N^*\}$ the strategy of the players at the Nash equilibrium and x_{-i} the strategy of all players except player i, the Nash equilibrium corresponds to:

$$U_i(x_i^*, x_{-i}^*) \geq U_i(x_i, x_{-i}^*), \forall x_i \in S_i \tag{11}$$

This Nash equilibrium is important as it guarantees that when all players maximise individually their utility function, the global system reaches an equilibrium point.

All the utility functions U_i specified in this article are concave and continuous in x_i. Moreover, all the constraints (on the power limits and the SOC) impose that for each player, the strategy set is a segment: $\forall i \in N, S_i = \{x_i | x_i \in [x_i^{min}, x_i^{max}]\}$, so it is a convex set. This guarantees the existence of at least one Nash equilibrium for our problem [17].

If we consider in a first approach a cost function that does not depend on the consumption and production profiles of the players but that it imposed by the distribution grid, for example a peak and off-peak hours price function, then [18] ensures the unicity of the Nash equilibrium.

3 Optimisation Implementation

In this section we present how we concretely tend to deploy the proposed optimisation process, and more specifically how we connect the physical model of the grid and the blockchain to the theoretical game theory framework. The combination of these three parts form a new tool which gives a concrete distributed framework for optimising self-consumption on real local grids, as illustrated on Fig. 1.

3.1 Role of Blockchain

Blockchain is a distributed and secured database divided in blocks. A block contains data and some additional information related to the previous block. Thus, all blocks form a chain [9]. Each user holds a copy of the database. Adding a new block to the existing chain requires a consensus between all users, so the blockchain works without any central supervisor nor trusted third-party.

In addition, blockchain supports the execution of specific algorithms, called smart contracts, that enable to automatically proceed to previously defined tasks, such as triggering a transaction between two users [19]. Practically, a smart contract is a piece of code defining some functions that is deployed over the blockchain and interacts with every node of the network. Thanks to its distributed architecture, blockchain and smart contracts are interesting tools to support smart grids decentralisation and we intend to use them in order to deploy the distributed optimisation process.

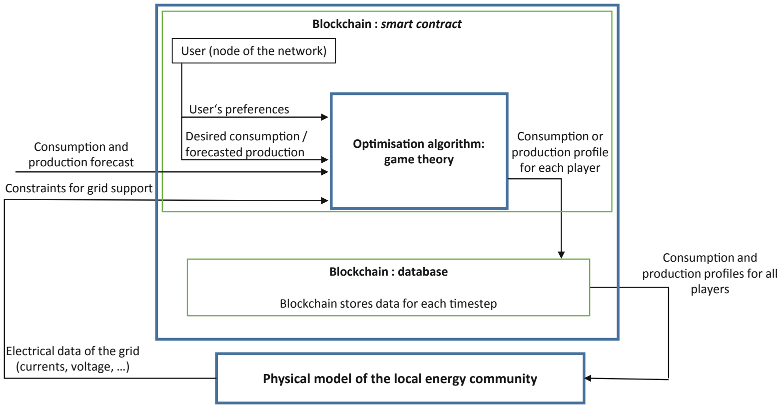

Fig. 1. Overview of the overall optimisation process

In our system, blockchain serves as the communication layer between the players and aggregates the results. It replaces the role of a central optimisation agent. More precisely, we deploy a private blockchain between all the elements of the grid. Thus, each player of the game represents one node of a peer-to-peer communication network. A smart contract deployed on the blockchain implements the game theory framework presented in the previous section. More precisely, the smart contract contains different functions to perform the following tasks: (1) collect the preferences coefficients of all users (coefficients α_i for EV, β_i for the battery, γ_i for the PV generators and δ_i for the loads); (2) trigger the optimisation process (optimising locally each user's utility); (3) gather the results; (4) send the results to the physical modal of the grid. Thus, we see blockchain as a tool to concretely implement our game theory framework in a real grid.

The main interest of this implementation is that, through the smart contract, blockchain gets rid of the need for a central optimisation supervisor that would know the production and consumption details and the preferences of all the grid elements. Moreover, blockchain has the benefit to have a distributed structure, so it guarantees security and trust between the elements of the grid. Blockchain is also more resilient to changes than a unique central agent: new element can simply be added to or deleted from the blockchain without any consequence on the overall framework.

3.2 Game Theory Algorithm

As we mentioned in the previous paragraph, each player of the game constitutes one node of the blockchain. This node locally optimises the user's utility for a defined time period. We make the assumption that the local PV forecast is available through the smart contract for all elements and that each load knows its desired consumption. Moreover, the smart contract provides the preferences coefficients in input for each player. The algorithm returns the consumption or production profile of each player that maximises its utility function.

3.3 Physical Model of the Real Grid

In the theoretical framework defined in Sect. 2, we have not taken into account the constraints related to the grid. More precisely, the proposed game theory framework implicitly assumes that the grid is able to transfer all the power flows according to the optimisation results. However, the grid elements are connected through lines that have a limited capacity. Therefore, it may be possible that the consumption and production profiles processed by the optimisation algorithms lead to some over-currents or over-voltages on the lines.

For this reason, we build a physical model of the grid at stake in which we model the physical properties of the lines (see Fig. 2). We use PowerFactory, a software used by grid operators for grid modelling and analysis [20]. The local network contains 4 buildings considered to be loads, 2 PV generators, one battery and 6 EV charging stations (Fig. 2).

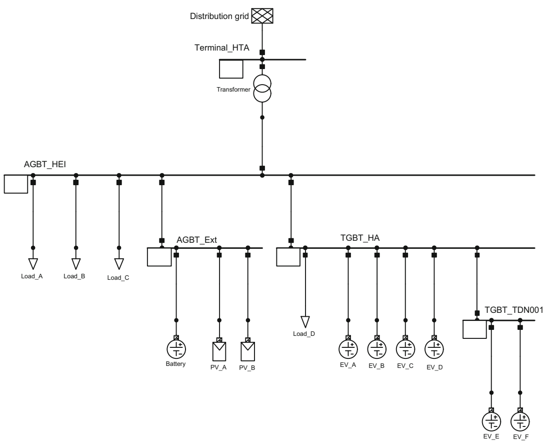

Fig. 2. Physical model of the grid

We aim to test the consumption and production profiles of all the players provided by the optimisation process on the grid model in order to check if they create line congestion or over-voltages. In this case, we can identify precisely the problems that occur on the physical model. Then we can impose additional constraints to the optimisation process (for example curtail the PV production) in order to obtain profiles that will respect the grid constraints.

The combination of the theoretical optimisation framework with the simulations on the physical model ensures that our solutions are realistic and will not damage the grid.

4 Results

To illustrate our approach, we present in this section some preliminary results. We consider the grid of Lille Catholic University (represented on Fig. 2), with only one electric vehicle connected between 13:40 and 20:10. We use consumption and production data for one day. We present two cases: in the first one, the elements want to consume the local PV production (scenario (a)); in the second one, they do not have a preference to consume local PV production (scenario (b)). Tables 1 and 2 show the preferences coefficients and the parameters of the different grid elements used for the simulations, respectively for scenario (a) and scenario (b). These first results were obtained with MATLAB.

Table 1. Parameters of grid elements for scenario (a)

Element	Coefficients			Parameters
EV	$\alpha_1 = 0.2$	$\alpha_2 = 0.1$	$\alpha_3 = 0.7$	Initial SOC = 40%
Battery	$\beta_1 = 0.1$	$\beta_2 = 0.1$	$\beta_3 = 0.8$	Initial SOC = 25%
PV generator$_a$	$\gamma_1 = 0.8$	$\gamma_2 = 0.2$	–	–
PV generator$_b$	$\gamma_1 = 0.6$	$\gamma_2 = 0.4$	–	–
Load$_a$	$\delta_1 = 0.1$	$\delta_2 = 0.1$	$\delta_3 = 0.8$	Flexibility = 10%
Load$_b$	$\delta_1 = 0.2$	$\delta_2 = 0.2$	$\delta_3 = 0.6$	Flexibility = 20%
Load$_c$	$\delta_1 = 0.2$	$\delta_2 = 0.2$	$\delta_3 = 0.5$	Flexibility = 10%
Load$_d$	$\delta_1 = 0.3$	$\delta_2 = 0.1$	$\delta_3 = 0.6$	Flexibility = 15%

Table 2. Parameters of grid elements for scenario (b)

Element	Coefficients			Parameters
EV	$\alpha_1 = 0.8$	$\alpha_2 = 0.2$	$\alpha_3 = 0$	Initial SOC = 40%
Battery	$\beta_1 = 0.3$	$\beta_2 = 0.7$	$\beta_3 = 0$	Initial SOC = 25%
PV generator$_a$	$\gamma_1 = 0.8$	$\gamma_2 = 0.2$	–	–
PV generator$_b$	$\gamma_1 = 0.6$	$\gamma_2 = 0.4$	–	–
Load$_a$	$\delta_1 = 0.3$	$\delta_2 = 0.7$	$\delta_3 = 0$	Flexibility = 10%
Load$_b$	$\delta_1 = 0.5$	$\delta_2 = 0.5$	$\delta_3 = 0$	Flexibility = 20%
Load$_c$	$\delta_1 = 0.1$	$\delta_2 = 0.9$	$\delta_3 = 0$	Flexibility = 10%
Load$_d$	$\delta_1 = 0.4$	$\delta_2 = 0.6$	$\delta_3 = 0$	Flexibility = 15%

Figures 3 and 4 illustrate the results obtained respectively for scenarios (a) and (b).

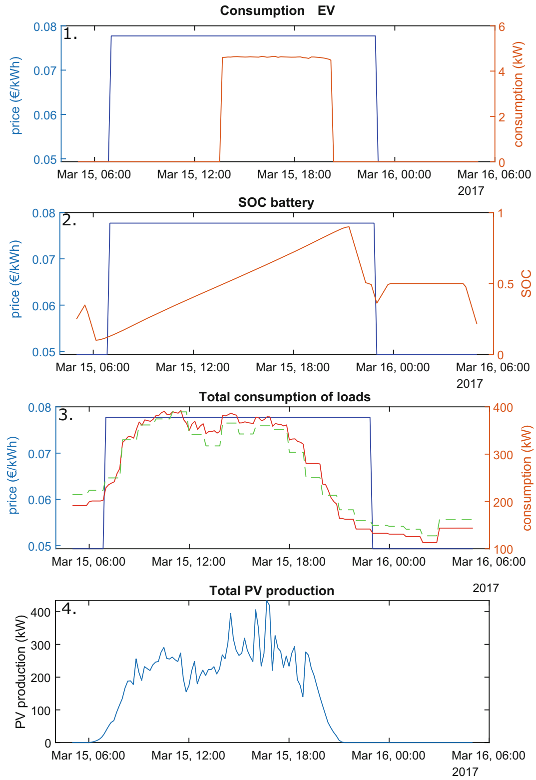

Fig. 3. Results for scenario (a), for: (1) the EV, (2) the battery, (3) the aggregated load (the green line shows the desired consumption, and the red line the actual consumption), and (4) the total PV production. (Color figure online)

From the comparison of the figures, we can notice that when the players are taking care to consume the local PV production, they really adapt their consumption to this production. Even if the effect is very slight for the EV, we can see when we compare Figs. 3 and 4 that the EV decreases its consumption when PV generators stop producing. We can particularly notice this effect at the end of the day after 18:00, when PV generators stop producing. In scenario (b), the EV does not change at all its consumption to fit to the PV production. For the battery, the effect is more visible. In scenario (b), it prefers to charge when the electricity price is low and to discharge when the electricity price is high, and to keep a median SOC (here 50%). In scenario (a), it is charging during all the period of PV production, no matter if the price is higher. For the loads, when they do not pay attention to consume local production (scenario (b)), they adjust their consumption profile in order to decrease the price they pay for electricity. However, when they prefer to consume the local PV production (scenario (a)), then they adjust their consumption to the PV production, leading to an increase

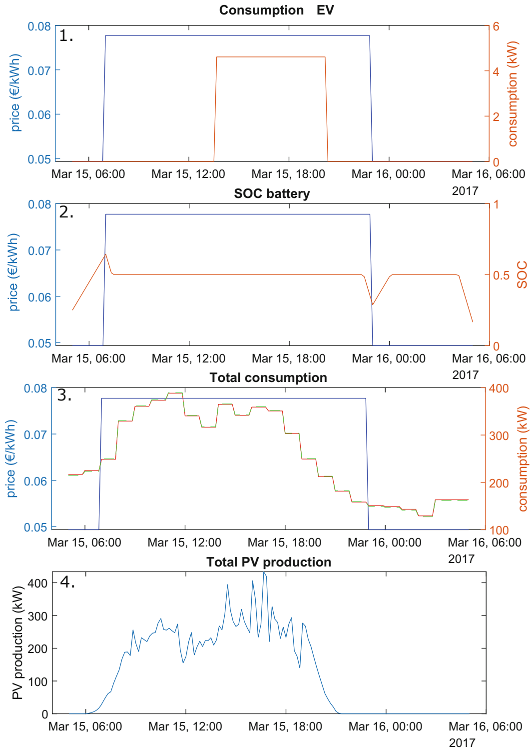

Fig. 4. Results for scenario (b), for: (1) the EV, (2) the battery, (3) the aggregated load (the green line shows the desired consumption, and the red line the actual consumption), and (4) the total PV production. (Color figure online)

of the self-consumption rate. In our case, the cost paid for electricity is then higher, due to the profile of the chosen cost function.

Figure 5 compares the self-consumption rate obtained for both scenarios. It confirms that when the players are more sensible to consumer the local PV production (scenario (a)), then the self-consumption rate increases (scenario (b)). Moreover, we calculate the peak to average ratio (PAR) in both scenarios (Table 3). Scenario (a) leads to a decrease of the PAR of about 13% compared to scenario (b). Indeed, when they favour the local PV production (scenario (a)), the players adapt their consumption so that it fits to the PV production. Thus, they require less energy from the distribution grid when PV generators are not producing anymore. Moreover, in this scenario, the battery stores energy when PV production is high and releases it at night. As a consequence, even if the global consumed energy is the same in both scenarios, in scenario (a), players manage to decrease the peak power seen from the distribution grid, resulting in a reduction of the PAR.

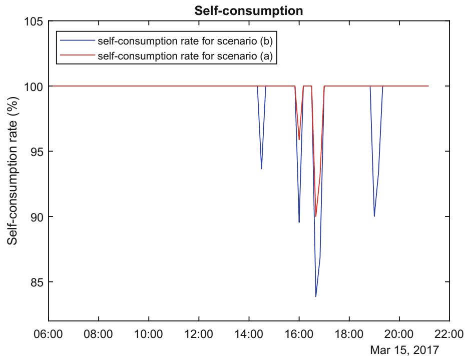

Fig. 5. Self-consumption rate for scenarios (a) and (b).

Table 3. Peak to average ratio (PAR) in both scenarios

	Scenario (a)	Scenario (b)
PAR	1.75	1.98

These preliminary results show that our proposed algorithm leads to an increase of the self-consumption rate and a decrease of PAR. The physical model ensures that in the studied scenarios, the university grid can support the consumption and production profiles. Simulations on the physical grid are necessary to guarantee that the algorithm provides feasible solutions. This is a very important point as the idea behind our work is to provide a concrete solution to improve energy sharing among a local energy community.

Moreover, another interesting perspective is to include a price function that reflects in real time the production and consumption on the local grid: when consumption is higher than local production, the price will increase. This would encourage the grid elements to preferentially consume the local production, even in case that they are only sensible to the electricity cost.

5 Perspectives and Conclusion

In this paper, we propose a concrete framework to improve energy sharing between producers and consumers among a local community energy, for example the grid of Lille Catholic University. In this way, we maximise the use of local photovoltaic production and thus the self-consumption rate.

Our approach combines three tools: game theory for distributed optimisation, a physical model of the grid to guarantee the stability of the grid, and a communication layer with blockchain. The combination of these tools is an innovative approach and constitutes a distributed method for better use of distributed renewable energy sources on local energy community. The approach with game theory enables each actor to specify its particular preferences and to act freely to reach these goals. Thus, our framework reflects the distributed nature of electric grids, where various actors are following very diverse goals.

The first results are promising and show an increase of self-consumption rate. However, we plan to continue this work, and specifically to focus on the following tasks. First, the development of the smart contract with the blockchain is a key point for a real distributed implementation. It will enable to concretely deploy the optimisation method on a peer-to-peer communication network. As we mentioned in Sect. 3, the smart contract will automatically trigger the optimisation algorithm and collect the results.

Second, the price function needs to reflect in real time the consumption and production inside the local grid. The creation of a small electricity market between the players is an interesting option to encourage loads to consume when the PV production is high. In this perspective, we expect interesting further results.

Moreover, some additional questions regarding the overall stability of the system should be answered, especially when we add a new player, for example when a new electric vehicle arrives at a charging station. The issue of the global efficiency of the system, in particular regarding the performances and the consumption of the blockchain.

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