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Increasing photovoltaic self-consumption with game theory and blockchain

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Abstract

INTRODUCTION: This paper presents a distributed approach to optimise self-consumption on a local energy community containing photovoltaic generators, electric vehicles, loads and a storage system.
OBJECTIVES: The goal is to maximise energy sharing between users while preserving the indivual objectives of each user.
METHODS: Game theory is employed to model users' behavior and preferences. A distributed algorithm is used to solve the optimisation problem. In addition, a physical model of the grid is built to verify if the solutions respect grid constraints. Finally, a private blockchain environnement is deployed to concretely implement this distributed framework with a smart contract.
RESULTS: It is shown that the proposed approach effectively leads to an increase of self-consumption rate on the local grid.
CONCLUSION: The proposed distributed framework, combining game theory and blockchain, shows real potential to improve energy sharing on energy communities.

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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 10 GWp in 2008 to more than 500 GWp at the end of 2018 [1]. PV generators differ from traditional 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]. Self-consumption rate is defined as the part of the electricity produced by the PV generators that is locally consumed over the total local production, while self-production refers to the part of the total energy consumption that is locally produced [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 flexibility of all the consumers in order to maximise the self-consumption and self-production rates. However, collective self-consumption projects and local energy communities are still at an early stage and a large-scale development requires a new framework to optimise the

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for private blockchains where a small number of users interact, and where these users can be trusted to create new blocks [29].

In the proposed system, blockchain serves as the communication layer between the users and aggregates the results. It replaces the role of a central optimisation agent. More precisely, a private Ethereum blockchain is deployed between all the elements of the grid. Thus, each player of the game holds one node of a peer-to-peer communication network. The blockchain works with a PoA mechanism. Each user's node is combined with a Python client which automatises the interactions with the blockchain and has more specifically the following three tasks. First, it assigns the right utility function to the user, depending of its type (electric vehicle, storage system, PV generator or load). Second, it collects the coefficient preferences of the user. Finally, it performs the local optimisation of the utility function and automatically sends the results to the blockchain.

A smart contract deployed on the blockchain implements the aggregation steps of the ADMM algorithm presented in the previous section. It collects the results of all users and calculates the global variables z and u, and sends the results to the users for a new iteration.

The blockchain framework is illustrated on Figure 2 for 3 users. An additional agent is created only in order to deploy the smart contract and maintain the network. It does not perform any other operation and does not receive any users' data.

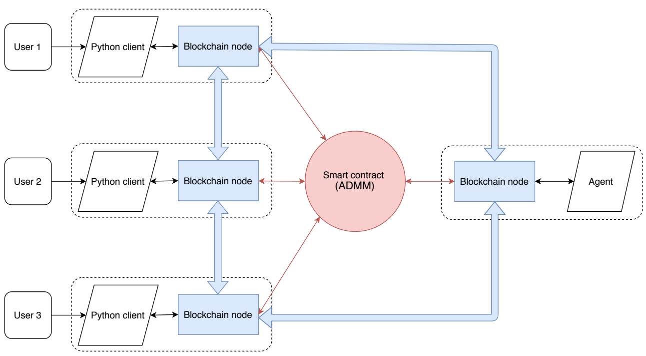

Figure 2. Blockchain framework

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 be built with 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 framework

As 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 the specified time period through the Python client.

The ADMM process is illustrated on Figure 3 from the point of view of one user.

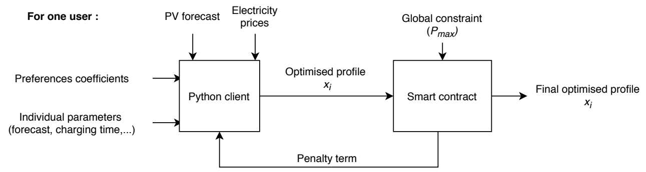

Figure 3. Optimisation for one user

The agent deploys the smart contract and specifies the period of optimisation and the electricity prices c and the total PV production forecast for the next day. Each user reads these information, and then indicates its preferences and physical parameters in the Python client, depending on its type (charging time and SOC limits for EV, SOC limits for the battery, production forecast for PV generators, flexibility and consumption forecast for loads). The Python client computes the local optimisation step and automatically sends the result into the smart contract. Then it receives the global results to perform another iteration if needed, until the final state is reached by the overall system.

3.3. Physical model of the real grid

In the theoretical framework defined in section 2, the physical constraints related to the grid have not been taken into account. 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, a physical model of the grid at stake is build, in which the physical properties of the lines are included (see figure 4), with PowerFactory. This software is used by grid operators for grid modelling and analysis [30]. The local network contains 4 buildings considered to be loads, 2 PV generators, one battery and 6 EV charging stations (figure 4). Buidling this model requires to obtain all needed electrical data of the energy community, especially the architecture and the lines capacity.

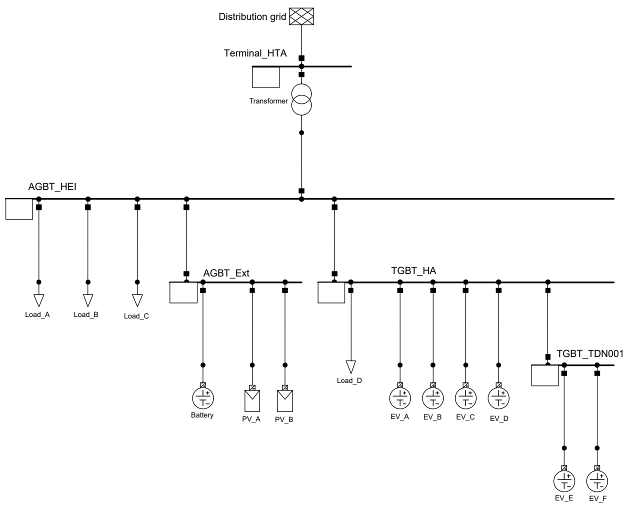

Figure 4. Physical model of the grid

The consumption and production profiles of all the players provided by the optimisation process are tested on the grid model in order to check if they create line congestion or over-voltages. In this case, the problems that occur can be precisely identified on the physical model. Then additional constraints can be imposed 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 the solutions are realistic and will not damage the grid.

3.4. Combination of tools

To summarize, the proposed approach combines a distributed optimisation based on game theory and solved by ADMM, a practical implementation with blockchain and a physical model of the grid. Figure 5 illustrates the overall system.

This framework is here specific to the case study, but could be adapted to other situations. The distributed optimisation algorithm has been detailed in section 2.4. The Ethereum blockchain only implements this algorithm, with a P2P network that reflects the electrical network. As mentioned previously, Python clients are used in combination with each Ethereum node (each user) to perform local optimisation of utility functions. The smart contract only computes the aggregation step of the algorithm. At the end of the algorithm, each user obtains a power profile that maximises its utility function while respecting the

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

Element	Preferences coefficients		
EV_a	$\alpha_1 = 0.1$	$\alpha_2 = 0.1$	$\alpha_3 = 0.8$
EV_b	$\alpha_1 = 0.1$	$\alpha_2 = 0.1$	$\alpha_3 = 0.8$
Battery	$\beta_1 = 0.2$	$\beta_2 = 0.8$	-
PV generator_a	$\gamma_1 = 0.5$	$\gamma_2 = 0.5$	-
PV generator_b	$\gamma_1 = 0.5$	$\gamma_2 = 0.5$	-
Load_a	$\delta_1 = 0.1$	$\delta_2 = 0.1$	$\delta_3 = 0.8$
Load_b	$\delta_1 = 0.1$	$\delta_2 = 0.1$	$\delta_3 = 0.8$
Load_c	$\delta_1 = 0.1$	$\delta_2 = 0.1$	$\delta_3 = 0.8$
Load_d	$\delta_1 = 0.1$	$\delta_2 = 0.1$	$\delta_3 = 0.8$

global constraints applied to the entire community. Theses solutions are then sent in a second step to the physical model of the grid to ensure that they do not lead to over-voltage or over current on the lines.

As the physical model is specific to the energy community studied, a replication of the proposed approach would require to build a new electrical model. However, the blockchain environment can be easily deployed on other situations, because it take into accounts diverse kinds of actors (generators, battery, tertiary loads and EV).

4. Results

To illustrate the developed approach, this section presents some preliminary results. The grid of Lille Catholic University (whose PowerFactory model is represented on figure 4) is used as case study, with only two electric vehicles respectively connected between 09:30 and 12:20, and between 10:40 and 19:10 and with initial SOC of 20% and 45% respectively. The battery has an initial SOC of 35%. Loads are assumed to have a flexibility of 25%.

For electricity prices, data from the EPEX SPOT European market [31] are used. The global power constraint is set to $P_{max} = 350$ kW and the timestep Δt to 20 minutes.

Two cases are presented: in the first one, the users prefer to consume the locally produced energy (scenario (a)) ; in the second one (scenario(b)), they have a preference to minimise their costs (or maximise their income). Tables 1 and 2 show the preferences coefficients used for the simulations, respectively for scenario (a) and scenario (b).

Both scenarios converge after 73 iterations. Figures 6 and 7 illustrate the results obtained respectively for scenarios (a) and (b), from the users point of view.

The comparison of these two figures shows that the proposed approach enables the users to reach

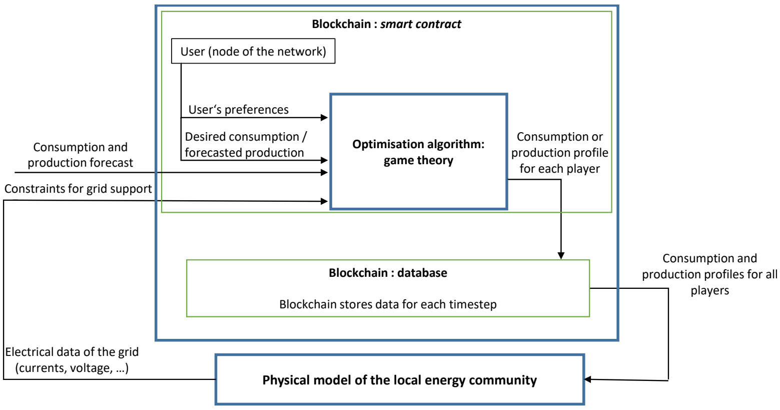

Figure 5. Overview of the overall optimisation process

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

Element	Preferences coefficients		
EV_a	$\alpha_1 = 0.1$	$\alpha_2 = 0.8$	$\alpha_3 = 0.1$
EV_b	$\alpha_1 = 0.1$	$\alpha_2 = 0.8$	$\alpha_3 = 0.1$
Battery	$\beta_1 = 0.8$	$\beta_2 = 0.2$	-
PV generator$_a$	$\gamma_1 = 0.8$	$\gamma_2 = 0.2$	-
PV generator$_b$	$\gamma_1 = 0.8$	$\gamma_2 = 0.2$	-
Load$_a$	$\delta_1 = 0.8$	$\delta_2 = 0.1$	$\delta_3 = 0.1$
Load$_b$	$\delta_1 = 0.8$	$\delta_2 = 0.1$	$\delta_3 = 0.1$
Load$_c$	$\delta_1 = 0.8$	$\delta_2 = 0.1$	$\delta_3 = 0.1$
Load$_d$	$\delta_1 = 0.8$	$\delta_2 = 0.1$	$\delta_3 = 0.1$

their individual goals. Indeed, in scenario (a), energy consumers (EV and loads) really follow the PV production profile. Loads shift their consumption in the middle of the day to consume a maximum of local PV energy. On the contrary, their profiles follow exactly the price function in scenario (b). Regarding the battery, its SOC profile slightly follows the PV production profile in scenario (a), but it is not enough to charge the battery. In scenario (b), the SOC is correlated to the price of electricity. For PV generators, each scenario results in a maximisation of the production. This is an effect of the utility function (equation 10) in which all terms tend to increase the production.

As a results, table 3 shows the costs or benefits for all users. It illustrates that in scenario (a), users are ready to pay more to consume preferentially the local PV production.

Figure 8 illustrates the power imported by the energy community from the grid in both scenarios. A negative value indicates that the community exports power to the distribution grid. First, the global power constraint (represented by the dotted line) is respected in both

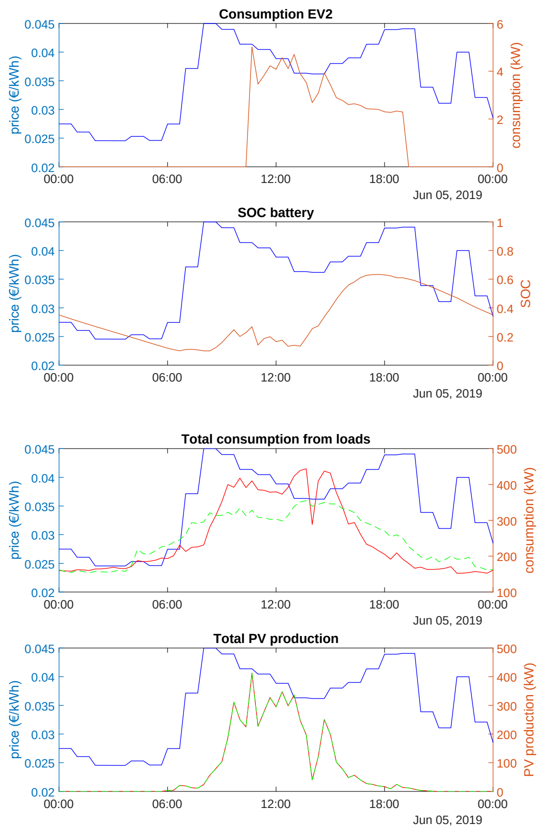

Figure 6. In red: power profiles scenario (a), for EV2, the battery, the aggregated loads and the total PV production (the green line shows the forecasted profile, and the red line the optimised one). In blue: electricity prices.

cases. Second, scenario (a) is more interesting for the distribution grid, because it avoids the morning and night peaks, it decreases the power send back to the grid and the power imported show less fluctuations (the standard deviation is only 63 kW in scenario (a), and 105 kW in scenario (b)). This is due to the will of users

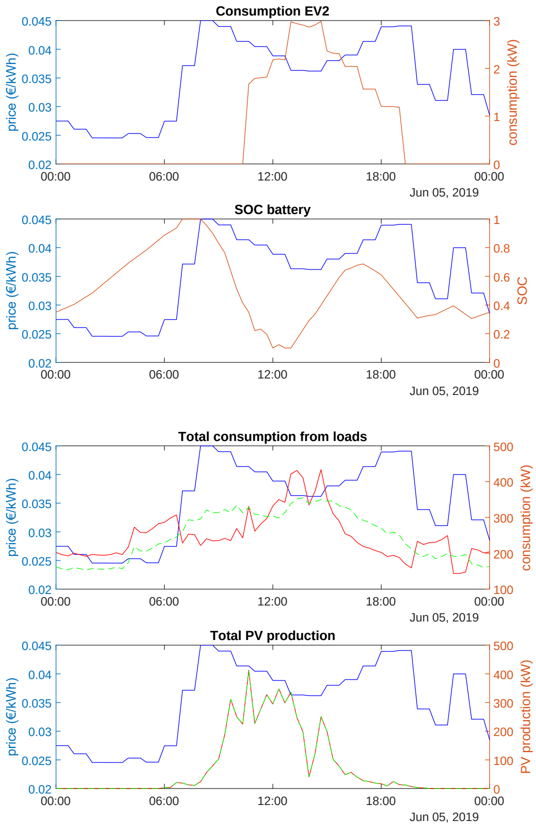

Figure 7. In red: power profiles scenario (b), for EV2, the battery, the aggregated loads and the total PV production (the green line shows the forecasted profile, and the red line the optimised one). In blue: electricity prices.

Table 3. Costs or benefits in scenarios (a) and (b)

Costs (>0) or benefits (<0)	Scenario (a)	Scenario (b)
Consumers (EV and loads)	223 €	214 €
PV generators	-71 €	- 71 €
Storage	1 €	- 4 €
Total	153 €	140 €

Table 4. Global self-consumption rate for scenarios (a) and (b)

	Scenario (a)	Scenario (b)
SC rate	99%	91%

to consume preferentially the local PV production: they adapt their consumption and thus they need less power from the distribution grid. As a result, the self-consumption rate of the energy community is higher in scenario (a) than scenario (b), as shown in table 4.

In a second step, the obtained solutions of both scenarios have been tested on the physical model of the grid, but do not create any problem. Therefore, in these scenarios, there is no need to add new constraints. 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 the work is to provide a concrete solution to improve energy sharing among a local energy community.

To summarize, the results show that the proposed approach leads to a stable state where individual goals of the users are met, while the global constraint is respected. It proves that this fully distributed approach is relevant for energy management on an energy community.

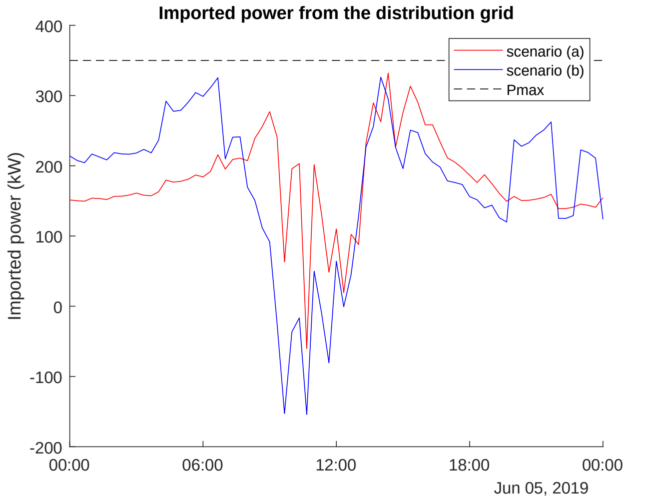

Figure 8. Imported power from grid in both scenarios

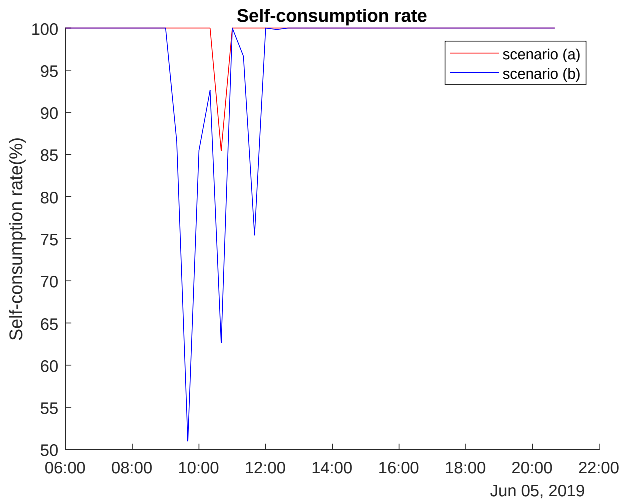

Figure 9. Self-consumption rate for scenarios (a) and (b).

An 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. This work will be also improved by a better version of the ADMM algorithm, with for example a more sophisticated penalty parameter that would result in a negotiation between the users to decrease their consumption when needed.

5. Perspectives and conclusion

In this paper, a concrete distributed framework to improve energy sharing between producers and consumers is proposed among a local community energy. In this way, the use of local photovoltaic production is maximised as well as the self-consumption rate while users' objectives are respected.

The 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 fully distributed method for better use of local renewable energy sources on energy communities. The approach with game theory enables each actor to specify its particular preferences and to act freely to reach these goals. Thus, the framework reflects the distributed nature of electric grids, where various actors are following very diverse goals.

The first results are promising and show a convergence towards an equilibrium where the global constraints is verified while individual goals of users are met. However, this work will be continued, with a specific focus on the following tasks. First, a complete analysis of the blockchain and of its energy consumption is required. This article focused on the results obtained by the distribution framework deployed in the blockchain, but a study of the entire system is required in order to conclude if the proposed framework is effectively relevant for an energy community. This analysis should cover the energy consumption of the blockchain, but also practical aspects like the communication speed between users and the security of the solution.

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, interesting further results are expected

Moreover, some additional questions regarding the overall stability of the system should be answered, especially when a new player is added, for example when a new electric vehicle arrives at a charging station.

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