A Low-Complexity Framework for Distributed Energy Market Targeting Smart-Grid

Kostas Siozios
Department of Physics
Aristotle University of Thessaloniki
Thessaloniki, Greece
Email: ksiop@auth.gr

Stylianos Siskos
Department of Physics
Aristotle University of Thessaloniki
Thessaloniki, Greece
Email: siskos@physics.auth.gr

***Abstract*—With the increasing connection of distributed energy resources, traditional energy consumers are becoming prosumers, who can both dissipate and generate energy in a smart-grid environment. This enables the wide adoption of dynamic pricing scheme, where demand and price forecast are applied for estimating energy cost and loads scheduling. Throughout this paper we propose a Peer-to-Peer (P2P) platform, as well as a light-weighted system orchestrator based on game theory to support the energy trading. Additionally, we discuss the hardware implementation of the proposed solution onto a low-cost reconfigurable device. Experimental results based on real data validate the efficiency of proposed framework, as we achieve considerable energy savings (on average cost reduction by 87%) compared to the corresponding cost from the main-grid.**

***Index Terms*—System Orchestrator, Smart-Grid, Energy Market, Game Theory, Embedded System**

I. INTRODUCTION

The demand for energy efficiency, the deployment of renewable energy sources and the onset of smart-grid technologies, foretell that in the near future an increased number of building facilities will become active participants in the energy market. From the system's point of view this will lead to autonomous micro-grids (smart-grids) with energy trading capabilities and flexibility in regard of shifting or reducing electrical loads as needed. A number of electric utilities (i.e., market-driven pricing), are already available even to the end users, where instead of having a flat-rate (24 hours a day, 7 days a week) pricing scheme, variable pricing mechanisms exist allowing the cost per kilowatt-hour may change based on the day, time of day, or a more dynamic event, such as the weather conditions or the expected load requirements [14].

The dynamic pricing is a concept that has immense possibilities for application in the energy sector, since it can be considered as a demand-side management tool that offers energy budgets at different rates. Although academicians and researchers highlight the flexibility of dynamic pricing as an useful and interesting tool, however regulators, suppliers and customers have stayed away from this concept, since there are concerns regarding the potential benefits over the costs of implementation and operation. Thus, the wide adoption of this scheme raises the question about how participants can benefit from such a competitive energy environment.

Typical solutions towards this direction employ financial options as a tool for energy producers to hedge against generation uncertainty [7]. Further enhancement is feasible with a combined and coordinated use of power from renewable sources and energy storage technologies [15]. Methods based on probability distribution (e.g. stochastic model), are also employed to compute optimal bid strategies for energy budgets in day-ahead or adjustment markets [10]. Authors in [8] discuss an energy sharing model with price-based demand and response. As the actions from a participant influences all the others, solutions based on equilibrium statement (such as the game theory) are usually employed to derive an optimum solution [16]. A similar non-cooperative game model is discussed in [11], where authors emphasize on the competition between demand and response for tackling the energy market problem.

Although promising, the previously mentioned approaches rely on a centralized manner with limited scalability efficiency. Specifically, the signaling overhead from a continuous centralized auction is notable, as bidders have to submit bids repeatedly to reach an agreement [3]. To overcome this limitation, Peer-to-Peer (P2P) trading mechanisms were proposed recently to support energy transactions at distributed manner [17]. In [1], a paradigm of P2P energy sharing among neighbor micro-grids was discussed for improving the utilization of local Distributed Energy Resources (DER). Similarly, authors in [2] minimize energy cost by integrating a demand side management system coordinated with P2P energy trading among the households in the smart grid environment. A paradigm of P2P energy sharing is discussed in [9] for improving the utilization of local DERs in order to minimize overall energy cost.

Throughout this paper we introduce a decision-making mechanism targeting to energy prosumers. The proposed solution computes energy bids based on a distributed P2P game theory approach. For demonstration purposes, the proposed solution was implemented onto a low-cost embedded device (Xilinx Zybo Z7 FPGA board). By enabling a number of auctions to be initiated ad-hoc simultaneously, and in a distributed manner, our framework exhibits increased scalability. Experimental results with various configurations and real data highlight the superiority of our approach, as it results to an equilibrium, where both energy producers and consumers

TABLE I: Summary of building properties.

Template	Details		Energy Demand	Savings from Renewable Sources	Energy from Grid
#1	Surface area: Thermal zones: Operating hours:	$350m^2$ 8 6:00–21:00	$E_1^D(t)$	$PV \leq 70\%$	$\geq 30\%$
#2	Surface area: Thermal zones: Operating hours:	$525m^2$ 10 8:00–21:00	$E_2^D(t)$	$PV \leq 52\%$ $Wind \leq 18\%$	$\geq 30\%$
#3	Surface area: Thermal zones: Operating hours:	$420m^2$ 10 8:00–17:00	$E_3^D(t)$	$PV \leq 35\%$ $Wind \leq 35\%$	$\geq 30\%$
#4	Surface area: Thermal zones: Operating hours:	$280m^2$ 6 7:00–20:00	$E_4^D(t)$	$PV \leq 18\%$ $Wind \leq 52\%$	$\geq 30\%$
#5	Surface area: Thermal zones: Operating hours:	$228m^2$ 4 6:00–18:00	$E_5^D(t)$	$Wind \leq 70\%$	$\geq 30\%$

maximize their profit.

II. Problem Analysis

For our analysis we consider a number of micro-grids (randomly selected from the template depicted in Table I), each of which includes a building (with energy demand $E_j^D(t)$) and a set of renewable power source(s). The studied buildings were modeled in a detailed manner[1] [4] [6], while the energy demand per consumer was computed based on EnergyPlus suite [6] for weather and electricity pricing data that correspond to publicly available information [1] [13].

The energy from renewable sources is either consumed in order to reduce the building's energy cost, or it is sold to other micro-grids/main-grid. For this purpose, the $AF_j(t)$ parameter denotes the available funds for building j to buy energy from other grids. More precisely, if the power from prosumer's renewable sources is not enough to meet the building's energy requirements, additional electricity is purchased from the rest micro-grids, or the main-grid. In such a case, the associate energy cost $(E_j^M(t) \times P_i(t))$ is subtracted from the $AF_j(t)$ budget. Otherwise (i.e. when the availability of renewable sources exceeds the demand), the spare energy is sold to other grids (by increasing the $AF_j(t)$ budget). The demand for additional energy from other grids and the reduction of AF parameter is formulated with Equations 1 and 2. This transaction is formulated with , respectively. Our analysis considers also the concept of Virtual Energy Storage (VES), where a cooperative group of micro-grids (cluster) store the energy from renewable sources in a common VES (battery). As we discuss later, such a concept improves the overall system's efficiency.

$$E_j^M(t) = \begin{cases} \left(E_j^D(t) - E_i^{RS}(t)\right) & \text{, if } E_j(t) \geq E^{RS}(t) \\ 0 & \text{, if } E_i^{RS}(t) \geq E_j^D(t) \end{cases} \quad (1)$$

$$AF_j(t) = \begin{cases} \left(AF_j(t-1) - E_j^M(t) \times P_j(t)\right) & \text{, if } E_i^{RS}(t) \leq E_j^D(t) \\ 0 & \text{, if } E_i^{RS}(t) \geq E_j^D(t) \end{cases} \quad (2)$$

[1]The building's modeling was part of PEBBLE project (http://www.pebble-fp7.eu) funded by the E.C. under grand agreement 248537.

The objective of proposed orchestrator is to compute optimal strategy in order to fulfill building's energy requirement with the minimum possible energy cost. Towards this direction, the orchestrator has to exploit in distributed manner with optimal way the available renewable sources, energy sharing (e.g. through VES), as well as energy transactions among micro-grids. Since the decisions are retrieved in distributed manner, we consider that each micro-grid (prosumer) is equipped with its own orchestrator. Without affecting the generality of proposed solution, we assume that the installed renewable power per studied micro-grid is enough in order to meet 70% of the maximum daily building's energy demand. The energy forecast per building $E_J^D(t)$ is computed based on a Neural Network and Fuzzy Logic approach discussed in our former publication [5]. Each building is also equipped with a number of weather sensors that monitor indoor/outdoor air temperature, humidity and radiant temperature. These values are necessary in order to support weather forecast and hence, estimate the upcoming loads for the building j.

The orchestrator's selections depend on the dynamic pricing $P_i(t)$, the forecast for associated building's energy requirements in the near future $E_j^M(t)$, as well as the maximization of the overall micro-grid's profit ($AF_j(t)$). The energy purchase and sell from/to other grids is conducted according to different rates. Specifically, a micro-grid sells energy to the main-grid at the price of feed-in tariff, which refers to the regulatory, minimum guaranteed price per kWh that an electricity utility has to pay to an independent energy producer. Otherwise, the trading energy cost per kWh ($P_i(t)$) is computed based on the demand and response law. More thoroughly, each building (energy consumer) j has a maximum unit price, or reservation bid $B_j^{max}(t)$, at which it is willing to participate to an auction, which is defined by the main-grid's energy cost per kWh. Similarly, assuming that an energy producer i has a maximum amount of energy ($E_i^{max}(t)$) to sell in the market, we define a reservation price $P_i^{min}(t)$ per energy unit sold, under which seller i will not trade energy. This allows different forms of dynamic pricing policies to multiple markets and customers. Consumers' willingness to pay for electricity services is also necessary in setting price limits depending on the demand and response curve, while the market segmentation can enhance the effects of such pricing schemes.

III. Proposed Auction Mechanism

Figure 1 gives the template of the proposed auction mechanism consisted of three entities, namely (i) the *demand side*, (ii) the *supply side*, and (iii) the *utilities*. Regarding the *demand* and *supply* sides, they correspond to a number of nodes that are in need of energy and a number of distributed energy sources that service a group of consumers. In our analysis we assume that N and K denote the sets of all sellers (energy producers) and buyers (energy consumers), respectively. Also, we consider that a certain percentage of these consumers is unable to meet their own energy requirements from the associated renewable sources due to factors such as intermittent generation and varying consumption levels at the grid's loads.

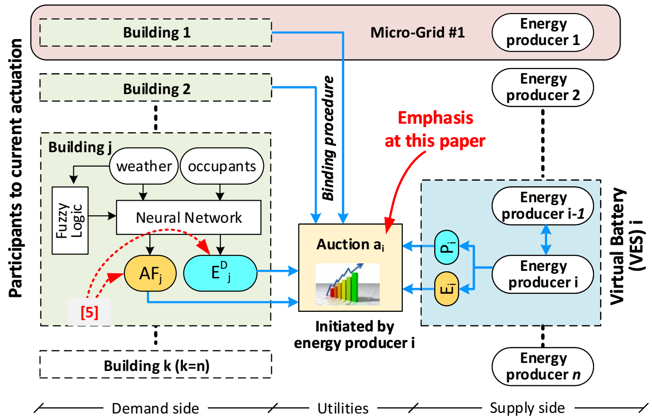

Fig. 1: The proposed auction mechanism.

In this respect, these consumers have to buy energy budgets from the rest micro-grids.

Rather than a centralized auction, the proposed framework enables energy transactions to be initiated ad-hoc by energy producers in order to decide: (i) to whom to sell, (ii) the amount of energy that will be sold and (iii) the price for this transaction. In other words, the energy producer acts as an auctioneer and the consumers place bids for energy. Let energy producer i initiates an ad-hoc auction a_i for selling energy budget $E_i(t)$ ($E_i(t) \leq E_i^{max}(t)$) at current trading price $P_i(t)$. Each building j that cannot meet its own energy demands submits bids ($B_j(t)$) for a given power budget $E_j^M(t)$, where $E_j^M(t) \leq E_i(t)$.

Regarding our case study, energy producers and consumers are the players of a non-cooperative game [12]. The players can participate to multiple auctions (games) simultaneously, each of which has a predefined number of iterations. Players update in turns their bindings iteratively according to their own strategy and eventually the game reaches to the end (equilibrium statement). This corresponds to a case, where each player tries to maximize its own payoff function while considering its rivals' bid strategies. The studied auction relies on the ascending-bid mechanism, where buyers start bid at a low price and the highest bidder wins and pays the last price bid. The auction is finalized when either there is an equilibrium (i.e. the combination of strategies comprises the best strategy for each of the players), or the game reaches its maximum number of rounds. Equation 3 formulates the studied game.

$$Game = \Big[G, S, Score_{(i,j)}\Big], \forall(i,j) \in (N,K) \tag{3}$$

, where $S = \Big[player^E_{(i,j)} \mid i = \{1,2,\dots,N\}, j = \{1,2,\dots,K\}\Big]$ corresponds to the set of participant players, whereas the selected strategy for consumer j that participates to an auction initiated by producer i is denoted as $G^E_{(i,j)}$. Regarding our game, the valid strategies are either to sell/buy the energy budget ($G^E_{(i,j)}$ = *sell*) or not ($G^E_{(i,j)}$ = *buy*) at the current price, or to counteract a lower ($G^E_{(i,j)} = lower$) or higher ($G^E_{(i,j)} = higher$) offer. The consumer's j offer price ($bid_j(t)$) regarding an energy budget $E_j^M(t)$ is defined by Equation 4:

$$bid_j(t) = bid_j(t-1) + \frac{T_j \times \Delta bid_j(t)}{F(r)} \tag{4}$$

, where $bid_j(t-1)$ denotes the previous offer, T_j is the number of auction's rounds that building j waits until satisfies its energy requirements and $F(r)$ is the aggressiveness that defines bid strategy. As we proceed to the maximum number of game's iterations R, the building's bid (bid_j) increases so that the probability of a match in the next round is elevated. Based on our analysis, optimal results in term of maximizing AF parameter are retrieved by considering that consumer's aggressiveness increases with an exponential manner. In case there is no equilibrium at the end of the game (i.e. maximum number of iterations), the building j buys the requested energy budget from the main-grid at the regulator's price (it is always higher than the corresponding cost from auctions). Similarly, if an energy producer cannot succeed in selling the energy budget, this budget is sold to the main-grid at the regulator's feed-in tariff (it is always lower than the trading price). In any case, the minimum and maximum auction prices are computed according to the regulator's minimum guaranteed price per kWh that an electricity utility has to pay to an independent energy producer and the current energy cost per kWh from the main-grid, respectively. Finally, $\Delta bid_j(t)$ expresses the sensitivity of the price.

Algorithm 1 gives the pseudo-code for solving the energy trading problem. The efficiency of players' selections is performed based on the score metric defined by Equation 5, which compromise two competitive objectives, namely the reduction of cost energy per kWh (factor A) and the maximization of available funds (factor C). Note that as we discussed in Figure 1, our analysis considers a case where players are micro-grids. Thus, the optimization of V parameter is performed at prosumer level.

$$V = \sum_{\forall i,j}(Score_{(i,j)}) = \sum_{\forall i,j}\Big(A \times C\Big) = \sum_{\forall i,j}\Bigg(\Big(P_i(t) \times E_j\Big) \times \Big(AF_j(t)\Big)\Bigg) \tag{5}$$

The worst case time complexity for Nash equilibrium regarding a $N \times K$-player game with four strategies per player (namely "buy energy", "sell energy", "increase bid", "decrease bid") is given by $O(N \times K \times 4^{N \times K}) \simeq O(4^{N \times K})$ [12]. As we have already discussed, in order to support higher scalability, we support multiple partial sub-game per traded energy budget from the same micro-grid.

IV. Evaluation Analysis

The efficiency of the proposed framework to perform distributed energy auctions is quantified in a case study consisted of 100 micro-grids randomly selected among the templates depicted in Table I. The experimentation affects a duration

Algorithm 1: Pseudo-code for solving the game matrix for auction a_i.

```
Input: E_i^max: max energy budget for selling
Input: B_j^max: max cost per energy unit for consumer j
Input: P_i^min: Min cost per energy unit for producer i
Opt_Score ← V (based on Eq. 5);
foreach partial sub-game initiated by grid i do
    while not reach max iterations do
        foreach consumer j ∈ [1, ··· K] do
            foreach player's strategy G^E_(i,j) ∈
             [yes/no/higher/lower] do
                Update bids according to Eq.4;
                Cur_Score ← V_current − V_previous;
                if Cur_Score ≤ Opt_Score then
                    Opt_sol ← Cur_sol;
                    Opt_Score ← Cur_Score;
                end
                T_j ++;
                Update F(r);
            end
        end
        check Equilibrium;
    end
end
if (Equilibrium = True) then
    energy transaction among players;
end
else
    energy transaction with main-grid;
end
update AF_j for participant players;
```

of 52-weeks, where public available data for weather [1] and regulator's guarantee energy prices [13], were employed. The energy requirement per building j, the energy production from its own renewable sources i, as well as the building's energy forecast for the next days are computed based on our former implementation [5]. Also, in order to enable buildings to participate in auctions, an initial amount of funds (AF_j^{init}) is assigned per prosumer. Specifically, the initial amount is equals to 60% of the yearly building's j energy cost without considering renewable energy sources.

By enabling buildings (consumers) to participate in multiple auctions simultaneously, it is expected to improve their bid strategy. Figure 2 quantifies the impact of this selection. Vertical axis at this figure gives the average energy cost per kWh among participant buildings, while the horizontal axis depicts the average number of simultaneous auctions that an energy consumer participates. For our case, we assume that an energy producer can initiate up to 50 games in parallel. This analysis indicates that consumers achieve an average cost reduction by 12% in case they apply the proposed trading framework (Scenario 1), while the savings are even higher (on average 36%) whenever energy producers initiate multiple

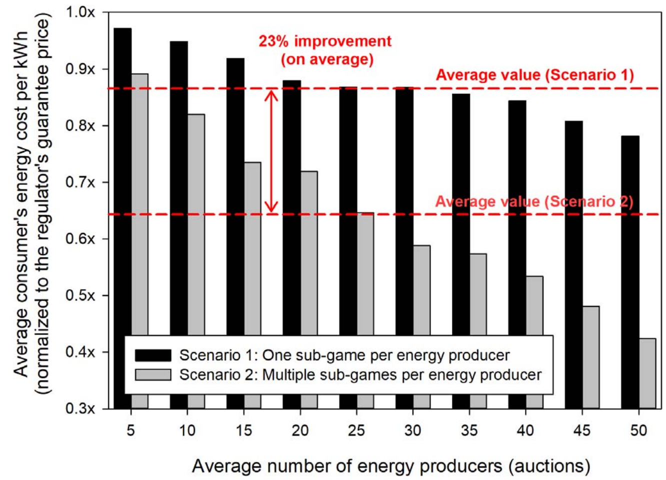

Fig. 2: Energy savings for consumers that participate to one and multiple auctions.

auctions in parallel (Scenario 2). For demonstration purposes, both results are normalized versus the corresponding energy cost per kWh from the main-grid (reference solution).

The maximization of AF parameter, and hence the reduction of energy cost per kWh, depends also on the number of iterations per auction. The higher number of iterations favor buyers (buildings) to bid with a more conservative approach. On contrast, auctions with fewer iterations enforce buyers to exhibit a more aggressive strategy (pay higher price from the begging of the auction) in order to reserve the energy budget from the bilateral market rather than from the main-grid. Note that the proposed auction mechanism, further improves this conservative bid approach, since consumers start bid from a low price, while producers decrease their expected profit per kWh.

This trend is also depicted in Figure 3, where horizontal and vertical axes denote the maximum number of iterations per auction (R) and the average cost per energy unit, respectively. For demonstration purposes, the vertical axis is plotted in normalized manner over the corresponding results for auctions with up to R=10 iterations. According to this figure, the average cost per kWh is monotonically reduced with the increase of game's iterations. However, since the number of iterations highly affects the problem's computational complexity, for the rest of this section we set the maximum number of rounds per auction to be R=90. Such a selection decreases the average cost per kWh by 46% as compared to the reference solution. It is well-worth to mention that the studied implementation of our framework corresponds to the worst-case scenario, since games with additional iterations (i.e., higher R values) achieve further savings in energy cost.

The size of VES is another parameter that affects the efficiency of our decision-making mechanism, since it influences the maximum energy sharing among the collaborated micro-grids (depicted in Figure 1). To study in more detail the impact of this parameter, we explore clusters consisted of

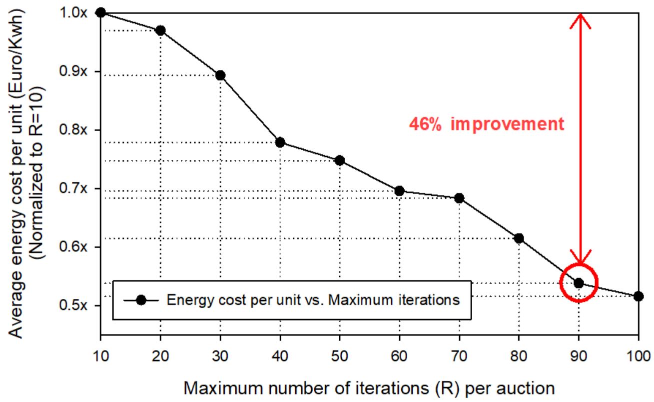

Fig. 3: Explore maximum number of iterations (R) per auction.

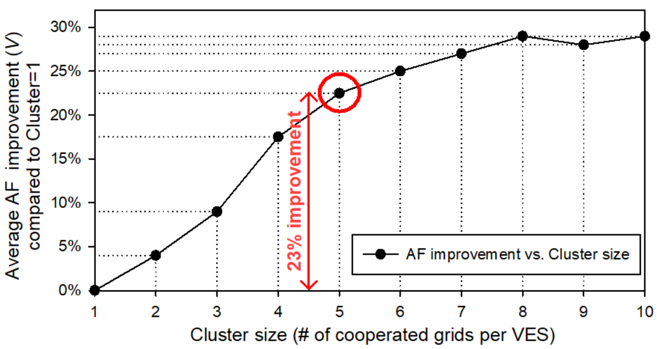

Fig. 4: Impact of cluster size to the auction's outcome.

different number of prosumers (ranging from 2 up to 10), where participants are randomly selected from the templates depicted at Table I. The outcome from this analysis is plotted in Figure 4, where the vertical and horizontal axes give the average AF improvement compared to the reference solution (without considering the VES clustering) and the cluster size (number of micro-grids per VES), respectively. According to this diagram larger clusters improve the overall profit for participant micro-grids (V) because it is more likely the buildings' energy requirements to be met from the collaborated energy producers rather than from the auction mechanism, or the main-grid. However, this gain seems to be saturated for clusters with more than 5 prosumers, since the overall VES's capacity is enough to meet the buildings' energy requirements. Without affecting the generality of introduced solution, for the rest of our experimentation we consider VES that cluster prosumers in groups of 5. In case larger clusters are employed, the energy savings are expected to be even higher; thus, the studied VES size is considered as a worst-case solution for our experimentation.

Since the main objective of our framework is to maximize the available funds (AF) for the participated micro-grids, we evaluate also the variation of this parameter for alternative configurations. For this purpose, the efficiency of two configuration scenarios was quantified as it is depicted in Figure 5, namely the *day-ahead* and the *week-ahead* markets. The

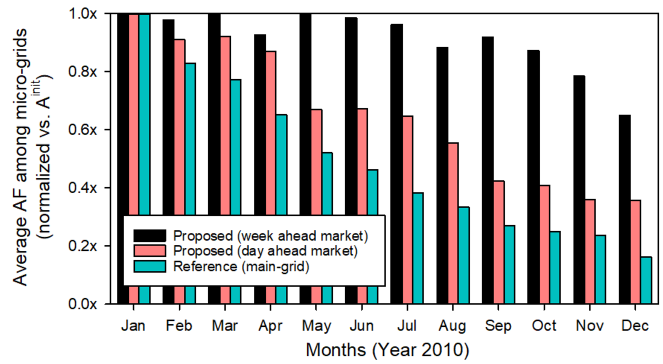

Fig. 5: Efficiency of energy transactions that take place: (i) at run-time, (ii) a week-ahead and (iii) a day-ahead.

reference solution for this analysis corresponds to the case where energy transactions are performed on demand with the main-grid at flat rate.

According to this analysis, we conclude that although transactions with the main-grid are performed upon demand (based on run-time building's energy requirements), the increased regulator's price maximizes buildings' operational cost. On the other hand, the proposed framework achieves energy savings for the spot (day-ahead) and forward (week-ahead) markets by 32% and 87%, respectively, on average. Small fluctuations at this diagram, especially for the week- and day-ahead markets are reasonable due to dynamic events, such as the weather conditions and the varying expected load requirements. More specifically, the consumers' strategy is to buy from the market in advanced additional energy in order to guarantee that energy demands will be met. Then, depending on their actual energy requirements and the energy savings from their own renewable sources, the spare energy is stored for future usage to the associated VES. Furthermore, based on Figure 5 we conclude that the week-ahead auctions result to higher AF compared to the corresponding day-ahead market mainly because they enable consumers to bid with a more conservative way.

Finally, we discuss the hardware implementation of the proposed framework onto a low-cost embedded device (Xilinx Zybo-Z7 ARM/FPGA SoC development board). By exploiting the massive application parallelism, such a board per prosumer enables energy producer i to execute multiple partial sub-games simultaneously. The implementation of proposed framework was performed with High-Level Synthesis (HLS) toolkit provided by the Xilinx Vivado suite. The implemented approach assumes a scenario where up to 50 partial sub-games are executed per FPGA board, while each of these sub-games involve up to 100 players (i.e., all the consumers are interested to buy energy from the market). By supporting the P2P feature, our implementation enables players (consumers) to enter and leave the game in a dynamic manner based on their energy requirements. For this purpose, the architectural concept depicted schematically in Figure 6 consisted of 8 interconnected FPGA boards, was developed and evaluated.

A critical parameter for the hardware implementation af-

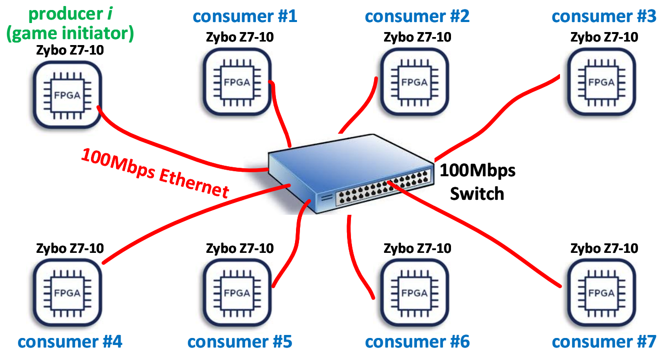

Fig. 6: Demonstration of the proposed P2P framework for 8 energy producers and up to 792 energy consumers.

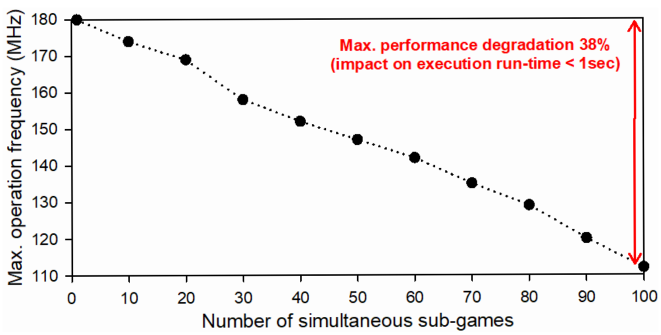

Fig. 7: Evaluation of execution run-time.

fects the performance of algorithm's execution. In order to study in detail this parameter, Figure 7 plots the variation at maximum operation frequency (vertical axis) for different number of simultaneous games executed onto the energy producer's i FPGA board (horizontal axis), each of which realizes the maximum number of partial sub-games ($H_i = 50$). These results indicate that even for the board case (i.e. the maximum number of micro-grids), the proposed hardware implementation exhibits a performance degradation about 38% as compared to the reference solution (with only one sub-game). This overhead is due to the additional signaling in order to support data transfer (e.g., bids) among players at different sub-games. However, it is well-worth to highlight that such a performance degradation does not have any meaningful impact to the system's behaviour, since the game's equilibrium is achieved in less than a second. Hence, we claim that the previously mentioned performance degradation is negligible for the studied problem, since auctions are not performed more often than once a day.

V. Conclusion

A framework for supporting distributed auction mechanisms in smart-grid environment, was introduced and implemented as part of a low-cost embedded device. By enabling energy producers to initiate auctions ad-hoc, the introduced solution leads to considerable energy cost reduction. Experimental results based on public available data for energy prices and weather conditions highlight the superiority of the proposed solution, as we achieve on average 87% energy savings. Finally, the hardware prototype of the proposed framework onto a low-cost embedded device proves equilibrium can be derived without any meaningful degradation in terms of performance and quality.

VI. Acknowledgment

This research has been co-financed by the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH-CREATE-INNOVATE (project code: T1EDK-01679).

References

[1] Public weather data. https://energyplus.net/weather. Online; accessed 15 June 2018.

[2] Muhammad Raisul Alam, Marc St-Hilaire, and Thomas Kunz. An optimal p2p energy trading model for smart homes in the smart grid. *Energy Efficiency*, 10(6):1475–1493, Dec 2017.

[3] Robert Butler Wilson and Hung-po Chao. Multi-dimensional procurement auctions for power reserves: Robust incentive-compatible scoring and settlement rules. 22:161–83, 02 2002.

[4] D. Crawley, L. Lawrie, F. Winkelmann, W. Buhl, Y. Huang, C. Pedersen, R. Strand, R. Liesen, D. Fisher, M. Witte, and J. Glazer. Energyplus: creating a new-generation building energy simulation program. *Energy and Buildings*, 33(4):319 – 331, 2001.

[5] P. Danassis, K. Siozios, C. Korkas, D. Soudris, and E. Kosmatopoulos. A low-complexity control mechanism targeting smart thermostats. *Energy and Buildings*, 139:340 – 350, 2017.

[6] U. S Department of Energy. Energyplus energy simulation software. http://apps1.eere.energy.gov/buildings/energyplus/, 2015.

[7] C. Wan *et.al.* Photovoltaic and solar power forecasting for smart grid energy management. *CSEE Journal of Power and Energy Systems*, 1(4):38–46, Dec 2015.

[8] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei. Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers. *IEEE Transactions on Power Systems*, 32(5):3569–3583, Sept 2017.

[9] T. Liu, X. Tan, B. Sun, Y. Wu, X. Guan, and D. H. K. Tsang. Energy management of cooperative microgrids with p2p energy sharing in distribution networks. In *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 410–415, Nov 2015.

[10] J. M. Morales, A. J. Conejo, and J. PÉrez-Ruiz. Short-term trading for a wind power producer. *IEEE Transactions on Power Systems*, 25(1):554–564, Feb 2010.

[11] Mahdi Motalleb and Reza Ghorbani. Non-cooperative game-theoretic model of demand response aggregator competition for selling stored energy in storage devices. *Applied Energy*, 202:581 – 596, 2017.

[12] John F. Nash. Equilibrium points in n-person games. In *Proceedings of the National Academy of Sciences of the United States of America*, 1950.

[13] Independent Power Transmission Operator. Public energy price data. http://www.admie.gr/nc/en/home/. accessed 15 June 2018.

[14] P. Palensky and D. Dietrich. Demand side management: Demand response, intelligent energy systems, and smart loads. *IEEE Transactions on Industrial Informatics*, 7(3):381–388, Aug 2011.

[15] Hongbo Ren, Qiong Wu, Weijun Gao, and Weisheng Zhou. Optimal operation of a grid-connected hybrid pv/fuel cell/battery energy system for residential applications. *Energy*, 113:702 – 712, 2016.

[16] Y. Wang, W. Saad, Z. Han, H. V. Poor, and T. Basar. A game-theoretic approach to energy trading in the smart grid. *IEEE Transactions on Smart Grid*, 5(3):1439–1450, May 2014.

[17] Chenghua Zhang, Jianzhong Wu, Yue Zhou, Meng Cheng, and Chao Long. Peer-to-peer energy trading in a microgrid. *Applied Energy*, 220:1 – 12, 2018.