Coordinated Neighborhood Energy Sharing Using Game Theory and Multi-Agent Systems

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***Abstract*—In this paper, a decentralized control algorithm is presented for coordinated energy sharing among smart homes in neighborhood areas using a game-theoretic approach and a multi-agent system (MAS). The aim of the study is to reduce the electricity bill of end-users with dynamic pricing where price is associated to aggregated consumption. To reduce the cost of consumption, a control algorithm performs home appliance scheduling and battery control while enabling energy sharing among neighbors in the neighborhood. We assume that photo-voltaic (PV) and battery systems are installed in smart homes and end-users are decision-makers willing to optimize the run time of electricity appliances and the control inputs of the battery. In particular, end-users aim to schedule controllable appliances and/or decide about battery charging during low price hours and discharging during high price hours. The battery can be charged by three strategies: using local PV generation, from neighborhood residual generation and grid energy jointly or distinctly. In this study, a MAS is used for modeling entities (homes and aggregator) in the neighborhood as agents. The aggregator agent is the supervisor agent which determines the aggregated profile and dynamic price by communicating with home agents. Home agents are independent and selfish decision-makers which only focus on the maximization of their own welfare while achieving near-optimal performance at Nash equilibrium of a formulated non-cooperative coordination game. Results show that each smart home can benefit from this scheme, compared to a baseline (no control) scenario, as well as reduce the neighborhood total cost and peak load consumption.**

***Index Terms*—load management, game theory, multi-agent system, neighborhood coordination, renewable energy.**

I. Introduction

By enabling the integration of distributed energy resources and advanced metering infrastructure in the residential sector through the smart home concept, end-users are becoming more and more involved in electricity operations and markets. A smart home is a small energy system which can consume, produce and store energy, as well as monitor and control its own electricity profile with efficient and flexible energy management. It can also communicate with other smart homes and/or entities in the smart grid. Thus, users benefit from this active participation by increasing their own welfare (mostly by reducing their electricity bill) while utilities can maintain market operation efficiency without jeopardizing grid reliability.

However, most of the time, uncoordinated energy management can cause undesirable effects (such as rebound peaks) or is not capable of achieving the desired efficiency [1]. To avoid these undesired circumstances, smart home strategies must be coordinated. Therefore, defining a coordination mechanism becomes a necessity during the adjustment of the smart homes electricity profile.

Most of the time, a centralized control method is used for coordination of smart homes where one central entity (utility or aggregator) gathers detailed information from smart homes and takes decisions [2]. In this method, coordination can be satisfied, but it implies high communication and computation requirements. Besides, users generally do not support the idea of having another entity controlling their own appliances. On the other hand, a decentralized control method can be deployed for the coordination of smart homes, and enable smart homes to choose their own strategy. For coordinative energy management, smart homes interact with each other and/or a central entity with frequent data exchange. Hence, they take into account the effect of other players' strategies while optimizing their own electricity profile.

In this regard, this paper focuses on the coordination mechanism and uses a game theoretic approach in the neighborhood, by establishing a decentralized control algorithm for smart homes. Game theory is a well-known decentralized decision-making process which is employed in various studies for smart home coordination. In [3], a consumption scheduling game is proposed where users shift their controllable appliances according to electricity price using integer linear programming and announce their profiles to each other. In [4], users interact with both the utility (for price) and other users (for profiles) while participating into a consumption game. In [5], three coordination models are presented for the consumption game. Although models are designed differently according to central unit necessity and profile update frequency, they all use a similar game formulation. There are also other game theoretic studies which focus on consumption games [6], [7], but do not consider generation or storage resources. In [9], differently, a dynamic game is used for efficient energy management in neighborhoods with smart homes having PV and community energy storage (CES). Smart homes sell and buy energy from the CES or the grid according to the announced price. On the contrary, a battery charging game is formulated in [8]. Users try to charge their batteries with the residual grid power left after local loads have been supplied. After that, the battery energy is used for self-consumption in smart homes. However, none of these studies consider advanced battery control which can charge from different sources (self-generated energy, neighborhood generation, and grid) and share energy with neighbors using a game theoretic approach.

In this paper, we develop a day-ahead decentralized control algorithm for neighborhood areas formed by multiple smart homes and one aggregator, all modeled as agents. An agent is an autonomous entity which reacts to environmental changes and interacts with other agents to cooperate or to compete for achieving its predefined objectives. Smart homes are the owners of the PV and battery, and are able to control the charge/discharge of their batteries with different sources. Home agents are the controllers of the smart homes, and can optimize their electricity profile according to a dynamic price with a genetic algorithm (GA) for reducing their electricity bill. The aggregator agent is the supervisor in the neighborhood area, and determines the aggregated electricity profile and dynamic price. We assume that home agents do not communicate with each other due to privacy concerns.

The remainder of this paper is organized as follows. In Section II, the system model and dynamic pricing model are described. In Section III, the baseline scenario is presented. In Section IV, the optimization problem is formulated. In Section V, the deployed coordination mechanism and non-cooperative game with Nash equilibrium are presented. Simulation results are given and the next steps are defined in Section VI. Finally, in Section VII, the paper is concluded.

II. System Model

A. Power System

The neighborhood electricity network is formed by one aggregator and a set $\mathbb{N}$ of smart homes with $\mathcal{N}$ the number of users ($\mathbb{N} = \{1, 2, i, ..., \mathcal{N}\}$). Each home is connected to not only the electricity network, but also a communication network through smart meters which provides bi-directional data exchange. Smart homes are controlled by the home agents and are equipped with electricity appliances, PV panels and batteries. Three types of smart homes are described according to their ownership of the resources: PV & battery, PV only, and no PV or battery.

1) Consumption Model: In the smart home, appliances are divided into two groups: must-run and shiftable appliances. In total, 13 types of appliances are modeled, among which 10 are must-run, and 3 are shiftable (washing machine, clothes dryer, dishwasher). Must-run appliances are not allowed to be controlled. On the other hand, shiftable appliances can be controlled by the home agent by altering the operation start time of the appliance and after they are started, they cannot be stopped until their operation cycle is over.

Let $\mathbb{T} = \{1, 2, t, ...\mathcal{T}\}$ the time index and $\triangle t$ the time interval between two time steps. We model the electricity profiles with a 1-minute time interval so every t represents a minute in the day. Hence $\triangle t$ is $1/60$. The set of each appliance is given by $\mathbb{A} = \{1, 2, a, ...\mathcal{A}_i\}$ and demand power is denoted by $P^d_{a,i}$. The consumption profile of the smart home is then given as:

$$\begin{gathered} P^c_{a,i}(t) = \begin{Bmatrix} P^d_{a,i} & : t \in [\alpha^s_a, \alpha^e_a] \\ 0 & : t \notin \mathbb{T} - [\alpha^s_{a,i}, \alpha^e_{a,i}] \end{Bmatrix} \\ P^l_i(t) = \sum_{a=1}^{\mathcal{A}_i} P^c_{a,i}(t), \qquad \forall t \in \mathbb{T} \end{gathered} \tag{1}$$

where $P^c_{a,i}(t)$ is the appliance consumption power, $P^l_i(t)$ is the total consumption power of the smart home, $\alpha^s_{a,i}$ and $\alpha^e_{a,i}$ are the operation start time and end time of the appliances, respectively.

2) Generation Model: Some users are assumed to have installed PV panels on their roof for renewable energy generation. On these smart homes, the generated power $P^g_i(t)$ is calculated by:

$$P^g_i(t) = N^s_i \cdot N^p_i \cdot P^{pv}_i \cdot (G(t)/G_{STC}), \quad \forall t \in \mathbb{T} \tag{2}$$

where N^s_i and N^p_i are the number of modules connected in series and parallel, respectively. P^{pv}_i is the rated power of a PV module in standard test conditions (STC), $G(t)$ is the irradiance value at t, and G_{STC} is the irradiance value (1000 W/m^2) in STC.

3) Storage Model: Batteries are the most commonly used type of storage device in smart homes, and enable saving surplus power generated by the PV system, for use at a later in time. In this study, we also assume that batteries can be charged during low price hours (i.e., when the electricity price is low) for consumption (discharge) during high price hours for economic self-consumption.

The batteries of the users are modeled by the following variables: charging/discharging efficiency (μ^c_i, μ^d_i), maximum charging/discharging power (ρ^c_i, ρ^d_i) and max./min. state-of-charge (SOC) levels (SOC^{max}_i, SOC^{min}_i). The constraints of the battery are given by:

$$\begin{gathered} \rho^d_i / \mu^d_i \leq P^b_i(t) \leq \rho^c_i \cdot \mu^c_i \\ SOC^{min}_i \leq SOC_i(t) \leq SOC^{max}_i \end{gathered} \tag{3}$$

where $P^b_i(t)$ is the battery power and $SOC_i(t)$ is the SOC level of the smart home battery.

B. Electricity Price

We use a dynamic price model associated with two quantities: an aggregated electricity profile $\mathbf{P_n}(t)$ of the neighborhood area, and a time-of-use (TOU) price. To model the dynamic fluctuations which occur based on $\mathbf{P_n}(t)$ in the neighborhood price, a cost function $q(t)$ is defined as:

$$q(t, \mathbf{P_n}(t)) = a(t) \cdot |\mathbf{P_n}(t)|^2 + b(t) \cdot |\mathbf{P_n}(t)| + c(t) \tag{4}$$

where $a(t)$, $b(t)$ and $c(t)$ are positive time dependent parameters. After that, the dynamic function is combined with the TOU price $d(t)$ to model the neighborhood price $\lambda(t, \mathbf{P_n}(t))$ with:

$$\lambda(t, \mathbf{P_n}(t)) = \begin{Bmatrix} d(t) + q(t, \mathbf{P_n}(t)) & : \mathbf{P_n}(t) > 0 \\ d(t) - q(t, \mathbf{P_n}(t)) & : \mathbf{P_n}(t) \leq 0 \end{Bmatrix} \tag{5}$$

By this model, users are not only influenced by $\mathbf{P_n}(t)$, but also by the TOU structure determined at the upper level of the neighborhood. Moreover, price function (5) is used for both consuming and selling energy (reverse power flow) inside (to neighbors) and outside (to the main grid) the neighborhood.

III. Baseline Scenario

We modeled the baseline scenario in which there is no communication and autonomous control opportunity for efficient and economic utilization of home resources. In all smart homes, whenever a home appliance is turned on by the user, the appliance starts to consume electric power with no scheduling. In smart homes with PV, users can only use the generated power if they run their appliances manually during sunny hours. Otherwise, the generated energy is fed back to the main grid, probably, during the low price hours due to high renewable generation. Lastly, in smart homes with PV and a battery, charge/discharge operations are performed instantly based on home consumption and generation power rate. Hence there is no opportunity for the battery to charge from the grid. According to our assumptions, battery power is determined considering constraints in (3) by:

$$P_i^b(t) = \begin{Bmatrix} (P_i^l(t) - P_i^g(t)) \cdot \mu_i^c & : P_i^l(t) - P_i^g(t) > 0 \\ (P_i^l(t) - P_i^g(t))/\mu_i^d & : P_i^l(t) - P_i^g(t) \leq 0 \end{Bmatrix} \tag{6}$$

Then, the daily electricity bill $\mathcal{C}_i$ of each user $\forall i \in \mathbb{N}$ is calculated by determining the home and neighborhood net electricity profiles $P_i^n(t)$ with:

$$\begin{gathered} P_i^n(t) = P_i^l(t) - P_i^g(t) + P_i^b(t) \\ \mathbf{P_n}(t) = \sum_{i=1}^{\mathcal{N}} P_i^n(t) \end{gathered} \tag{7}$$

$$C_i = \sum_{t=1}^{\mathcal{T}} P_i^n(t) \cdot \lambda(t, \mathbf{P_n}(t)) \cdot \triangle t \tag{8}$$

IV. Problem Formulation

In this section, the day-ahead optimization problem used by home agents to minimize the electricity bill of users in scheduling window $[0, \mathcal{T}]$ is formulated. Based on $\lambda(t, \mathbf{P_n}(t))$, while home agents schedule controllable appliances for use during low price hours, they also control their batteries to charge during low price hours and to discharge during high price hours.

Firstly, for the control of the shiftable appliances, the control interval $[\beta_a^s,\, \beta_a^e]$ is defined by the user. The home agent aims to run the appliance at the most beneficial time by altering the operation time $[\alpha_a^s, \alpha_a^e]$ in $[\beta_a^s,\, \beta_a^e]$ as given below:

$$[\alpha_a^s, \alpha_a^e] \in [\beta_a^s, \beta_a^e] \tag{9}$$

Secondly, there can be some appliances for which the operation time depends on other appliances, such as the washing machine and the clothes dryer. Logically, a clothes dryer is expected to run after a washing machine finishes its operation. Therefore, the constraint for the control of these appliances is added to the optimization and formulated as:

$$\alpha_{wm}^e < \alpha_{cd}^e + (\alpha_{wm}^e - \alpha_{wm}^s) \tag{10}$$

$$\beta_{wm}^e < \beta_{cd}^e + (\alpha_{wm}^e - \alpha_{wm}^s) \tag{11}$$

where wm and cd indices refer to washing machine and clothes dryer for each variable, respectively.

Lastly, the home agent determines the battery power $P_n^b(t)$ for efficient battery control using the aggregated profile $\mathbf{P_n}(t)$ beside $\lambda(t, \mathbf{P_n}(t))$. The reason is that we assume that the home agent is allowed to discharge the battery for its own and/or neighbors consumption, but battery energy cannot be fed back to the grid by discharging (as per our assumptions). Therefore, the maximum allowed amount of energy which can be shared is $\mathbf{P_n}(t)$ through home battery discharge.

As mentioned before, we used 1-minute time resolution for modeling electricity profiles in the scheduling window $[0, \mathcal{T}]$. Therefore, to optimize the battery management, we would need to use a control index for every minute in this interval, i.e., $\mathcal{T}$ (1440 inputs) for a day-long optimization, which would cause a heavy computation burden. To ease the optimization process, a battery control interval $\mathcal{Z}$ (equal to 30 minutes) is defined to reduce the number of inputs from $\mathcal{T}$ to $\mathcal{T}/\mathcal{Z}$ (48 inputs). After that, the battery is controlled by three logical inputs $\delta_i(z) \in \{0, 2\}$ as:

$$R_i(t) = \mathbf{P_n}(t) - P_i^n(t) \tag{12}$$

$$P_i^b(t) = \begin{Bmatrix} \textbf{f.charge} \cdot \mu_i^c & : \delta_i(z) = 0 \\ \textbf{p.charge} \cdot \mu_i^c & : \delta_i(z) = 1, P_i^g(t) > P_i^l(t) + R_i(t) \\ \textbf{n.charge} \cdot \mu_i^c & : \delta_i(z) = 2, P_i^g(t) > P_i^l(t) + R_i(t) \\ \textbf{idle} & : \delta_i(z) = 2, P_i^g(t) > 0, P_i^g(t) \leq P_i^l(t) + R_i(t) \\ \textbf{discharge}/\mu_i^d & : \delta_i(z) = 2, P_i^g(t) = 0, P_i^l(t) + R_i(t) > 0 \end{Bmatrix} \tag{13}$$

where $R_i(t)$ is the aggregated perspective profile which is the aggregated electricity profile of the neighborhood except user i. **f.charge** is full charging with $(P_i^g(t){+}P_i^u(t))$ ($P_i^u(t)$ is the grid power), **p.charge** is partial charging with just $P^g(t)$, **n.charge** is normal charging with $(P^g(t){-}P_i^l(t){-}R_i(t))$, **idle** means nothing happens, and **discharge** is discharging with $(P_i^l(t) + R_i(t))$. It is can bee seen that the battery is only discharged when $\delta_i(z) = 2$. Otherwise, the battery is charged in the most beneficial way by selecting $\delta_i(z) \in \{0, 2\}$, based on the electricity profiles $P_i^g(t), P_i^l(t)$ and $R_i(t)$. Moreover, (13) is adaptable to chargeable/dischargeable situations during the same control interval $\mathcal{Z}$. For instance, when a home agent decides $\delta_i(z) = 2$, a battery may shift between three decisions during $[t_0,\, t_0 + \mathcal{Z}]$. It means that it can shift decision from **discharge** to **idle** or **n.charge** with the change of profile comparison. It will thus be more flexible during $\mathcal{Z}$ minutes. After that, the home agent determines the shared power by the battery discharge $P_i^s(t)$ when the control index is chosen as $\delta_i(z) = 2$ with the **discharge** command.

$$P_i^s(t) = P_i^b(t) - P_i^l(t) \tag{14}$$

where $P_i^s(t)$ is the provided energy by battery discharge to the neighborhood which is left after user consumption. Finally, the home agent calculates the home net electricity profile and optimizes the following objective function:

$$P_i^n(t) = P_i^l(t) - P_i^g(t) + P_i^b(t) + P_i^s(t) \tag{15}$$

$$
\begin{aligned}
\min \quad & \left(\mathcal{C}_i = \sum_{t=1}^{\mathcal{T}} P_i^n(t) \cdot \lambda(t, \mathbf{P_n}(t)) \right) \\
\text{s.t.} \quad & \text{eqs. } (3), (9), (10), (11)
\end{aligned} \tag{16}
$$

When solving the optimization problem, the home agent aims to use and sell energy during the high price hours, and to charge with self-generation (from PV, with no cost) or low price neighborhood/grid power. It should be noted that we do not need to separate neighborhood generation from grid power. The reason is that if there is a residual neighborhood generation, $d(t)$ will decrease associated to residual power, as given in (5). Therefore, while home agents try to charge their batteries with low price, they use residual neighborhood generation during these hours.

V. Game Theoretic Coordination

In the decentralized coordination model, the objective function is solved by the home agents repeatedly until the schedules of the smart homes are coordinated. The deployed coordination mechanism is presented in two sections: communication structure (details about the exchanged data), and game theory (non-cooperative game with Nash equilibrium).

A. Communication Structure

Based on solving the above formulation, the diagram for the coordination model is given in Fig. 1. Firstly, home agents initialize the data to send to the aggregator, as ($P_i^n(t) = P_i^l(t)$, $P_i^s(t) = 0$). After that, the aggregator agent determines the initial aggregated neighborhood profiles and electricity price and sends them to the home agents. While home agents are optimizing their electricity bill, they first calculate $R_i(t)$ and use $\lambda(t, \mathbf{P_n}(t))$ for optimization. Then, they determine the new ($P_i^n(t)$, $P_i^s(t)$) to inform the aggregator agent about the changes that they made in their electricity profiles.

However, it should be noted that users may not want to share exact information with the aggregator due to privacy concerns. They send average data calculated for each interval $\mathcal{K}$ of scheduling length $\mathcal{T}$. The informed data for each profile is converted to $P_i^n(t) \rightarrow \hat{P}_i^n(k)$ for the net power profile and to $P_i^s(t) \rightarrow \hat{P}_i^s(k)$ for the shared power profile by the battery discharge, as a $[1 \times \mathcal{T}] \rightarrow [1 \times (\mathcal{T}/\mathcal{K})]$ matrix. The aggregator agent determines the aggregated profile $\hat{\mathbf{P}}_\mathbf{n}(k)$ in (k-space) with a new electricity price $\hat{\lambda}(k, \hat{\mathbf{P}}_\mathbf{n}(k))$ using (4) and (5), and then sends them to the home agents. When home agents receive them, they first calculate $\hat{R}_i(k)$ and convert data to t-space ($\hat{R}_i(k) \rightarrow R_i(t)$, $\hat{\lambda}(k, \hat{\mathbf{P}}_\mathbf{n}(k)) \rightarrow \lambda(t, \hat{\mathbf{P}}_\mathbf{n}(t))$) and run the optimization. The process continues until convergence is reached with a Nash equilibrium, as defined in Section V-B.

After the system has converged, the final decisions of the home agents need to be modified to eliminate mismatches between communicated data (k-space) and actual data (t-space). The reason is that home agents are not aware of the actual profile while they are optimizing, thus mismatches occur between the actual data (t-space) and the communicated data (k-space). To eliminate these mismatches, the aggregator applies *proportional source matching* according to the principle introduced in [10], when $\mathbf{P_n}(t) < \mathbf{P_s}(t)$ as:

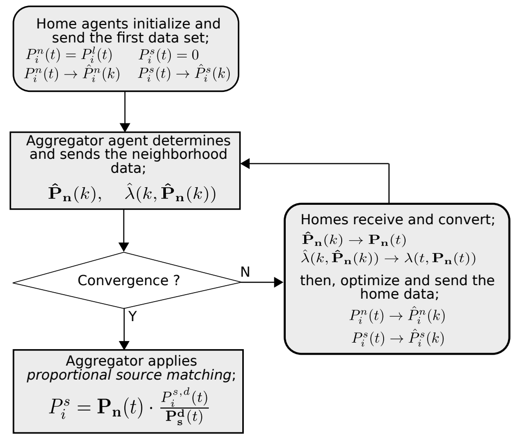

Fig. 1. Flow chart of decentralized coordination.

$$
P_i^s(t) = \mathbf{P_n}(t) \cdot \frac{P_i^{s,d}(t)}{\mathbf{P_s^d}(t)} \tag{17}
$$

where $P_i^{s,d}(t)$ is the last selling decision of a home agent and $\mathbf{P_s^d}(t)$ is the last aggregated selling profile according to a home agent decision. According to (17), the final shared power profile by battery discharge is determined based on the ratio between the aggregated final sharing decision and the final home sharing decision.

B. Nash Equilibrium Game

We consider a non-cooperative game $\mathcal{G}$ where each player aims to maximize its own payoff function in each turn by choosing the best strategy. The definition of the deployed game $\mathcal{G} = [\mathbb{N}, \{\mathbf{c_i}, \mathbf{b_i}\}, U_i]$ is as follows:

1) *Players*: each user $i \in \mathbb{N}$ in the neighborhood area.
2) *Strategies*: the determined electricity profiles $\{\mathbf{c_i}, \mathbf{b_i}\}$ of each user $i \in \mathbb{N}$.

$$
\begin{aligned}
\mathbf{c_i} &= [P_i^n(1), P_i^n(2), P_i^n(t), ..., P_i^n(\mathcal{T})] \\
\mathbf{b_i} &= [P_i^s(1), P_i^s(2), P_i^s(t), ..., P_i^s(\mathcal{T})]
\end{aligned} \tag{18}
$$

where c_i and b_i are the set of net electricity and shared power profiles with battery discharge, respectively.

3) *Payoffs*: $U_i(\{\mathbf{c_i}, \mathbf{b_i}\}; \{\mathbf{c_{-i}}, \mathbf{b_{-i}}\})$ for each user $i \in \mathcal{N}$ from (16) is given as:

$$
\begin{aligned}
U_i(\{\mathbf{c_i}, \mathbf{b_i}\}; \{\mathbf{c_{-i}}, \mathbf{b_{-i}}\}) &= -C_i \\
&= -\sum_{t=1}^{\mathcal{T}} P_i^n(t) \cdot \lambda(t, \mathbf{P_n}(t))
\end{aligned} \tag{19}
$$

where $\{\mathbf{c_{-i}}, \mathbf{b_{-i}}\}$ is the strategies of all users except i for net and shared power (with battery discharge) profiles.

Definition 1: The Nash equilibrium is a solution concept which represents a state where no player can improve its payoff by altering its strategy:

$$
U_i(\{\mathbf{c_i^*}, \mathbf{b_i^*}\}; \{\mathbf{c_{-i}^*}, \mathbf{b_{-i}^*}\}) \geq U_i(\{\mathbf{c_i}, \mathbf{b_i}\}; \{\mathbf{c_{-i}^*}, \mathbf{b_{-i}^*}\}) \tag{20}
$$

where * indicates the strategy of each type of variable at the Nash equilibrium state.

Theorem 1: The Nash equilibrium of the defined game $\mathcal{G} = [\mathbb{N}, \{\mathbf{c_i}, \mathbf{b_i}\}, U_i]$ exists.

Proof 1: $C_i(t)$ is convex for each t, and the payoff $U_i(\{\mathbf{c_i}, \mathbf{b_i}\}; \{\mathbf{c_{-i}}, \mathbf{b_{-i}}\})$ is a concave function with respect to $\{\mathbf{c_i}, \mathbf{b_i}\}$. Hence, the Nash Equilibrium exists, referring to [11].

VI. Simulation Results

In this section, a simulation is performed to determine the results of the coordination algorithm for a neighborhood area. We assume that the neighborhood is formed by $\mathcal{N} = 20$ smart homes, with5 with PV and a battery, 5 with just PV and 10 with none. The day is divided into $\mathcal{T} = 1440$ intervals. Communication data is determined with the average of every $\mathcal{K} = 30$ minutes and the battery control interval is the same ($\mathcal{Z} = 30$). For $d(t)$, the approximate French regulated TOU tariff is used where $d(t) = 0.1270$ €/kWh during the 01:30-07:00 and 12:00-14:30 periods, and $d(t) = 0.1560$ €/kWh during 07:00-12:00, 14:30-01:30 periods. The variables of (4) are assumed constant and arbitrarily decided as $a(t) = 2 \times 10^{-5}$, $b(t) = 15 \times 10^{-5}$, and $c(t) = 0$.

To evaluate the performance of the proposed algorithm, we use the JAVA Agent DEvelopment Framework (JADE) for modeling neighborhood agents and MATLAB for the *ga* optimization and numerical calculations. For the data exchange between JADE and MATLAB, TCP/IP ports are used by assigning a different port number to each agent. Lastly, simulations are obtained on a desktop computer with an Intel Core i7-3770 CPU @ 3.4 GHz, 7.8 GB RAM and a 64-bit Ubuntu 14.04 LTS operating system.

A. Performance Evaluation

The performance of the coordination algorithm is evaluated by comparing the proposed approach with the baseline scenario. In the neighborhood, the size of the PV and battery systems are selected in the range of 0.75-4 kW and 5-15 kWh, respectively. The cost results of the smart homes are given in Table I for a one day simulation. Compared to the baseline case, each smart home is able to achieve some cost reduction after participating into the coordination game in the neighborhood. The amount of reduction changes based on the ownership of resources (PV, battery) and the defined appliance scheduling interval set by the users. Therefore, the gained benefit is different for each smart home. For example, although home 19 does not have any resources and controllable appliances, it gains some profit due to the changing neighborhood profile thanks to its neighbors. As a result, the neighborhood area cost is decreased by $7.91\,\%$ with the participation of the players.

Fig. 2(a) depicts the electricity profiles output of smart home 01 for both baseline and coordination models together with the home consumption and generation profiles. In the baseline model, generated PV energy is only utilized for self-consumption by basic battery charging/discharging, thus the home never needs to use energy from the grid. However, with the coordination algorithm, the home agent charges the battery with grid energy rather than by using home PV generation, especially in the early morning. The reason is the home agent uses the most preferable time for charing the battery to earn more economic benefit, hence the home agent uses the advantage of high FIT price and sells the residual PV generation (before 12:00) and charges from the grid during

TABLE I
Daily electricity cost of smart homes.

Homes	Cost of Smart Homes Baseline	Cost of Smart Homes Coordinated	Homes	Cost of Smart Homes Baseline	Cost of Smart Homes Coordinated
$H01^{**}_{++-}$	-1.03 €	-1.32 €	$H11_{++-}$	2.93 €	2.82 €
$H02^{**}_{+-+}$	-1.08 €	-1.23 €	$H12_{+-+}$	2.43 €	2.35 €
$H03^{**}_{+-+}$	-0.76 €	-0.87 €	$H13_{+-+}$	3.10 €	3.02 €
$H04^{**}_{+-+}$	0.64 €	0.48 €	$H14_{--+}$	3.15 €	3.06 €
$H05^{**}_{---}$	-1.68 €	-2.47 €	$H15_{+-+}$	2.62 €	2.55 €
$H06^{*}_{+-+}$	1.81 €	1.77 €	$H16_{+--}$	3.38 €	3.31 €
$H07^{*}_{+--}$	2.13 €	2.08 €	$H17_{+-+}$	3.03 €	2.90 €
$H08^{*}_{+-+}$	1.16 €	1.11 €	$H18_{+++}$	3.11 €	2.97 €
$H09^{*}_{--+}$	1.71 €	1.64 €	$H19_{---}$	2.46 €	2.42 €
$H10^{*}_{+-+}$	1.24 €	1.19 €	$H20_{+--}$	2.29 €	2.24 €
Neighborhood cost: *Baseline* 32.62 €, *Coordinated* 30.04 €					

*** indicates a home with PV and battery, * indicates a home with PV*
+,- indicate the existence and non-existence of a controllable appliance. (1st washing machine, 2nd clothes dryer, 3rd dish washer)

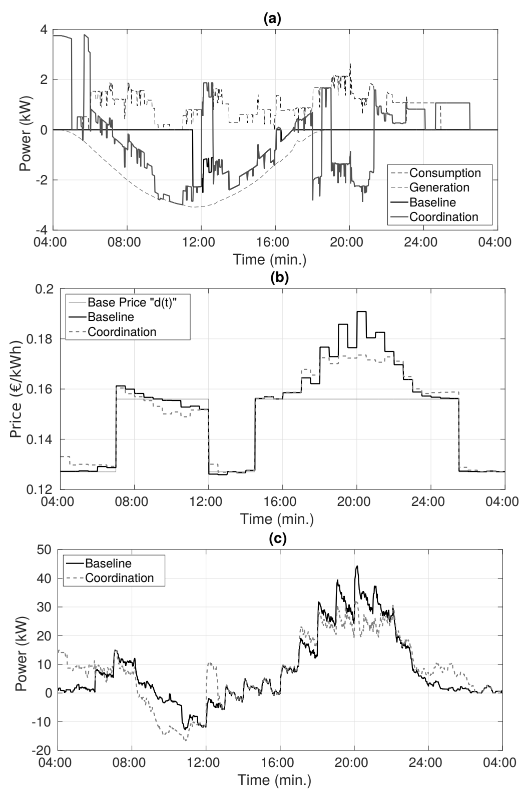

Fig. 2. Determined home and neighborhood profiles with dynamic price. (a) Electricity profiles of smart home 10, (b) baseline and coordinated case neighborhood electricity prices, (c) neighborhood baseline and coordinated case electricity profiles.

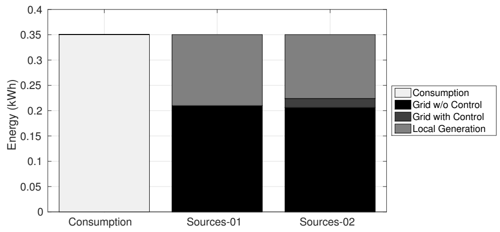

Fig. 3. Neighborhood energy analysis. (Source-01: simulation results of baseline scenario, Source-02: simulation results of coordination algorithm)

low price hours (early morning and/or right after 12:00). Based on this, the neighborhood price is given in Fig. 2(b), and is determined according to the aggregated profile of the area shown in Fig. 2(c). According to Fig. 2(c), the proposed coordination method with energy sharing by battery discharge is able to achieve $26.81\,\%$ peak reduction.

In Fig. 3, we analyze the energy sources used for providing electricity to the aggregated consumption of the neighborhood. The total energy demand of the 20 smart homes (0.35 MWh) is supplied by the three source types; *i) Grid w/o Control*: energy is supplied by the grid and consumed at the same time; *ii) Grid with Control*: energy is supplied by the grid but consumed at a different time; and *iii) Local Generation*: energy is supplied by the neighborhood resources. For the baseline scenario, energy is directly provided from the grid (0.21 MWh) when there is no self-consumption (0.10 MWh) option from PV or battery in smart homes, and/or uncoordinated sharing (0.04 MWh) (where users consume from neighbors surplus PV generation by using their appliances at high generation hours by chance). On the other hand, multiple options (energy sources) are used by the proposed algorithm with the control and sharing ability. Firstly, batteries in smart home can charge from the grid when the electricity price is low and discharge for own or neighbors consumption during high price hours as referred by *Grid with Control* (0.02 MWh) in Fig. 3. Secondly, the energy generated by the neighborhood sources can be used more efficiently for self-consumption in the smart home and/or energy sharing with neighbors (0.12 MWh). By this way, home agents aim to provide energy directly from the grid (0.21 MWh) only for the low price hours, with and without altering their appliances operation. It can be seen that although the amount of energy supplied by the grid (*Grid with and w/o Control*) for consumption is higher by 0.02 MWh in the coordinated scenario due to charging the battery from the grid, a cost and peak reduction are achieved, compared to the baseline scenario by taking advantage of the control algorithm. Therefore it should be noted that the energy fed back to the grid is higher by 0.02 MWh in the coordinated scenario.

B. Next Steps

This study does not consider distribution system constraints, such as line and transformer capacity, and the interactions between the distribution system operator, the utility and the aggregator. A coordination of aggregators at the upper level of the neighborhood where multiple neighborhoods and distributed energy sources are connected to the same distribution grid can also provide more efficient and economical energy management. Another aspect is that the forecasting errors are not considered for consumption and generation profiles. However, the strategy to handle mistmatches between actual and communication profiles described earlier could be extended to account for larger errors. Therefore, we aim to extend our study by improving our coordination algorithm by considering grid constraints, investigating the mitigation of forecasting errors (in consumption and generation profiles), considering the coordination of several aggregators, and investigate the payback time for investments in PV and battery.

VII. Conclusion

This paper has presented a decentralized coordination mechanism that uses non-cooperative a game-theoretic approach and MAS in a neighborhood area. The proposed coordination model aims to reduce the electricity bill of the users by deploying a dynamic pricing determined according to a base structure and the aggregated electricity profile of neighborhood. Results showed that the presented method is able to reduce electricity bills of all types of smart homes, as well as the aggregated peak consumption of the neighborhood.

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