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Chis, Adriana; Koivunen, Visa

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Coalitional game based cost optimization of energy portfolio in smart grid communities

Adriana Chiş, *Student Member, IEEE*, and Visa Koivunen, *Fellow, IEEE*

Abstract—In this paper we propose two novel coalitional game theory based optimization methods for minimizing the cost of electricity consumed by households from a smart community. Some households in the community may own renewable energy sources (RESs) conjoined with energy storage systems (ESSs). Some other residences own ESSs only, while the remaining households are simple energy consumers. We first propose a coalitional cost optimization method in which RESs and ESSs owners exchange energy and share their renewable energy and storage spaces. We show that by participating in the proposed game these households may considerably reduce their costs in comparison to performing individual cost optimization. We further propose another coalitional optimization model in which RESs and ESSs owning households not only share their resources, but also sell energy to simple energy consuming households. We show that through this energy trade the RESs and ESSs owners can further reduce their costs, while the simple energy consumers also gain cost savings. The cost savings obtained by the coalition are distributed among its members according to the Shapley value. Simulation examples show that the proposed coalitional optimization methods may reduce the electricity costs for the RESs and ESSs owning households by 18%, while the sole energy consumers may reduce their costs by 3%.

Index Terms—Coalitional game, demand side management, smart households, renewable energy, energy storage, cost reduction.

NOMENCLATURE

Abbreviations

DSM	Demand side management
ESS	Energy storage system
RES	Renewable energy source

Sets, cardinalities and indices

\mathcal{T}, T, t	Optimization period, number of time-slots, and their index
\mathcal{N}, N, n	Households in the community, their number, and index
\mathcal{M}, M, m	Households owning RESs and/or ESSs (grand coalition), their number, and index
\mathcal{P}, P, p	Sole energy consuming households, their number, and index
\mathcal{G}, G, g	Households forming a coalition, their number, and index

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The authors are with the Department of Signal Processing and Acoustics, Aalto University, FI-02150 Espoo, Finland (e-mail: adriana.chis@aalto.fi, visa.koivunen@aalto.fi)

Parameters

C_m	Storage capacity of ESS_m
η_m	Leakage factor of ESS_m per time-slot
ρ_m	Charging/discharging rate of ESS_m per time-slot
$u_{n,m,p}(t)$	Electricity demand of household n, m, p in time-slot t
$w_m(t)$	Renewable energy production of household m in time-slot t
$\xi(t)$	Wholesale market price per unit of electricity in time-slot t
$\lambda(t)$	Price per unit of electricity sold by households \mathcal{M} to households \mathcal{P} in time-slot t
α	Proportion of $\lambda(t)$ versus $\xi(t)$
π	Storage degradation price per unit of energy charged/discharged from ESS_m
σ	Penalty price incurred per unit of excess renewable energy not stored
τ	Price incurred by household n, m, p for transferring/receiving one unit of electricity
$C_{n,m,p}^{\text{grid}}$	Cost incurred by household n, m, p for energy bought from utility company in period \mathcal{T}
C_m^{storage}	Cost incurred by household m for storage degradation in period \mathcal{T}
$C_{m,p}^{\text{operation}}$	Cost incurred by household m, p for energy transfer operations in period \mathcal{T}
C_p^{purchase}	Cost incurred by household p for energy bought from the households \mathcal{M} in period \mathcal{T}
$c_{m,g}^{\text{indiv}}$	Cost incurred by household m, g in period \mathcal{T} if (\mathbf{P}_I) is performed
c_p^{indiv}	Cost incurred by household p in period \mathcal{T} if (\mathbf{P}_{III}) is performed
$c_{\mathcal{M}}^{\text{ResEss}}$	Aggregate cost incurred by households \mathcal{M} in period \mathcal{T} if (\mathbf{P}_{II}) is performed
$c_{\mathcal{M}}^{\text{community}}$	Aggregate cost incurred by households \mathcal{M} in period \mathcal{T} if (\mathbf{P}_{III}) is performed
$v(\mathcal{M})$	Worth of coalition \mathcal{M}
$v(\mathcal{M})^{\text{ResEss}}$	Worth of coalition \mathcal{M} if (\mathbf{P}_{II}) is performed
$v(\mathcal{M})^{\text{community}}$	Worth of coalition \mathcal{M} if (\mathbf{P}_{III}) is performed
$\Phi(v)$	Shapley value
$\Phi_m(v)$	Payoff assigned to a player m by Shapley value

Variables

$r_m(t)$	Amount of energy charged/discharged to/from ESS_m in time-slot t
$s_m(t)$	Total amount of energy stored in ESS_m in time-slot t

$a_{n,m,p}(t)$ Amount of energy exchanged by household n, m, p with other households in time-slot t
 $b_{n,m,p}(t)$ Amount of energy bought by household n, m, p from utility company in time-slot t

I. INTRODUCTION

OPTIMIZATION of energy consumption imposes changes both at the energy supply side and at the energy demand side. One key global challenge existing today is the achievement of sustainable energy production. More and more energy users choose to install renewable energy sources (RESs) which seem to be a sustainable solution for the current environmental problems, but also for other troubling issues existing in the power network today. Installation of RESs at distribution level can result in significant reduction of power transmission losses, lower operational costs and an overall cut of electricity costs.

Energy consumption optimization at the distribution level can also be obtained through demand side management (DSM) methods. DSM refers to the modification of the energy consumption patterns of the end-users with the purpose of lowering costs, reducing load peaks on the grid and increasing grid reliability. Energy storage systems (ESSs) together with a smart metering infrastructure can be an easy and efficient way of implementing such methods without the need of highly modifying the energy consumption patterns of energy consumers such as residential households and business centers.

One major disadvantage of the RESs is the intermittent nature of their energy production, i.e. not providing reliable energy production. ESSs can be used in conjunction with RESs in order to store the surplus of the produced energy, but also for DSM operations. However, installation of ESSs with high capacities can be very costly. One way of addressing these drawbacks of RESs and ESSs is by employing cooperation among RESs and ESSs owners. Cooperation can improve the integration of renewable energy, reduce the need of large ESSs and provide cost savings for the participants in the cooperation.

Different problems involving energy trading and cooperation among microgrids equipped with RESs and ESSs have been studied in [1]–[7]. Methods based on Nash bargaining theory to incentivize the collaboration between microgrids are proposed in [1] and [2]. In [3], off-line and on-line methods for energy sharing among two cooperating microgrids are investigated. Two off-line algorithms are proposed for solving the cooperation problem between the two microgrids under random realisations of the energy profiles. In [4], prospect theory has been proposed to formulate a static game between autonomous microgrids that are trading energy. An approach for cooperative power control in a network of interconnected microgrids is proposed in [5]. A problem for energy trading among islanded microgrids is formulated in [6]. A problem for power management in a network composed of a macrogrid and cooperative minigrids is investigated in [7]. The problem in [7] is decomposed in two-tier control problems: one for power usage optimization in the macrogrid and one for power control in each microgrid.

The problem of sharing an ESS is investigated in [8] and [9]. Multiple RESs owners share a common ESS in [8]. The

work in [8] proposes methods for distributing the ESS space among the RESs owners and for maximizing the individual profit of users. In [9], a concept for energy storage ownership between domestic customers and local network operators is proposed.

Game theoretic methods for energy management in smart grids have been proposed in [10]–[14]. A noncooperative game among storage units has been proposed in [10]. A cooperative game among households is proposed in [11] with the goal of flattening the community’s load. A non-cooperative and a cooperative game among energy users in a grid comprising traditional users, distributed energy generation and storage systems are proposed in [12]. A coalition-formation game is proposed in [13] for microgrids to trade power in order to reduce the load and the power losses over the grid. A coalitional game in which microgrids supply energy to a shared facility controller is proposed in [14].

In this paper we propose two novel coalitional game theory based models for optimizing energy portfolios within a smart grid community by sharing renewable energy and storage resources as well as trading energy among households. We consider a community of households some of which own RESs together with ESSs. Some other households in the community may own ESSs only, whereas the remaining households are simple energy consumers. We assume that the households are equipped with smart energy management meters that can predict with sufficient accuracy their energy demand profiles and the profiles of renewable energy production during a finite time period ahead. The households are connected to a centralized energy control unit that finds solutions to the proposed energy cost optimization problems and controls the flow of energy within the community through a two-way communication system. In case of insufficient renewable or stored energy resources, the electricity demands of the households may be fulfilled with electricity bought from the utility company which offers customers the possibility of buying electricity at wholesale market prices. The main contributions to this paper are described below:

- We formulate three cost optimization problems: 1) A method through which households that own RESs and ESSs can perform demand response and individually optimize their costs using own resources. This method is used as a comparison benchmark for the coalitional optimization methods. 2) A coalitional optimization method in which the RESs and ESSs owners minimize their cumulated costs by exchanging energy and sharing the produced renewable energy and storage spaces. 3) A coalitional optimization method in which the RESs and ESSs owning households minimize their cumulated costs by exchanging energy among themselves, sharing their resources and storage spaces and also selling energy to sole energy consuming households in the community. The sole energy consumers are not participating in the coalitional game. They only act as agents that buy energy from the coalitional group of RESs and ESSs owners at a cheaper price than the one offered by the utility company. The proposed optimization problems are convex and linear and can be easily solved through standard linear programming methods.

- We model the energy resource sharing and trading as a coalitional game among the RESs and ESSs owners. All members of the coalition participate in the game at all times. The cost savings obtained through the proposed coalitional optimization are divided among the coalition members using a method based on Shapley value. Shapley value leads to a fair solution since the payoff earned by each player is calculated based his contribution to the overall obtained savings.
- We perform extended simulations and demonstrate that the proposed collaborative method obtains significant cost savings for the RESs and ESSs owners in comparison to the individual cost optimization problem. We also show that by selling energy to the sole energy consumers at a smaller price than the one offered by the utility company, the RESs and ESSs owners can further reduce their electricity costs. At the same time, the sole energy consumers may also reduce their cost by buying part of their needed energy at a lower price than that of the utility company.

The work proposed in this article differs from the energy cooperation methods for cost minimization existing in the literature [1]–[9]. In this paper, a novel coalitional game theoretic formulation is proposed for cost minimization in a system composed of households owning RESs and ESSs, households owning ESSs only and households which are pure energy consumers. A small local trading market is created. In order to minimize their cost, the RESs and ESSs owners form a coalition in which they may exchange energy, share their storage spaces and also sell energy to the pure consumers at a lower price than that offered by the utility company. The electricity cost is reduced for the RESs and ESSs owners, but also for the pure consumers. The Shapley value method proposed in our work for allocation of the cost savings has a different fairness concept from the Nash bargaining solution proposed in [1], [2]. In [1], [2], the microgrids participate in a cooperative cost minimization problem for energy trading. In the energy trading problem each microgrid obtains an individual cost which could be greater or smaller than the individual costs obtained though the single microgrid, non-cooperative cost minimization problem. In order to adjust these costs and avoid increases in the individual costs of the microgrids, Nash bargaining solution is applied for determining an optimal cost sharing [1], or payments for the energy exchanged by the microgrids [2], respectively. These values are calculated by maximizing the product of individual profits of only those microgrids contributing to the social cost minimization. In our work, all members of the coalition participate in the game at all times. The Shapley value represents an average value of fairness. Shapley value distributes the cost savings among the members of the coalition according to the average marginal contribution of each member to the overall cost savings obtained by the coalition.

The cost minimization problems proposed in this work are different also from the cooperative DSM approach proposed in [12]. In [12] the energy users minimize their aggregate costs by optimizing their dispatchable energy production and storage usage. In this article, the use of storage, the energy amounts exchanged among RESs and ESSs owners, the ones sold to

pure consumers and the energy amounts purchased from the power grid are optimized.

Preliminary results related to this work are presented in [15]. In this paper we extend these results by formulating the coalitional optimization method in which the RESs and ESSs owning residences minimize their costs by exchanging energy and also by selling energy to pure consumers. We also improve the optimization problems by adding costs related to energy storage, energy transfer among households and penalty terms related to storage of excess renewable energy. We perform extensive simulations that demonstrate the performance of the proposed methods.

The performed simulations show that the coalitional game among the RESs and ESSs owning households can obtain a cost reduction of approximately 12% in comparison to individual cost optimization. The introduction of the sole energy consuming households can achieve a further cost reduction of 6% for the RESs and ESSs owners, resulting in a total 18% reduction of their cost. The sole energy consumers can also achieve a cost reduction of about 3% in comparison to buying all needed electricity from the utility company.

The rest of this paper is organized as follows. Section II presents the system model. Section III presents the three cost optimization methods. The coalitional game model and the Shapley value method are presented in Section IV. Simulation results and conclusions are presented in Sections V and VI.

II. SYSTEM MODEL

We consider a community of N households that can trade and exchange energy with each other through a central energy control unit as illustrated in Fig. 1. The control unit is connected to each household through a two way communication and energy flow system. The energy control unit is equipped with a smart control board that solves the proposed cost optimization problem. The control unit also contains an electronic energy distribution system for controlling the energy flow within the community. The utility company may exchange information with the control unit only to ensure privacy.

We denote by \mathcal{N} the set of households in the community and by n is denoted the index of a household from this set. A subset of smart residences from the community, denoted by \mathcal{M} , $\mathcal{M} \subseteq \mathcal{N}$, with cardinality $|\mathcal{M}| = M$, either produce renewable energy, which implies owning ESSs as well, or own ESSs only. The index of a household from this set is denoted by m . We denote by \mathcal{P} , with cardinality $|\mathcal{P}| = P$, $\mathcal{P} = \mathcal{N} \setminus \mathcal{M}$, the remaining subset of households from the community which are sole energy consumers. The index of a household from this set is denoted by p . The energy optimization is performed over a finite time horizon \mathcal{T} of length T , which is divided into equally long time-slots denoted by t , $\mathcal{T} = [t, t = 1, \dots, T]$.

A. The Energy Storage Model

All households from subset \mathcal{M} own ESSs. The maximum storage capacity associated with each ESS_m is denoted by C_m . The maximum amount of energy that can be charged or discharged from a storage in a time-slot is limited by the charging/discharging rate, ρ_m . In this work the charging

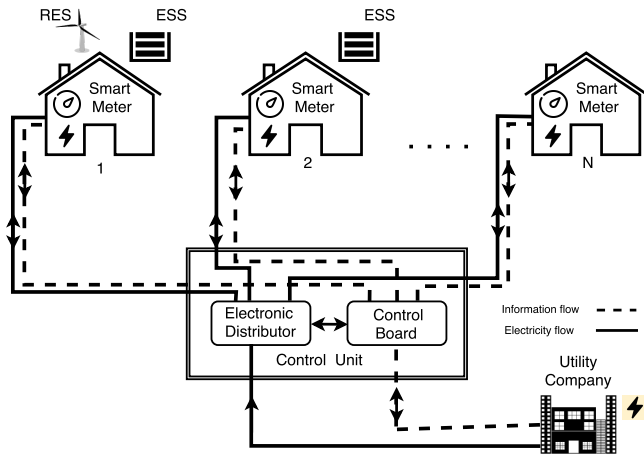


Fig. 1. System architecture. Households owning RESs and/or ESSs and pure energy consuming households exchange energy with each other and buy electricity from the utility company through a central control unit. The control unit is connected to each household through a two way communication and energy flow system. The energy control unit is equipped with a smart control board and an electronic energy distribution system for solving the proposed cost optimization problem and controlling the flow of energy within the community, respectively.

rate is equal to the discharging rate. Another parameter that characterizes a storage system is the storage leakage factor, η_m , which shows the proportion of energy that a storage loses during a time unit. This parameter has values between 0 and 1, but typically $\eta_m \ll 1$.

We further define by $\mathbf{r}_m = [r_m(t), t = 1, \dots, T]$ the set of amounts of energy charged or discharged from a storage unit ESS_m during period \mathcal{T} . These values can have either positive or negative values. If $r_m(t) > 0$ then energy is charged into the storage, while if $r_m(t) < 0$ then energy is being discharged from the storage in time-slot t . The amount of energy charged or discharged from storage in a time-slot is bounded by the charging/discharging rate ρ_m :

$$-\rho_m \leq r_m(t) \leq \rho_m, \quad \forall t \in \mathcal{T}, \forall m \in \mathcal{M}. \quad (1)$$

Let $\mathbf{s}_m = [s_m(t), t = 1, \dots, T]$ be the energy storage vector containing the total amounts of energy stored in an ESS_m at the end of each time slot. The dynamics of the ESS_m is defined by the following equation:

$$s_m(t) = (1 - \eta_m)s_m(t-1) + r_m(t), \quad \forall t \in \mathcal{T}, \forall m \in \mathcal{M}, \quad (2)$$

where $s_m(0)$ would be the initial storage value, i.e the amount of energy remained in storage at the end of the previous optimization period. The amount of energy existing in storage at any time-slot must obey the storage capacity constraint:

$$0 \leq s_m(t) \leq C_m, \quad \forall t \in \mathcal{T}, \forall m \in \mathcal{M}. \quad (3)$$

B. The Energy Consumption Model

The electricity demand of each household in the community is considered to be known ahead for the entire period \mathcal{T} and it is not flexible. The set of electricity demands of a residence, $n \in \mathcal{N}$, in the community is denoted by $\mathbf{u}_n = [u_n(t), t = 1, \dots, T]$. The set of per-time-slot amounts of

renewable energy, $\mathbf{w}_m = [w_m(t), t = 1, \dots, T]$, produced by those households $m \in \mathcal{M}$ owning RESs is considered predicted with sufficient accuracy over the whole period \mathcal{T} , hence it is considered known as well. Methods for prediction of residential electricity demand and of renewable energy generation are proposed, for example, in [16], [17] and [18], [19], respectively. Note that for those households from the set \mathcal{M} that do not own RESs, but only ESSs, the renewable energy vector is zero, i.e. $\mathbf{w}_m = 0$. In this paper, the problem of exchanging and trading the energy among the households is formulated as a coalitional game in which the participants may produce, store and exchange energy. Hence, the set of energy amounts that a household n from the community may exchange with the rest of households from the community within period \mathcal{T} is denoted by $\mathbf{a}_n = [a_n(t), t = 1, \dots, T]$. These variables may have either positive or negative values. If $a_n(t) > 0$ in a certain time slot t , it means that household n provides this amount of energy to the rest of the households in the community, while if $a_n(t) < 0$ then household n receives this amount of energy from the other members of the community. The set of energy amounts that a household n may have to purchase from the utility company during period \mathcal{T} is denoted by $\mathbf{b}_n = [b_n(t), t = 1, \dots, T]$. The energy purchased by a household from the utility company in a time-slot t must obey the energy consumption constraint. This constraint is specific for each type of optimization and for each set of households in the community.

The households belonging to set \mathcal{M} , owning RESs and/or ESSs, can optimize their cost individually, without collaborating with other members of the community. In this case the following energy consumption constraint may be imposed:

$$u_m(t) - w_m(t) - b_m(t) + r_m(t) \leq 0, \quad \forall t \in \mathcal{T}, \forall m \in \mathcal{M}. \quad (4)$$

This inequation states that in a time-slot t the electricity demand of a household, $u_m(t)$, must be fulfilled by the available renewable energy, $w_m(t)$, the energy purchased from the grid, $b_m(t)$, and by energy from in the storage, $r_m(t)$.

In the collaborative case, the households belonging to set \mathcal{M} may obey the following energy consumption constraint:

$$u_m(t) - w_m(t) - b_m(t) + r_m(t) + a_m(t) \leq 0, \quad \forall t \in \mathcal{T}, \forall m \in \mathcal{M}. \quad (5)$$

The interpretation of this constraint is similar to that of constraint (4). The difference is that in the collaborative scenario one participant to the optimization may also receive or transfer an amount of electricity $a_m(t)$ from or to other households in the community.

The energy consumption constraint for the pure consuming households \mathcal{P} is defined as follows:

$$u_p(t) - b_p(t) + a_p(t) = 0, \quad \forall t \in \mathcal{T}, \forall p \in \mathcal{P}. \quad (6)$$

This category of households can only receive energy from the other members of the community. This imposes the following constraint:

$$a_p(t) \leq 0, \quad \forall t \in \mathcal{T}, \forall p \in \mathcal{P}. \quad (7)$$

Alternatively, they can buy electricity from the utility company. For all the households in the community the amount of

energy purchased from the power grid in time-slot t , $b_n(t)$, may have only positive or zero values:

$$b_n(t) \geq 0, \forall t \in \mathcal{T}, \forall n \in \mathcal{N}. \quad (8)$$

In this work the case of selling back electricity to the power grid is not considered.

III. THE COST MINIMIZATION PROBLEM

In this section two coalitional game based approaches for minimizing energy costs among cooperating households are proposed. In the first proposed coalitional optimization problem the households that own RESs and ESSs share their energy storage spaces and their renewable energy resources and exchange energy among themselves. We show that through participating in this coalitional optimization the households that own RESs and/or ESSs may significantly reduce their electricity costs in comparison to the case in which they would individually optimize their energy costs, using only their own renewable resources and energy storages. Moreover, we propose another coalitional game model in which we show that by including the households that only consume energy in the optimization model, the households owning RESs and ESSs may reduce their costs even further by selling energy to these households at a price lower than the one offered by the utility company. As a consequence, the sole energy consuming households can also reduce their energy costs.

The wholesale market electricity prices per unit of energy are given by the utility company and they are known ahead for each time-slot t in the period \mathcal{T} . We denote this set of electricity prices by $\xi = [\xi(t), t = 1, \dots, T]$.

In the following subsections we describe the proposed cost minimization problems. First we formulate a cost minimization problem which can be performed by each household $m \in \mathcal{M}$ individually, without collaborating. Then we formulate the coalitional cost minimization problem that includes only the residences that own RESs and ESSs. Finally, we formulate the coalitional cost minimization problem which includes the households that are sole electricity consumers as well.

A. Individual cost minimization problem (\mathbf{P}_I)

The cost of electricity bought from the utility company by any household $n \in \mathcal{N}$ is defined as:

$$C_n^{\text{grid}} = \sum_{t=1}^T \xi(t)b_n(t), \forall n \in \mathcal{N}. \quad (9)$$

In addition to this cost, each household $m \in \mathcal{M}$ is also incurred with an energy storage degradation cost. It is well known that while being charged and discharged multiple times storage units suffer a certain degradation and the efficiency of a storage is affected after a number of charging/discharging cycles. Also, using storage units for cost optimization puts an extra stress on these units. We define by π a price that accounts for the storage degradation when charging/discharging one unit of energy. The resulting storage degradation cost for an ESS_m within period \mathcal{T} can be defined as:

$$C_m^{\text{storage}} = \pi \sum_{t=1}^T |r_m(t)|, \forall m \in \mathcal{M}. \quad (10)$$

Households $m \in \mathcal{M}$, owning RESs and/or ESSs can individually optimize their costs, without collaborating with the other members of the community. We denote by c_m^{indiv} the individual cost of a household from set \mathcal{M} :

$$c_m^{\text{indiv}} = C_m^{\text{grid}} + C_m^{\text{storage}}. \quad (11)$$

The individual cost minimization problem for one single household $m \in \mathcal{M}$ can be stated as follows (\mathbf{P}_I):

$$\min_{\mathbf{b}_m, \mathbf{r}_m, \mathbf{s}_m} c_m^{\text{indiv}} + \sigma \sum_{t=1}^T [b_m(t) + w_m(t) - u_m(t) - r_m(t)],$$

such that the constraints (1)-(4), (8) are satisfied. The last term of the objective function: $\sigma \sum_{t=1}^T [b_m(t) + w_m(t) - u_m(t) - r_m(t)]$, is a penalty term which forces the amount of renewable energy that exceeds the demand of the user in period \mathcal{T} , i.e. the amount of renewable energy that is not consumed, to be stored in the ESS_m . The proposed cost minimization problem uses and stores the renewable energy in an optimized manner such that the demand of the user is met and the cost is minimized in period \mathcal{T} . Due to the highly variable aspect of the renewable energy production equality sign cannot be employed in the energy consumption constraint (4). Consequently, this constraint does not force charging of all the renewable energy into the ESS. The formulated optimization problem is reluctant to charge into the ESS more than the minimum amount of energy that is necessary to achieve the minimum cost in time period \mathcal{T} . The penalty term is then introduced in the objective function in order to ensure that the exceeding amount of renewable energy is stored in the ESS. This amount will be used later in the following optimization period. By σ we define a penalty price for a unit of this excess renewable energy that may not be stored, even though the storage capacity is not met. As mentioned in Section II, the set \mathcal{M} of households contains households that own both RESs and ESSs and households that own ESSs only. For the second category, the renewable energy vector is zero, $\mathbf{w}_m = 0$, and the optimization is performed by using their energy storages alone.

The set of solution variables of the individual cost minimization problem is $\{\mathbf{b}_m, \mathbf{r}_m, \mathbf{s}_m\}$.

B. Coalitional cost minimization problem for households owning RESs and/or ESSs (\mathbf{P}_{II})

In this scenario the households belonging to the set \mathcal{M} collaborate and share their renewable resources and storage units in order to optimize their aggregate costs. Besides the cost of electricity purchased from the power grid and the cost incurred for storage degradation, a third type of costs shall be added to the optimization problem in the collaborative scenario. This cost represents the cost for operating and maintaining the central control unit. The optimization is performed by a central energy management unit that performs the optimization and controls the energy flow and transfer within the community. For this, we define by τ the price charged for transferring or receiving one unit of energy from one household to another. The overall cost incurred by a household m during the period \mathcal{T} for the energy transfer operations is equal to:

$$C_m^{\text{operation}} = \tau \sum_{t=1}^T |a_m(t)|, \forall m \in \mathcal{M}. \quad (12)$$

We denote by $c_{\mathcal{M}}^{\text{ResEss}}$ the aggregate cost incurred by all households owning RESs and ESSs:

$$c_{\mathcal{M}}^{\text{ResEss}} = \sum_{m=1}^M C_m^{\text{grid}} + \sum_{m=1}^M C_m^{\text{storage}} + \sum_{m=1}^M C_m^{\text{operation}}. \quad (13)$$

The coalitional cost minimization problem for the households $m \in \mathcal{M}$ that own RESs and/or ESSs is formulated as **(P_{II})**:

$$\min_{\{\mathbf{b}_m, \mathbf{r}_m, \mathbf{s}_m, \mathbf{a}_m\}_{m=1}^M} c_{\mathcal{M}}^{\text{ResEss}} + \sigma \sum_{m=1}^M \sum_{t=1}^T [b_m(t) + w_m(t) - u_m(t) - a_m(t) - r_m(t)],$$

such that the constraints (1)-(3), (5) and (8) are satisfied. A penalty term is added to the objective also in case of the coalitional optimization. The penalty term has same purpose as that in **(P_I)**. In this case penalty term is expressed by: $\sigma \sum_{m=1}^M \sum_{t=1}^T [b_m(t) + w_m(t) - u_m(t) - a_m(t) - r_m(t)]$ and it works in corroboration with energy consumption constraint (5).

To ensure a correct functionality of the optimization problem we add another balance constraint which makes sure that the total amount of energy that is given away by some households in a time-slot is equal to the total amount of energy received by the rest of households from the set \mathcal{M} in that time-slot:

$$\sum_{m=1}^M a_m(t) = 0. \quad (14)$$

The final set of constraints for this problem is (1)-(3), (5), (8), (14). The set of solution variables is $\{\mathbf{b}_m, \mathbf{r}_m, \mathbf{s}_m, \mathbf{a}_m\}_{m=1}^M$.

C. Coalitional cost minimization problem for the whole community of households **(P_{III})**

In this problem we include as well the households $p \in \mathcal{P}$ which are sole energy consumers. This set of households participates to the community coalitional energy optimization by just buying energy from those owning RESs and ESSs. The problem described further minimizes the aggregate cost incurred by the RESs and ESSs owners through selling energy to the pure consumer households. The pure consuming households also reduce their costs by buying electricity at a cheaper price than that offered by the utility company.

We define by $\boldsymbol{\lambda} = [\lambda(t), t = 1, \dots, T]$ the set of per-time-slot prices corresponding to one unit of energy sold by households $m \in \mathcal{M}$, owning RESs and ESSs, to households $p \in \mathcal{P}$. These prices are lower than the per-time-slot prices offered by the utility prices: $\lambda(t) = \alpha \xi(t)$, where $0 \leq \alpha \leq 1$. For a household p the cost of purchasing energy from the community in period \mathcal{T} can be stated as:

$$C_p^{\text{purchase}} = \sum_{t=1}^T \lambda(t) [-a_p(t)], \forall p \in \mathcal{P}. \quad (15)$$

We denote by $c_{\mathcal{M}}^{\text{community}}$ the overall cost incurred by those households from the community owning RESs and ESSs after

selling energy to those that are sole energy consumers. This cost is expressed as:

$$c_{\mathcal{M}}^{\text{community}} = \sum_{m=1}^M C_m^{\text{grid}} + \sum_{m=1}^M C_m^{\text{storage}} + \sum_{m=1}^M C_m^{\text{operation}} - \sum_{p=1}^P C_p^{\text{purchase}}. \quad (16)$$

The term $\sum_{p=1}^P C_p^{\text{purchase}}$ defines the aggregate amount of energy sold by the RESs and ESSs owners to the pure consumers. We formulate the whole community optimization problem that includes also the sole energy consuming households as **(P_{III})**:

$$\min_{\{\mathbf{b}_n, \mathbf{r}_m, \mathbf{s}_m, \mathbf{a}_n\}_{m=1, n=1}^{M, N}} c_{\mathcal{M}}^{\text{community}} + \sigma \sum_{m=1}^M \sum_{t=1}^T [b_m(t) + w_m(t) - u_m(t) - a_m(t) - r_m(t)],$$

such that the constraints in (1)-(3), (5)-(8) and (14) are satisfied, with the difference that (14) is reformulated for the whole community \mathcal{N} :

$$\sum_{n=1}^N a_n(t) = 0. \quad (17)$$

We add also to this problem a penalty term which has the same purpose as the penalty terms in **(P_I)** and **(P_{II})** :

$$\sigma \sum_{m=1}^M \sum_{t=1}^T [b_m(t) + w_m(t) - u_m(t) - a_m(t) - r_m(t)].$$

We denote by c_p^{indiv} the cost incurred by a household $p \in \mathcal{P}$ that participates in the community optimization **(P_{III})**. This cost is equal to: $c_p^{\text{indiv}} = C_p^{\text{grid}} + C_p^{\text{operation}} + C_p^{\text{purchase}}$. For making sure that all sole energy consumers $p \in \mathcal{P}$ also benefit and reduce their energy cost the following constraint is imposed:

$$c_p^{\text{indiv}} < \sum_{t=1}^T u_p(t) \xi(t), \forall p \in \mathcal{P}. \quad (18)$$

This constraint states that the cost paid by a sole energy consuming household that participates in the optimization should be less than the cost the household would pay by simply purchasing electricity directly from the utility company.

The final set of constraints for this problem is (1)-(3), (5)-(8), (17) and (18). The set of solution variables is $\{\mathbf{b}_n, \mathbf{r}_m, \mathbf{s}_m, \mathbf{a}_n\}_{m=1, n=1}^{M, N}$.

It can be observed that the objective functions and the constraints of the formulated optimization problems possess linear relationships among the variables of the problems. Hence, we are able to model both optimization problems as linear programs. The solutions of the proposed optimization problems can be easily obtained through algorithms such as the interior point algorithm [20].

IV. THE COALITIONAL GAME MODEL FOR HOUSEHOLDS OWNING RESs AND ESSs

The proposed coalitional cost optimization problems **(P_{II})** and **(P_{III})** are using the ESSs as well as the renewable energy production of the households from the set \mathcal{M} in order to minimize the joint electricity cost of these residences. In this work, we formulate this collaborative cost optimization as a characteristic coalitional game with transferable utility among the RESs and ESSs owning households.

A coalitional game in characteristic form [21] is uniquely defined by the pair (\mathcal{M}, v) . \mathcal{M} represents the set of players participating in the game, $|\mathcal{M}| = M$, while $v : 2^{\mathcal{M}} \rightarrow \mathbb{R}$ is the characteristic function of the game. The characteristic function quantifies the worth (revenue) of a coalition such that $v(\emptyset) = 0$ and $v(\mathcal{M})$ represents the total revenue of the coalition \mathcal{M} in the game characterized by function v . In the coalitional game proposed in this work, the players \mathcal{M} are represented by the set of households owning RESs and ESSs. The coalition is formed at all times by all the residences from the set \mathcal{M} , hence this coalition is called the grand coalition. The worth (revenue) of the grand coalition is defined as the amount of cost savings obtained by the coalitional group in the collaborative scenarios, (\mathbf{P}_{II}) and (\mathbf{P}_{III}) , in comparison with the total electricity cost that the members of the coalitional group would pay in the case of performing individual cost optimization (\mathbf{P}_I) . Let us denote by $v(\mathcal{M})^{\text{ResEss}}$ the worth of the grand coalition in case of problem (\mathbf{P}_{II}) . This worth is expressed as:

$$v(\mathcal{M})^{\text{ResEss}} = \sum_{m=1}^M c_m^{\text{indiv}} - c_{\mathcal{M}}^{\text{ResEss}}. \quad (19)$$

Here c_m^{indiv} is the individual cost of a household in case of (\mathbf{P}_I) , computed using the formulation in (11), and $c_{\mathcal{M}}^{\text{ResEss}}$ is the joint electricity consumption costs of a coalition of households resulted from (\mathbf{P}_{II}) , computed using (13).

Further, we denote by $v(\mathcal{M})^{\text{community}}$ the worth of the coalition in case of problem (\mathbf{P}_{III}) . In this case the worth is expressed as:

$$v(\mathcal{M})^{\text{community}} = \sum_{m=1}^M c_m^{\text{indiv}} - c_{\mathcal{M}}^{\text{community}}. \quad (20)$$

Here $c_{\mathcal{M}}^{\text{community}}$ is the joint electricity consumption cost of the coalition of households resulted from (\mathbf{P}_{III}) and computed using formulation in (16), while c_m^{indiv} is again the individual cost of a household obtained through (\mathbf{P}_I) .

In coalitional games with transferable utility, the worth of the coalition has to be distributed among the members of the coalitional group using a fairness rule. Hence, we need to define a method to distribute the worth of the coalition of households among its members. There are various fairness methods in the literature for division of rewards like nucleolus, egalitarian, Shapley value [21], [22]. In this work, we choose that the amount of cost savings obtained by the coalition is divided among its members using the Shapley value [22]. The Shapley value is a one-point payoff solution through which the worth of the coalition is distributed among the players according to the average marginal contribution that each player is bringing to the coalitional game and to the cost savings. The Shapley value solution represents an average measure of fairness.

We denote generally by $v(\mathcal{M})$ the worth of the grand coalition for any of the proposed coalitional optimization problems: $v(\mathcal{M}) = v(\mathcal{M})^{\text{ResEss}}$ in case of (\mathbf{P}_{II}) , or $v(\mathcal{M}) = v(\mathcal{M})^{\text{community}}$ in case of (\mathbf{P}_{III}) . We denote by $\Phi(v)$ the Shapley value operator which is in charge of assigning to each game represented by function $v(\mathcal{M})$ a vector of pay-offs $\{\Phi_1(v), \Phi_2(v), \dots, \Phi_M(v)\}$, for each member m of the

coalition \mathcal{M} , such that $\sum_{m \in \mathcal{M}} \Phi_m(v) = v(\mathcal{M})$. Let us denote by \mathcal{G} , $\mathcal{G} \subseteq \mathcal{M}$, any non-empty subset of households from the set \mathcal{M} that may form a coalitional group, the cardinality of the set \mathcal{G} being $|\mathcal{G}| = G$. The marginal contribution the on cost savings of a player with respect to a the overall cost savings obtained by a possible subset of players \mathcal{G} is defined by the value: $v(\mathcal{G} \cup \{m\}) - v(\mathcal{G})$. Then, the Shapley value, $\Phi(v)$, assigns to each player $m \in \mathcal{M}$ a payoff $\Phi_m(v)$ given by the following expression:

$$\Phi_m(v) = \sum_{\mathcal{G} \subseteq \mathcal{M} \setminus \{m\}} \frac{G!(M-G-1)!}{M!} [v(\mathcal{G} \cup \{m\}) - v(\mathcal{G})]. \quad (21)$$

The sum above is computed over all possible subsets \mathcal{G} (even of single players) of \mathcal{M} not containing player m . $\mathcal{G} \cup \{m\}$ and $v(\mathcal{G})$ are computed using the formulation in (19), in case of (\mathbf{P}_{II}) , and the formulation in (20), in case of (\mathbf{P}_{III}) , respectively.

The payoffs determined by Shapley value for each individual household are discounted from the household's individual cost c_m^{indiv} . Hence, the final cost for electricity consumption of that households would be $c_m^{\text{indiv}} - \Phi_m(v)$.

V. SIMULATION EXAMPLES

In this section we present simulation examples and quantitative results that demonstrate the performance and cost savings achieved by the proposed methods. For simulating and testing the performance of the proposed methods we considered a smart grid community composed of $N=9$ households. The set \mathcal{M} of residences is composed of 6 households. In our simulations we denote these households by $\mathcal{M} = \{m1, m1, \dots, m6\}$. Out of this set, 3 households, $\{m1, m2, m3\}$, own RESs as well as ESSs, while the other 3 households, $\{m4, m5, m6\}$, own ESSs only. The remaining $|\mathcal{P}|=3$ households in the community are sole energy consumers: $\mathcal{P} = \{p1, p2, p3\}$. We perform simulations over a time horizon \mathcal{T} of length $T=24$ hours divided into hourly time slots. For the presented results, except those in Fig. 4, we considered equal ESS_m capacities, C_m , of 5kWh. We also assumed equal hourly charging/discharging rates, ρ_m , of 2kWh per hour. The storage loss factor is assumed to be $\eta_m = 0.001, m = 1, \dots, M$. The utility company pricing data, ξ , is true wholesale market pricing data taken from Finnish Nord Pool Spot database [23] for May 2013. Other pricing data used in simulations is the following: $\pi=0.0005$ € per each kWh of charged/discharged energy, $\sigma=0.005$ € per each kWh of excess renewable energy not stored, $\tau=0.001$ € per each kWh of electricity transferred or received by each household. The price of energy sold by the RESs and ESSs owners to the sole energy consumers is $\lambda = \alpha\xi, \alpha = 0.9$, i.e. the sole consumers get a 10% discount compared to the price offered by the utility company. The influence of α over the performances of the proposed methods is depicted in Fig. 3.

In this paper we show simulation results of the proposed methods over 31 days. In these simulations we assumed empty storages, $s_m(0)=0, m = 1, \dots, M$, at the beginning of the first 24-hours optimization period. Further, each proposed optimization method updated its corresponding initial

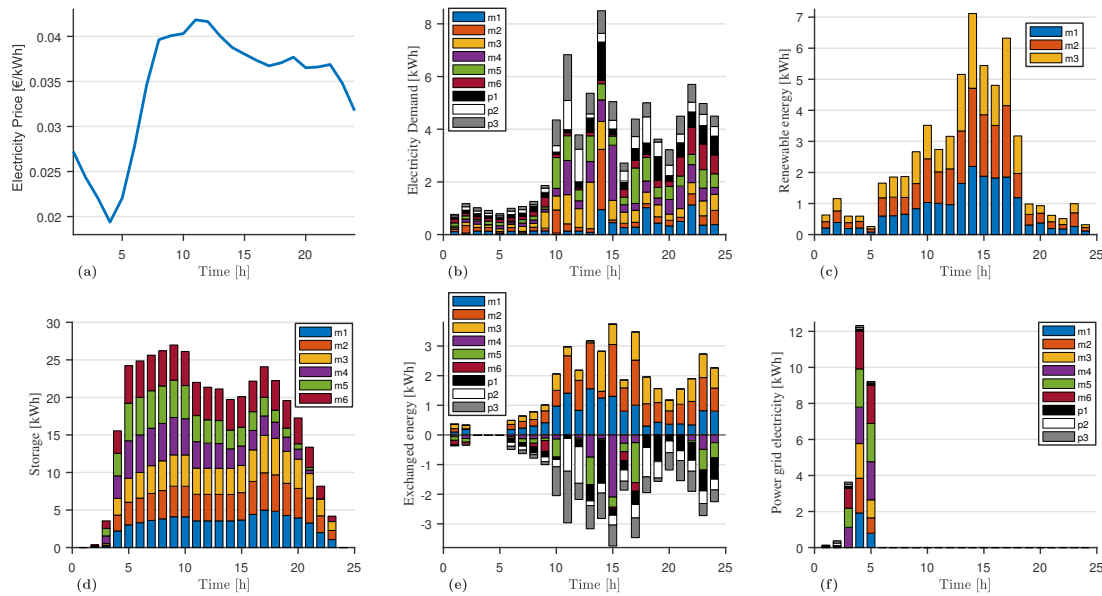


Fig. 2. (a) 24-hours utility company electricity price. (b) 24-hours electricity demand of the households. (c) 24-hours renewable energy production of households owning RESs. (d) 24-hours ESSs profiles. (e) 24-hours amounts of electricity exchange between all households in the community. The positive blocks show amounts of energy provided by some households to the others, whereas the negative blocks show amounts of energy received by the other households. (f) Electricity purchased from the utility company by the households. RES and ESS owning households buy energy from the utility during the hours when the price is low.

storage values, for each new optimization period, with the storage levels resulted at the end of the previous period $s_m(0)^T = s_m(24)^T - 1$. Hence, the proposed optimization methods may have had different initial storage levels at the beginning of each 24-hours optimization periods from the 31-days simulation. In order to simulate the 24-hours electricity demands of the households, \mathbf{u}_n , we used the load modeling framework presented in [24]. We assumed residences with the following numbers of inhabitants: {3, 4, 4, 2, 5, 4, 3, 4, 2}. We considered that the households were equipped with wind energy producing systems. For simulating renewable energy data values we used the following mathematical model to approximate the power generated by a wind turbine [25]: $P_w = (1/2)DK_pAV^3$, where D represents the air density, $K_p=0.3$ is the power coefficient of the turbine, A is the swept area of the turbine, $A = 3.14R^2$, $R = 2.63\text{m}$, and V is the wind speed. For this, we used true weather data for May 2013 in Helsinki region [26]. To represent the energy production of each household, we added a small variation to the values calculated with the above formulation. The simulations were performed using Matlab on a conventional laptop computer. For solving the linear programs resulted from modeling the proposed optimization problems we used the CVX package for convex optimization [27]. It takes about 0.8 seconds to solve the optimization problems using a general purpose personal computer. The computation of the Shapley value in (21) for a coalitional problem (\mathbf{P}_{II}) or (\mathbf{P}_{III}) involves finding solutions for $2^M - 1$ unique subsets of players, for all combinations of players in the set \mathcal{M} . The results of the performed simulations are presented further.

Fig. 2 (a)-(f) shows an example of 24-hours input data and results of (\mathbf{P}_{III}) . We used the pricing and weather data for May 17 [23], [26]. Fig. 2.(a) shows the electricity prices, ξ , in

€/kWh . Fig. 2.(b) shows the individual and cumulated hourly electricity demands of all households in the community. Fig. 2.(c) shows the individual and cumulated hourly renewable energy production of households $\{m1, m2, m3\}$ that own RESs. Fig. 2.(d) shows the individual and cumulated hourly profiles of the ESSs, i.e how much energy exists in the energy storages of households $m \in \mathcal{M}$ at the end of each hour. Fig. 2.(e) shows the amounts of energy exchanged during each hour by all the households in the community. At each time-slot, the positive blocks show the amounts of energy that are provided by some households to the others, whereas the negative blocks show the amounts of energy that are being received by the other households. In this example it can be observed that in most cases the households which produce renewable energy provide energy to those households that own ESSs only and to the sole energy consuming households in the network. Fig. 2.(f) shows the amounts of energy purchased from the power grid by all households in the community. It can be seen that the RESs and ESSs owning households buy energy from the utility company during those hours when the electricity price is low. In this particular example the pure consumers buy very little energy from the utility company, instead they buy most of their needed electricity from the RESs and ESSs owners.

Fig. 3 shows in (a) the 31-days cumulative electricity costs of the households $m \in \mathcal{M}$ that own RESs and ESSs and in (b) the cumulative electricity costs of the households $p \in \mathcal{P}$ that are sole energy consumers. It can be observed in (a) that (\mathbf{P}_{II}) (29.6€) provides for these residences a cost reduction of about 12% versus (\mathbf{P}_I) (33.65€). (\mathbf{P}_{III}) (27.7€) provides an additional 6% reduction in cost, resulting in an overall 18% cost reduction for the RESs and ESSs owners. In (b) it can be observed that the sole energy consumers, through participating to (\mathbf{P}_{III}) (30.38€), reduce their costs by approximately 3%

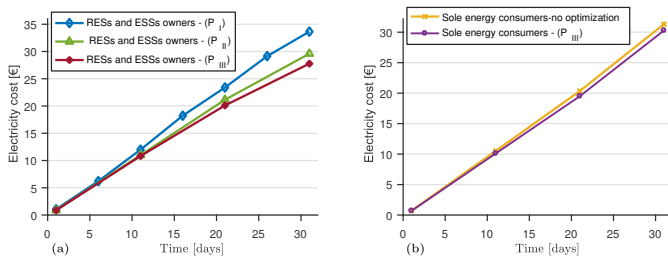


Fig. 3. Comparison between the 31-days cumulative electricity costs of the RESs and ESSs owners (a) and of the sole energy consumers (b), obtained through the proposed optimization methods. (P_{II}) results in a cost reduction of about 12% in comparison to (P_I) . In case of (P_{III}) , the RESs and ESSs owners obtain a cost reduction of about 18% compared to (P_I) . The sole energy consumers obtain a cost reduction of about 3%.

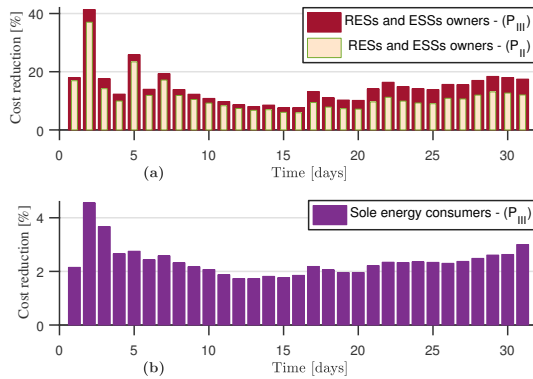


Fig. 4. (a) 31-days cumulative percentage of cost reduction obtained by RESs and ESSs owners through methods (P_{II}) and (P_{III}) in comparison to (P_I) . Their cost reduction varies between 6% and 37% in case of (P_{II}) and between 7.5% and 41% in case of (P_{III}) . (b) 31-days cumulative percentage of cost reduction obtained by the sole consumers through method (P_{III}) in comparison to buying all needed electricity from the power grid. Their cost reduction varies between 1.8% and 4.5%.

in comparison to buying all needed electricity from the utility company (31.32€).

Fig. 4.(a) shows the 31-days cumulative electricity cost reductions, calculated in percentage, obtained by the RESs and ESSs owners through methods (P_{II}) and (P_{III}) in comparison with the cumulative electricity costs obtained using (P_I) . In case of (P_{III}) , the daily cost reduction in comparison to (P_I) varies between 7.5% on day 15 and 41% on day 2. During the last five days of the 31-days period the cost reduction obtained by (P_{III}) is between 15.5% and 18.5%. In case of (P_{II}) , the daily cost reduction in comparison to (P_I) varies between 6% on day 15 and 37% on day 2. The cost reduction obtained by (P_{II}) during the last five days of the 31-days period is between 10.5 and 12.5%. It can be observed that the cost reduction obtained by problem (P_{III}) is always higher than the reduction obtained by (P_{II}) . Fig. 4.(b) shows the daily cumulative percentage cost reductions obtained by the sole energy consumers in case of (P_{III}) and compared to costs of buying electricity from utility company only. The daily cost reduction for the pure consumers varies between 1.8% in day 15 and 4.5% in day 2. In day 31 their cost reduction is 3%.

In Fig. 5 we show how the 31-days cumulated cost savings obtained by the RESs and ESSs owners, but also by the sole consumers, in the proposed coalitional optimization problem

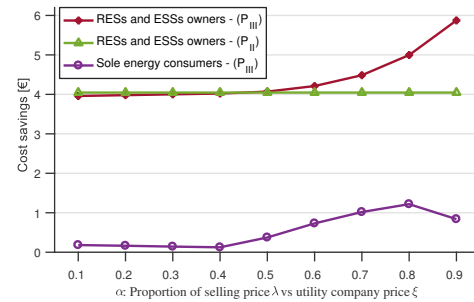


Fig. 5. The variation of the 31-days cumulated cost savings of the proposed coalitional problems in comparison to α , the proportion of the price of electricity sold by the RESs and ESSs owners λ versus the utility company price ξ . (P_{III}) obtains positive results for $\alpha \geq 0.5$. The highest gain is obtained by the RESs and ESSs owners when $\alpha = 0.9$.

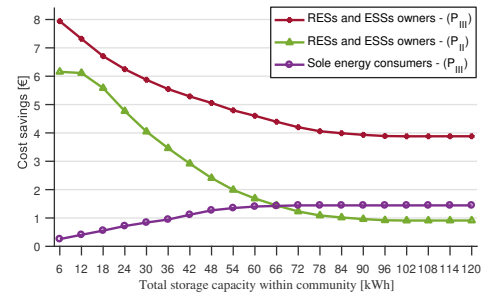


Fig. 6. The variation of the 31-days cumulated cost savings obtained by the proposed coalitional methods, in comparison to (P_I) , versus the total storage capacity existing within the community. The cost savings of the RESs and ESSs owners decrease with the increase of the storage capacity for both proposed coalitional cost minimization methods. The gains of the sole energy consumers increases with the increase of storage capacity.

(P_{III}) are varying for different values of the set of prices λ . As specified in Section II, λ is the set of electricity prices corresponding to the energy sold by the RESs and ESSs owners to the sole energy consuming households. The values of λ are smaller than the utility company set of electricity prices, ξ : $\lambda = \alpha\xi$, where $\alpha: 0 \leq \alpha \leq 1$. In this simulation we used the following values for α : $\{0.1, \dots, 0.9\}$. It can be observed from Fig. 5 that (P_{III}) obtains positive results for the RESs and ESSs owners when $\alpha \geq 0.5$. The highest cost reduction in comparison to (P_I) is always obtained by the RESs and ESSs owners when the price of sold energy is $\lambda = 0.9\xi$, i.e $\alpha=0.9$. In the given scenario the sole energy consumers obtain the highest cost reduction, of about 5% from from cost of purchase from utility company, when $\alpha = 0.8$. The cost reduction of the sole energy consumers is a consequence of the cost minimization performed by the RESs and ESSs owners. Households $m \in \mathcal{M}$ minimize their cost by selling energy to households $p \in \mathcal{P}$. The higher are the prices λ , the higher are the amounts of energy sold by the households $m \in \mathcal{M}$. Hence, the cost reduction of the sole energy consumers gets higher with the amounts of energy purchased from RESs and ESSs owners. Because the objective of the proposed problem is to minimize the cost of the RESs and ESSs owners, we chose to use the value $\alpha=0.9$ in simulations.

Fig. 6 shows the variation of the 31-days cumulated cost

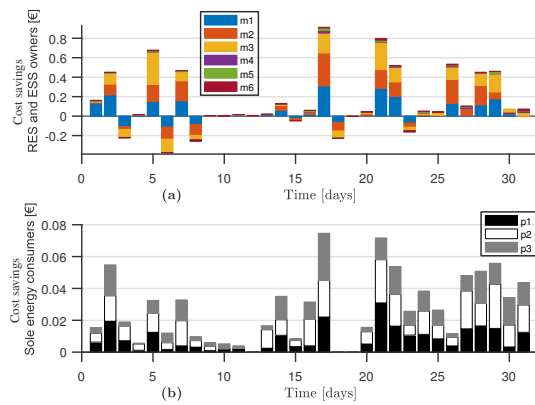


Fig. 7. (a) The daily amount of cost savings achieved by the RESs and ESSs owning households by cooperating in (P_{III}) . The blocks composing a bar show the payoffs received by the households from the coalition as distributed by the Shapley value method. (b) The daily cost savings achieved by the sole energy consuming households through participating in the whole community optimization.

savings obtained by the proposed coalitional optimization methods (P_{II}) and (P_{III}) in comparison to (P_I) for different total storage capacity values existing within the community. We assumed initial capacities of 1kWh for each ESS_m , resulting in an overall storage capacity of 6kWh within the community. Then we increased the storage capacity of each ESS_m by 1kWh, until reaching 20kWh, which resulted in an overall 120kWh storage capacity within the community. It can be observed that (P_{III}) and (P_{II}) have the highest gains in comparison to (P_I) when the capacity is small. The monetary gains of the RESs and ESSs owners are actually decreasing while the capacity increases. This is due to the fact that the result of (P_I) is used as a comparison benchmark in (19) and (20) for the calculation of the revenues of the coalitional optimizations. The increase of the ESSs capacities allows for better performance of the (P_I) problem. Hence, the coalitional optimizations' gains for RESs and ESSs owners are not so significant any more. However, we can see that the gains of the proposed coalitional methods don't totally decrease. Actually, even with very large storage capacities, the proposed methods (P_{III}) and (P_{II}) still obtain significant monetary gains in comparison to (P_I) . Contrary to the gains of RESs and ESSs owners, it can be observed that the gains of the sole energy consumers become larger as the storage capacity within the community increases.

The bar plot in Fig. 7 depicts the daily cost savings of the community and of the individual households for the case in which the cooperation is done according to the problem proposed in (P_{III}) . Fig. 7(a) shows the cost savings of the RESs and ESSs owners. The daily cost savings are divided among the members of the community as shown by the blocks composing each bar. Each block indicates the amount of monetary payoff received by a household as resulted from the Shapley value calculation. We can observe that a big part of the daily cost savings are allocated to the renewable energy producers. It can also be observed that during five days of the month, days 3,6,8,18 and 23 the coalitional optimization does not perform better than the individual optimization. This is also

due to the fact that, as mentioned before, the storages of the EESs owners do not have same initial values for the individual optimization as for the coalitional optimization. During some days, the initial storage values may be full for the individual optimization, while for the coalitional optimization the initial storage values may be empty. For the majority of the days of the month each household in the community receives some monetary revenue for their participation in the coalitional optimization. Fig. 7(b) shows the cost savings of the sole energy consuming households as resulted from the optimization, by buying energy from the RESs and ESSs owners at a lower price than the one offered by the utility company. Each of the sole energy consuming household obtains daily cost savings.

VI. CONCLUSIONS

In this paper we proposed two novel coalitional game theory based optimization methods for minimizing the cost of electricity consumed by households in a smart grid community. We also modeled a coalitional game among the RESs and ESSs owning households in which the cost savings obtained by the coalition are divided among its members using the Shapley value method. We formulated three cost optimization problems. We first formulated an optimization problem through which RESs and ESSs owners from the community may individually optimize their costs. Then we proposed a coalitional optimization through which the RESs and ESSs owning households can form a coalition for exchanging energy and sharing their renewable energy and storage units. Simulation examples showed that through participating to this coalitional optimization game, these households can reduce their energy consumption costs by roughly 12%. We proposed a secondary coalitional cost optimization model through which the RESs and ESSs owning households share their renewable energy and storage units among themselves, but also sell electricity to the pure consuming households in the community. We show that by selling electricity at a cost lower than the one offered by the utility company, the RESs and ESSs owners may further reduce their costs with about 6%, resulting in a total 18% cost reduction in comparison with the cost incurred for individually optimizing their cost. Also, by participating to the coalitional optimization, the sole energy consuming households may also obtain electricity cost reductions of about 3%.

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Visa Koivunen (F'11) received his D.Sc. (EE) degree with honors from the University of Oulu, Dept. of Electrical Engineering. He received the primus doctor award among the doctoral graduates in years 1989-1994. He is a member of Eta Kappa Nu. From 1992 to 1995 he was a visiting researcher at the University of Pennsylvania, Philadelphia, USA. Since 1999 he has been a full Professor of Signal Processing at Aalto University (formerly Helsinki UT), Finland. He received the Academy professor position (distinguished professor nominated by the Academy of Finland). Years 2003-2006 he was also adjunct full professor at the University of Pennsylvania, Philadelphia, USA. He has also been a part-time Visiting Fellow at Nokia Research Center (2006-2012) and Princeton University (2007-). He has spent two full sabbaticals at Princeton University.

Dr. Koivunen's research interest include statistical, communications, sensor array and multichannel signal processing. He has published more than 400 papers in international scientific conferences and journals and holds 6 patents. He co-authored the papers receiving the best paper award in IEEE PIMRC 2005, EUSIPCO'2006, EUCAP (European Conference on Antennas and Propagation) 2006 and COCORA 2012. He has been awarded the IEEE Signal Processing Society best paper awards for the years 2007 and 2017. He served as an associate editor for IEEE Signal Processing Letters, IEEE Trans. on Signal Processing and two IEEE JSTSP special issues. He was a member of editorial board for IEEE Signal Processing Magazine. He has been a member of the IEEE Signal Processing Society technical committees SPCOM-TC and SAM-TC. He was the general chair of the IEEE SPAWC 2007 conference in Helsinki, Finland and Program Chair for the IEEE SPAWC 2015. He was awarded the 2015 EURASIP (European Association for Signal Processing) Technical Achievement Award for fundamental contributions to statistical signal processing and its applications in wireless communications, radar and related fields. He is a member of the IEEE Fourier Award committee, Fellow reference committee and served as IEEE SPS Distinguished Lecturer for 2015-2016.



Adriana Chiş (S'13) received her B.Sc. and M.Sc. degrees in electronic engineering and telecommunications from the Technical University of Cluj-Napoca, Romania, in 2009 and 2011, respectively. She is currently working towards the D.Sc.(Tech.) degree with the Department of Signal Processing and Acoustics, School of Electrical Engineering, Aalto University, Finland.

Her research interests include areas of signal processing, machine learning, game theory and optimization for smart power grids.