COLLABORATIVE APPROACH FOR ENERGY COST MINIMIZATION IN SMART GRID COMMUNITIES

Adriana Chiş and Visa Koivunen

Department of Signal Processing and Acoustics, Aalto University, Espoo, Finland
Email: adriana.chis@aalto.fi, visa.koivunen@aalto.fi

ABSTRACT

In this paper we propose a novel demand side management method for minimizing the cost of electricity consumed by households from a smart community. Some households in the community may own renewable energy sources (RESs) and energy storing systems (ESSs). Other households in the community may own ESSs only, while the remaining households are pure energy consumers. The RESs and ESSs owning households can individually optimize their costs by using their available storage spaces and renewable energy production. In this paper we propose a collaborative model in which the RESs and ESSs owners may minimize their costs by exchanging energy and sharing the produced renewable energy and energy storing spaces. They also sell energy to the plain energy consumers at a lower price than that offered by the utility company. We model the collaborative cost minimization as a constrained optimization problem that may be solved as a linear program. Simulation show that the proposed collaborative method may reduce the RESs and ESSs owners' costs by 12 to 50% in comparison to performing individual optimization. The pure energy consumers can also reduce their costs by about 7-8% in comparison to the case of buying all needed energy from the utility company.

Index Terms— Smart grids, smart households, demand side management, cost reduction, renewable energy, energy storage

1. INTRODUCTION

Demand side management operations for reducing electricity consumption costs or load peaks on the grid can be performed efficiently using energy storing systems (ESSs). ESSs can also be used in conjunction with renewable energy sources (RESs) for storing the renewable energy surplus and thus offering increased reliability of renewable energy production. Collaborative methods for energy trading and sharing at distribution level can improve the integration of renewable energy within the power grid, but also provide cost reductions for the participants in the collaborative method.

Cooperative methods for energy trading have been studied in [1–8]. Cooperation between microgrids using methods based on Nash bargaining theory have been studied in [1] and [2]. In [3] an approached for power control within a network of microgrids has been proposed. A prospect theoretic based static game has been proposed in [4] for energy trading among microgrids. One noncooperative game and one cooperative game have been proposed in [5] for energy trading among users that own distributed energy generators and storages. A cooperative game for balancing a community's load has been proposed in [6]. Coalitional game theoretic approachers for energy sharing among households have been proposed in [7, 8].

In this paper we propose a novel collaborative demand side management method for optimizing energy consumption and cost within a community of residential households. We consider a community of households. Some residences own RESs in conjunction with ESSs. Some other residences own ESSs only. The remaining households are pure energy consumers. The households are connected to a centralized energy management unit that controls the energy flow within the community through a two-way communication system and performs the cost optimization method proposed in this paper. We assume that the residences are equipped with smart energy meters that can predict the energy consumption as well as the renewable energy production with sufficient accuracy over e limited time period ahead.

The contributions of this paper are the following: We formulate two cost minimization problems for demand side management. First we introduce a method through which the RESs and ESSs owners may individually optimize their costs by using their own renewable energy production and storage spaces. Then we propose a novel collaborative cost optimization method. The objective is to reduce energy cost collaboratively by taking advantage of RESs and ESSs resources within the community of participating households. The novelty of this work stands in the unique problem formulation in which the RESs and ESSs owning households minimize their cost by sharing their renewable energy production and storage spaces and also by selling excess renewable energy and demand response services to pure energy consumers at a lower price than the utility company. The pure consuming households also reduce their costs by buying part of their needed electricity at a lower price than that offered by the utility company. In case of insufficient renewable energy production within the smart grid community, the households may buy energy from the utility company.

We perform extensive simulations through which we test the performance of the proposed method for different amounts of renewable energy available within the community. The results demonstrate that the proposed collaborative cost minimization approach provides significant savings in energy cost. Our simulation examples show a cost reduction of 12 to 50% for the RESs and ESS owning households in comparison with performing individual optimization. The pure energy consumers also reduce their costs by about 7-8% in comparison with buying all the needed energy from the utility company.

2. SYSTEM MODEL

We consider a community of N households forming a set $\mathcal{N}$ indexed by n. The subset of households owning RESs and ESSs, or own ESSs only is denoted by $\mathcal{M}$, $\mathcal{M} \subseteq \mathcal{N}$, with cardinality $|\mathcal{M}| = M$ and indexed by m. The remaining households from the community are pure energy consumers. This set of residences is denoted by $\mathcal{P}$, $\mathcal{P} = \mathcal{N} \setminus \mathcal{M}$, $|\mathcal{P}| = P$, and indexed by p. The energy cost optimization is performed over a finite time horizon $\mathcal{T}$ which is divided into equally long time slots indexed by t, $\mathcal{T} = [t, t{=}1, \ldots, T]$. The per-time-slot

978-1-5090-5990-4/17/$31.00 ©2017 IEEE

electricity demands of each household in the community is known for the whole period $\mathcal{T}$: $\mathbf{u}_n = [u_n(t), t{=}1,\ldots,T], n \in \mathcal{N}$. The set of renewable energy amounts produced by the households $m \in \mathcal{M}$ are considered predicted with sufficient accuracy and known over period $\mathcal{T}$: $\mathbf{w}_m = [w_m(t), t{=}1,\ldots,T]$. For those households from set $\mathcal{M}$ that own ESSs only, the renewable energy vector is zero: $\mathbf{w}_m = 0$. The set of energy amounts that a household $n \in \mathcal{N}$ may exchange with the rest of households from the community within period $\mathcal{T}$ is denoted by $\mathbf{a}_n = [a_n(t), t{=}1,\ldots,T]$. If $a_n(t) > 0$ then 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 $n \in \mathcal{N}$ may buy from the utility company in period $\mathcal{T}$is denoted by $\mathbf{b}_n = [b_n(t), t{=}1,\ldots,T]$.

The parameters associated with each ESS_m are defined as follows. The per-time-slot amounts of energy charged or discharged from a ESS_m in period $\mathcal{T}$ are denoted by $\mathbf{r}_m = [r_m(t), t{=}1,\ldots,T]$. If $r_m(t) > 0$ then energy is charged into ESS_m, while if $r_m(t) < 0$ then energy is being discharged from ESS_m in time-slot t. The amount of energy charged or discharged from storage in a time slot is limited by the charging/discharging rate ρ_m. The leakage factor of a storage is denoted by η_m. This parameter shows the proportion of the stored energy that the storage is losing within a time slot and has values between 0 and 1, typically $\eta_m \ll 1$. Let $\mathbf{s}_m = [s_m(t), t{=}1,\ldots,T]$ be the energy storage vector containing the total amounts of energy stored in an ESS_m at the end of each time slot. The maximum storing capacity of an ESS_m is denoted by C_m.

The utility company offers customers possibility of buying electricity at market-exchange prices. These prices are given ahead for the entire period $\mathcal{T}$: $\boldsymbol{\xi} = [\xi(t), t{=}1,\ldots,T]$. The set of prices corresponding to the energy sold by the households owning RESs and ESSs to the pure energy consumers is defined by $\boldsymbol{\lambda} = [\lambda(t), t = 1,\ldots,T]$. These prices are lower than the per-time-slot prices offered by the utility prices: $\lambda(t) = \alpha\xi(t)$, where $0 \leq \alpha \leq 1$. Other pricing data used in the proposed method is the following: π is the storage degradation price corresponding to charging/discharging one unit of energy from an ESS, τ is the price charged per unit of energy transferred among households and μ is a penalty price per unit of excessive renewable energy that may not be stored.

3. COST OPTIMIZATION PROBLEMS

In this section the proposed cost optimization problems are defined. First we formulate a cost minimization problem which can be implemented by each household $m \in \mathcal{M}$ individually, using only their own renewable resources and/or storage spaces. Then, we formulate the collaborative cost minimization problem in which the RESs and ESSs owners reduce their costs by exchanging energy and sharing their produced renewable energy and storage spaces, but also by selling energy to the simple energy consuming households.

3.1. Individual cost optimization

The problem for minimizing the cost of electricity consumed within period $\mathcal{T}$ by a single household $m \in \mathcal{M}$ is stated as follows:

$$\min_{\mathbf{b}_m,\mathbf{r}_m,\mathbf{s}_m} \sum_{t=1}^{T} \xi(t)b_m(t) + \pi \sum_{t=1}^{T} |r_m(t)| + \mu\sum_{t=1}^{T} [b_m(t) + w_m(t) - u_m(t) - r_m(t)],$$

such that the following constraints are satisfied:

$$b_m(t) \geq 0,\ \forall t \in \mathcal{T}, \forall\, m \in \mathcal{M}, \tag{1}$$

$$u_m(t) - w_m(t) - b_m(t) + r_m(t) \leq 0,\ \forall t \in \mathcal{T}, \forall\, m \in \mathcal{M}, \tag{2}$$

$$-\rho_m \leq r_m(t) \leq \rho_m,\ \forall t \in \mathcal{T}, \forall\, m \in \mathcal{M}, \tag{3}$$

$$s_m(t) = (1 - \eta_m)s_m(t-1) + r_m(t),\ \forall t \in \mathcal{T}, \forall\, m \in \mathcal{M}, \tag{4}$$

$$0 \leq s_m(t) \leq C_m,\ \forall t \in \mathcal{T}, \forall\, m \in \mathcal{M}. \tag{5}$$

The first term of the objective function, $\sum_{t=1}^{T} \xi(t)b_m(t)$, represents the cost of electricity purchased from the utility company. The second term of the objective function, $\pi \sum_{t=1}^{T} |r_m(t)|$, represents the storage degradation cost, i.e. the cost corresponding to the degradation suffered by an ESS through charging/discharging energy during period $\mathcal{T}$. The last term of the objective function represents a penalty term: $\mu \sum_{t=1}^{T} [b_m(t) + w_m(t) - u_m(t) - r_m(t)]$. This term works in conjunction with the energy consumption constraint (2) and makes sure that the produced renewable energy which exceeds the demand in period $\mathcal{T}$ is stored and kept in storage to be consumed within next period.

The constraint in (1) states the fact that the energy purchased from the utility company can only have positive or zero values. The inequation in (2) shows the energy consumption constraint: 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, $r_m(t)$. The three remaining constraints (3)-(5) show the energy storage constraints. The amount of energy charged or discharged from storage in a time slot, $r_m(t)$, is bounded by the charging/discharging rate ρ_m, (3). The charging dynamics of an ESS_m is defined in (4). Here, $s_m(0)$ is the initial storage value, or amount of energy remained in storage at the end of the previous optimization period. The amount of energy stored in an ESS_m at any time-slot must obey the storage capacity constraint (5).

3.2. The collaborative cost optimization

The collaborative cost optimization problem can be formulated as follows:

$$\min_{\{\mathbf{b}_m,\mathbf{r}_m,\mathbf{s}_m,\mathbf{a}_n\}_{m=1}^{M},{}_{n=1}^{N}} \sum_{m=1}^{M}\sum_{t=1}^{T} \xi(t)b_m(t) + \pi \sum_{m=1}^{M}\sum_{t=1}^{T} |r_m(t)| + \tau \sum_{m=1}^{M}\sum_{t=1}^{T} |a_m(t)| - \sum_{p=1}^{P}\sum_{t=1}^{T} \lambda(t)[-a_p(t)] + \mu\sum_{m=1}^{M}\sum_{t=1}^{T}[b_m(t) + w_m(t) - u_m(t) - a_m(t) - r_m(t)],$$

such that the following constraints are satisfied:

$$b_m(t) \geq 0,\ \forall t \in \mathcal{T}, \forall\, m \in \mathcal{M}, \tag{6}$$

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

$$u_p(t) - b_p(t) + a_p(t) = 0,\ \forall t \in \mathcal{T}, \forall\, p \in \mathcal{P}, \tag{8}$$

$$\sum\nolimits_{t=1}^{T} \xi(t)b_p(t) + \tau \sum\nolimits_{t=1}^{T} |a_p(t)| + \sum\nolimits_{t=1}^{T} \lambda(t)[-a_p(t)] < \sum\nolimits_{t=1}^{T} u_p(t)\xi(t),\ \forall\, p \in \mathcal{P}, \tag{9}$$

$$u_m(t) - w_m(t) - b_m(t) + r_m(t) + a_m(t) \leq 0, \forall t \in \mathcal{T}, \forall m \in \mathcal{M}, \tag{10}$$

$$-\rho_m \leq r_m(t) \leq \rho_m,\ \forall t \in \mathcal{T}, \forall\, m \in \mathcal{M}, \tag{11}$$

$$s_m(t) = (1 - \eta_m)s_m(t-1) + r_m(t),\ \forall t \in \mathcal{T}, \forall\, m \in \mathcal{M}, \tag{12}$$

$$0 \leq s_m(t) \leq C_m,\ \forall t \in \mathcal{T}, \forall\, m \in \mathcal{M}, \tag{13}$$

$$\sum\nolimits_{n=1}^{N} a_n(t) = 0. \tag{14}$$

Just like in the case of the individual cost optimization problem, in this problem the first two terms of the objective function, i.e.

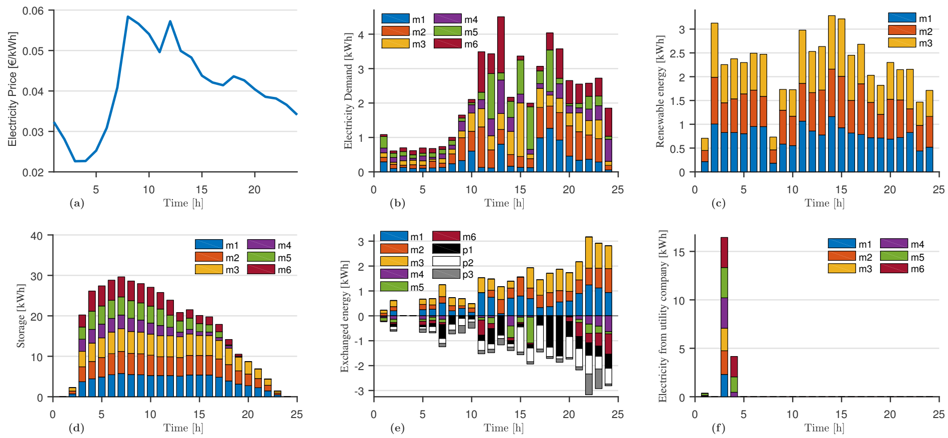

Fig. 1. (a) 24-hours utility company electricity price. (b) 24-hours electricity demand of the households owning RESs and ESSs. (c) 24-hours renewable energy production of households owning RESs. (d) 24-hours ESSs profiles. (e) 24-hours amounts of electricity exchange between all households in the community. The bars above zero show amounts of energy provided by some households to the others, whereas the bars below zero show amounts of energy received by the other households. (f) Electricity purchased from the utility company by RESs and ESSs owners. Households buy energy from the utility during the hours when the price is low.

$\sum_{m=1}^{M}\sum_{t=1}^{T}\xi(t)b_m(t)+\pi\sum_{m=1}^{M}\sum_{t=1}^{T}|r_m(t)|$, represent the cost incurred jointly by households $\mathcal{M}$ for the energy purchased from the utility company and the cost incurred for storage degradation. In this problem we add two more terms to the objective function. The third term, $\tau\sum_{m=1}^{M}\sum_{t=1}^{T}|a_m(t)|$, is the overall cost corresponding to operating the energy transfers among households. The optimization is performed by a central energy management unit that performs the optimization and controls the energy flow and transfer within the community. Hence, the third term represents the cost for operating the central control unit. The fourth term of the objective function, $\sum_{p=1}^{P}\sum_{t=1}^{T}\lambda(t)[-a_p(t)]$, represents the cost corresponding to the energy that the RESs and ESSs owners are selling to the plain energy consuming households in the community. A penalty term is added to the objective also in this problem, $\mu\sum_{m=1}^{M}\sum_{t=1}^{T}[b_m(t)+w_m(t)-u_m(t)-a_m(t)-r_m(t)]$. This penalty works in corroboration with constraint (10) and ensures that the produced renewable energy is either consumed, or transferred to the storage.

In the case of the collaborative cost optimization problem the constraints (6), (11)-(12) have same meaning as constraints (1), (3)-(5) from the individual optimization problem, i.e. the utility company energy consumption constraint and the energy storage constraints. Constraints (8) and (10) are energy consumption constraints. Constraint (8) is the energy consumption constraint for the simple energy consumers which can fulfill their demands, $u_p(t)$, by buying energy from the utility company, $b_p(t)$, or from the RESs and ESSs owning households in the community, $a_p(t)$. This imposes also constraint (7), which shows that households from set $\mathcal{P}$ can only receive energy from other members of the community. Constraint (10) is the energy consumption constraint for the RESs and ESSs owners which is similar to constraint (2), but also contains the variable $a_m(t)$ which shows the amount of energy to be exchanged with other residences. Additionally, we have constraint (9) which shows that the cost paid by a sole energy consuming household that participates in the optimization should be less than the cost that the household would pay by purchasing all needed electricity from the utility company. Finally, constraint (14) makes sure that in a time slot, the total amount of energy given away by some households is equal to the total amount of energy received by the rest of households from the community.

4. SIMULATION RESULTS

In this section we present simulation results that show the cost savings obtained by the proposed method. We considered a smart community of N= 9 households. The set $\mathcal{M}$ has 6 households: $\mathcal{M} = \{m1, m1, \dots\ m6\}$. 3 households from this set, $\{m1, m2, m3\}$, own RESs and ESSs, while the other 3 households, $\{m4, m5, m6\}$, own ESSs only. The remaining $|\mathcal{P}|$=3 households in the community are plain energy consumers: $\mathcal{P} = \{p1, p2, p3\}$. In these simulations we considered equal ESS_m capacities, C_m=10kWh, and equal charging/discharging rates, ρ_m= 3kWh. The storage loss factor was assumed $\eta_m = 0.001, \forall m \in \mathcal{M}$. We perform simulations over periods $\mathcal{T}$ of length T=24 hours divided into hourly time slots. The utility company prices, $\boldsymbol{\xi}$, are true market exchange prices taken from Finnish Nord Pool Spot database [9] for May 2013. Other pricing data used in simulations is the following: π=0.0001 €, μ=0.001 €, τ=0.0001 €. In this simulations we chose the prices of energy sold by the RESs and ESSs owners to the sole energy consumers to be $\boldsymbol{\lambda} = \alpha\boldsymbol{\xi}, \alpha = 0.9$, i.e. the sole consumers get a 10% discount compared to the utility company prices.

In this paper we show simulation results of the proposed method over 31 days. We assumed empty storage, $s_m(0)$=0, $\forall m \in \mathcal{M}$, at the beginning of the first 24-hours optimization period. Further, each method updated its corresponding initial storage values with the storage levels resulted at the end of the previous period $s_m(0) = s_m(24)$. For simulating the 24-hours electricity demands of the households, $\mathbf{u}_n$, we used the load modeling framework in [10]. We assumed the following numbers of inhabitants for the households: {3, 4, 4, 2, 5, 4, 3, 4, 2}. We considered that the households were equipped with wind turbines. For approximating the power generated by a wind turbine we used the following mathematical model [11]: $P_w = (1/2)DK_pAV^3$, where D is the air density, K_p=0.3 is the turbine power coefficient, A is the swept area, $A = 3.14R^2$,$R =$ 2.63m, and V is the wind speed. For this, we used weather data for May 2013 in Helsinki region [12].

The objective functions and constraints of the formulated optimization problems possess linear relationships among the variables. Hence, the optimization problems are in a form of linear programs.

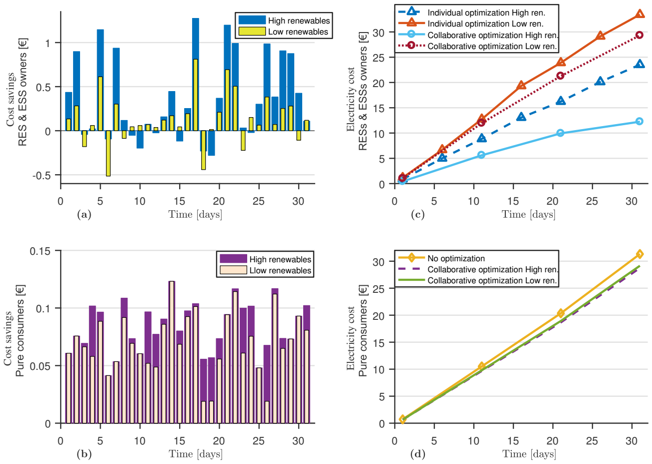

Fig. 2. (a) The daily cost savings achieved by the RESs and ESSs owning households in the collaborative scenario in comparison to the individual optimization. (b) The daily monetary revenues achieved by the simple energy consumers by participating in the collaborative optimization. Comparison between the 31-days cumulative electricity costs of the RESs and ESSs owners (c) and of the sole energy consumers (d). The collaborative optimization obtains for the households owning RESs and ESSs a cost reduction of 12 to 50% in comparison to the individual cost optimization (c). The sole energy consumers obtain a cost reduction of 7-8% in comparison to buying all energy from utility company (d).

The solutions of the optimization problems can be found using algorithms such as the interior point method [13]. For solving the linear programs we used the CVX package for convex optimization [14].

Fig. 1 (a)-(d) shows an example of 24-hours input data and results of the collaborative optimization problem. We used the pricing and weather data for May 21. Fig. 1.(a) shows the electricity prices, $\boldsymbol{\xi}$, in $€/kWh$. Fig. 1.(b) shows individual and cumulated hourly electricity demands of the households that own RESs and ESSs. Fig. 1.(c) shows the individual and cumulated renewable energy production of households that own RESs. Fig. 1.(d) shows the individual and cumulated hourly profiles of the ESSs, i.e how much energy is stored in the energy storage at the end of each hour. Fig. 1.(e) shows the amounts of energy exchanged during each hour by all households in the community. The bars above zero show the amounts of energy that are provided by some households, whereas the bars below zero 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. 1.(f) shows the amounts of energy purchased from the power grid by those households that own RESs and ESSs. The houses buy electricity from the utility company during the hours of a day when prices are usually low.

Fig. 2 (a)-(d) show the daily aggregate cost savings and the 31-days cumulative costs obtained by the formulated optimization method. We tested the performance of the proposed method for different renewable energy production values. Using the hourly renewable energy production values obtained with the model presented above, 500 samples were generated by adding a Gaussian random variation to these values. We then selected the maximum and minimum values among the generated samples. Hence, we created two vectors, the vector of maximal renewable energy values, $\mathbf{w}_m^{\text{High}} = [\max_l\{w_m^l(t) = \mathcal{N}(w_m(t), \sigma^2), l = 1, \ldots, 500\}, t = 1, \ldots, T]$, and the vector of minimal renewable energy values $\mathbf{w}_m^{\text{Low}} = [\min_l\{w_m^l(t) = \mathcal{N}(w_m(t), \sigma^2), l = 1, \ldots, 500\}, t = 1, \ldots, T]$. Here $\mathcal{N}$ denotes the Gaussian distribution with mean $w_m(t)$ and variance σ^2=0.05. Fig. 2(a) shows the daily aggregate cost savings obtained by the RESs and ESSs owning households through participating in the proposed collaborative optimization in comparison to performing the individual cost optimization. The RESs and ESSs owning households obtain cost savings in majority of the days of the month. It can be observed that the cost savings are more significant for higher amounts of renewable energy. It can also be observed that in few days of the month the collaborative optimization does not perform better than the individual optimization. Fig. 2(b) shows the aggregate cost savings of the pure energy consuming households as result of the optimization, by buying energy from the RESs and ESSs owners at a lower price than the one offered by the utility company. These households obtain costs savings every day of the month. Fig. 2(c) shows a comparative plot between 31-days cumulative electricity costs of the households owning RESs and ESSs in four cases: the cumulative total individual optimization costs for higher amounts of renewable energy (23.52 €), the cumulative collaborative optimization costs for higher amounts of renewable energy (12.24€), the cumulative total individual optimization costs for lesser amounts of renewable energy (33.43 €) and the cumulative collaborative optimization costs for lesser amounts of renewable energy (29.31€). In case of simulations with higher amounts of renewable energy, the proposed collaborative optimization obtains an overall cost reduction up to 50% in comparison to the individual cost optimization. In case of simulations with lesser amounts of renewable energy the cost reduction of the collaborative optimization is about 12% in comparison to the individual optimization. Fig. 2(d) shows a similar comparative plot for the cumulative costs of the pure consuming households. This plot includes the 31-days cumulative costs of buying all needed energy from the utility company (31.32€) in comparison with the cumulative costs obtained by participating in the collaborative optimization for simulations with higher amounts of renewable energy (28.74€) and simulations with lesser amounts of renewable energy (29.16€). The cost reduction obtained by the pure energy consumers in the collaborative scenario about 7-8%.

5. CONCLUSIONS

In this paper we proposed a novel collaborative demand side management method for optimizing energy consumption and cost within a community of residential households. In this work we formulated two cost minimization problems. We first formulated an individual optimization problem in which the RESs and ESSs owning households from the community could individually optimize their costs. We then proposed a collaborative cost optimization model through which the RESs and ESSs owners minimize their costs by exchanging energy, sharing their renewable energy and storage units and also by selling electricity to the pure consuming households in the community at a price lowe than that offered by the utility company. The pure consumers also reduce their costs. The problems were modeled as linear programs. We performed simulations for different amounts of renewable energy available within the community. The results showed that the proposed collaborative optimization reduces the cost of the RESs and ESSs owning households by a value between 12% to 50% in comparison to the individual optimization case. The sole energy consuming households may also reduce their electricity costs by about 7-8%.

6. REFERENCES

[1] H. Wang and J. Huang, "Cooperative planning of renewable generations for interconnected microgrids," *IEEE Trans. on Smart Grid*, vol. 7, no. 5, pp. 2486–2496, Sept 2016.

[2] H. Wang and J. Huang, "Incentivizing energy trading for interconnected microgrids," *available as early access article in IEEE Trans. on Smart Grid*, 2016.

[3] A. Ouammi, H. Dagdougui, L. Dessaint, and R. Sacile, "Coordinated model predictive-based power flows control in a cooperative network of smart microgrids," *IEEE Trans. on Smart Grid*, vol. 6, no. 5, pp. 2233–2244, Sept 2015.

[4] L. Xiao, N. B. Mandayam, and H. Vincent Poor, "Prospect theoretic analysis of energy exchange among microgrids," *IEEE Trans. on Smart Grid*, vol. 6, no. 1, pp. 63–72, Jan 2015.

[5] I. Atzeni, L. G. Ordóñez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, "Noncooperative and cooperative optimization of distributed energy generation and storage in the demand-side of the smart grid," *IEEE Trans. on Signal Processing*, vol. 61, no. 10, pp. 2454–2472, May 2013.

[6] J. Rajasekharan and V. Koivunen, "Cooperative game-theoretic approach to load balancing in smart grids with community energy storage," in *2015 23rd European Signal Processing Conference (EUSIPCO)*, Aug 2015, pp. 1955–1959.

[7] A. Chiş, J. Lundén, and V. Koivunen, "Optimization of plug-in electric vehicle charging with forecasted price," in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, March 2017.

[8] A. Chis and V. Koivunen, "Coalitional game based cost optimization of energy portfolio in smart grid communities," *Submitted to the IEEE Transactions on Smart Grid*, [Online]. Available: https://arxiv.org/abs/1705.04118 2017.

[9] [Online]. Available: www.nordpoolspot.com.

[10] I. Richardson, M. Thomson, D. Infield, and C. Clifford, "Domestic electricity use: A high-resolution energy demand model," *Energy and Buildings*, vol. 42, no. 10, pp. 1878–1887, 2010.

[11] T. Burton, D. Sharpe, N. Jenjkins, and E. Bossanyi, *Wind Energy Handbook*, Wiley, 2001.

[12] [Online]. Available: www.ilmatieteenlaitos.fi.

[13] Yinyu Ye, *Interior point algorithms: theory and analysis*, Wiley, 1997.

[14] M. Grant and S. Boyd, CVX: Matlab Software for Disciplined Convex Programming, Version 2.0 Beta, Sept 2013.