Cooperative Renewable Energy Management with Distributed Generation

Johann Leithon*, Stefan Werner*†, Visa Koivunen*
* Dept. of Signal Processing & Acoustics, Aalto University. Emails: firstname.secondname@aalto.fi.
† Dept. of Electronic Systems, Norwegian University of Science and Technology. Email: stefan.werner@ntnu.no.

***Abstract*—We propose an energy cost minimization strategy for cooperating households equipped with renewable energy generation and storage capabilities. The participating households minimize their collective energy expenditure by sharing renewable energy through the grid. We assume location and time dependent electricity prices, as well as parametrized transfer fees. We then formulate an optimization problem to minimize the energy cost incurred by the participating households over any specified planning horizon. The proposed strategy serves as a performance benchmark for online energy management algorithms, and can be implemented in real time by incorporating adequate forecasting techniques. We solve the optimization problem through relaxation, and use simulations to illustrate the characteristics of the solution. These simulations show that energy sharing takes place when there are differences in the load/generation and price profiles across participants. We also show that no energy sharing takes place when the load is above the local generation at all times.**

***Index Terms*—Renewable energy optimization, storage management, non-convex optimization.**

I. Introduction

The power grid is undergoing an important transformation, and the adoption of information technologies to modernize the electricity grid is expected to enable the general public to participate in various energy-saving initiatives [1], [2]. These initiatives are, often times, part of demand side management programs [3], which are used by utility companies to reduce peak loads and make their distribution systems more cost and energy efficient [4], [5]. Demand side management can be achieved through direct load control or dynamic electricity pricing. In the latter, utility companies design pricing schemes to influence users' power consumption patterns, and thus achieve the desired demand response.

Households benefit from dynamic electricity pricing to reduce their energy bills [6]. Users can schedule their tasks to avoid peak pricing periods, or use storage devices to defer grid energy consumption to low pricing hours, without sacrificing comfort. Given the growth that the production of renewable energy (RE) has had in the past decade [7], it is of interest to investigate how RE can be used to reduce households' energy expenditure, and what impact does cooperation have on RE usage performance. This has motivated us to propose an optimization strategy for a group of grid-tied households equipped with RE generation and storage facilities.

Specifically, in this paper we propose an optimization strategy to minimize the collective energy expenditure incurred by a group of households over a finite planning horizon. The households are allowed to share RE through the grid at a transfer fee set by the utility company. To ensure generality, we assume location and time dependent electricity prices, as well as parametrized transfer fees. We formulate and solve a mathematical problem to determine the optimal energy cooperation strategy among participating households. We also use simulations to illustrate the characteristics of the optimal strategy.

The main contribution of this paper is a mathematical framework that can be used to determine the optimal energy cooperation strategy in a very general setting. The obtained strategy allows us to find performance bounds, which can be used to benchmark online energy management algorithms. Moreover, the proposed strategy can be implemented in real time by incorporating adequate forecasting techniques. In this paper we also investigate the characteristics of the solution and highlight the conditions under which energy sharing is an optimal strategy.

Closely related works on building/home energy management include [8]–[13], where strategies are proposed to minimize the building's electricity bill by scheduling its deferrable appliances. The frameworks in [8] and [11] take into account comfort constraints imposed by users. Electrical vehicles are considered as part of the set of appliances in [10], and energy storage devices (ESDs) are accounted for in [9], [13].

Energy management in a microgrid environment has been studied in [14]–[17], where strategies based on capacity planning are proposed to achieve cost minimization. Cooperative energy management has been investigated in [18]–[23], where strategies are proposed for economic dispatch, load matching, and power loss minimization. RE trading schemes have been analyzed in [24], where a profit maximization strategy is devised for an energy harvesting company. Finally, strategies based on evolutionary algorithms and game theory have been proposed in [25]–[28].

Unlike existing works, our proposed strategy assumes a non-deferrable power consumption, thus respecting users' preferences. Moreover, our proposal aims at minimizing the energy cost incurred by a group of users participating in a demand response program, which was not considered in [18]–[23]. Also, we assume that the participating households do not compete with each other, as the achievable cost savings can be dividing among participants following a fairness-based approach. Finally, this paper discusses the conditions under which energy sharing should be adopted as an optimal strategy, and the situations in which it can be avoided. Thus, our results can be used for network planning

ISBN 978-90-827970-1-5 © EURASIP 2018

purposes, and their corresponding capital budgeting.

II. System Model

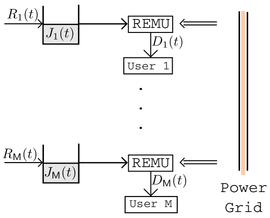

Fig. 1. System Model. REMU stands for renewable energy management unit.

A. Planning Horizon, Objective, and Decision Variables

We consider M grid-tied households, as shown in Fig. 1, and seek to minimize their collective energy cost incurred in the planning horizon $[0, T]$, with $T > 0$. Each household is subject to different energy consumption patterns, and electricity prices. The power consumed by the ith household is denoted by $L_i(t) > 0,\ t \in [0, T]$, and is assumed to be non-deferrable. The power drawn from the grid is thus controlled through storage management by scheduling the use of RE in $[0, T]$. The decision variables are the charging and discharging schedules of all the ESDs in the system, as well as the energy transfer operations among the households.

B. Renewable Energy Production and Storage Allocation

Each household is equipped with an RE generator and a storage device. Households share RE through the grid, thus incurring transfer fees. The total power received by household i from others is denoted by $\Gamma_i(t)$, while the total power transferred from the household i to other households is denoted by $\Theta_i(t)$. If the power transferred from household i to household j is denoted by $\Pi_{i,j}(t) \geq 0,\ \forall\ t$, then:

$$\Gamma_i(t) = \sum_{j \neq i}^{M} \Pi_{j,i}(t), \quad \Theta_i(t) = \sum_{j \neq i}^{M} \Pi_{i,j}(t),\ \forall\ t. \quad (1)$$

Following energy conservation, $\Gamma_i(t)$ and $\Theta_i(t)$ must satisfy:

$$\sum_{i=1}^{M} \Gamma_i(t) = \sum_{i=1}^{M} \Theta_i(t),\ \forall\ t. \quad (2)$$

C. Energy Storage Devices (ESDs)

The ESDs in the system have the following characteristics:

- Charging/discharging losses: The charging/discharging efficiency rates of the ESD at the ith household are respectively α_i and β_i, and satisfy $0 < \alpha_i \leq 1$ and $0 < \beta_i \leq 1$. A lossless charging/discharging operation happens when the charging/discharging efficiency rate is 1.
- ESD dynamics: The RE available in the ESD at the ith household is $J_i(t) \geq\ \forall\ t\ \in\ [0, T]$, and satisfies:

$$J_i(t) = J_i(0) + \int_0^t \left[\alpha_i C_i(x) - \frac{1}{\beta_i} \left[D_i(x) + \Theta_i(x) \right] \right] dx, \quad (3)$$

where $C_i(t) \geq\ 0$ and $D_i(t) \geq\ 0,\ \forall\ t$, are, respectively, the power charged to the ith ESD, and the power used up by the ith household.

- Bounded storage capacity: The capacity of the ESD at the ith household is denoted by Ψ_i. Therefore, $C_i(t)$ and $D_i(t)$, $i \in \{1, \ldots, M\}$ must be such that:

$$0 \leq J_i(t) \leq \Psi_i, \forall\ t\ \in\ [0, T]. \quad (4)$$

- Bounded charging/discharging rate: Each ESD has a limited charging/discharging rate, and hence,

$$C_i(t) \leq q_{C,i},\ D_i(t) + \Theta_i(t) \leq q_{D,i},\ \forall\ i,\ \forall\ t\ \in\ [0, T], \quad (5)$$

where $q_{C,i} > 0$ and $q_{D,i} > 0$ are respectively the maximum charging and discharging rates of the ESD at the ith house.

D. Renewable Energy Generation

The total power generated at the ith facility is $R_i(t) \geq 0,\ \forall\ t\ \in\ [0, T]$. Therefore, the power charged into the ESD at the energy farm satisfies:

$$C_i(t) \leq \min\{q_{C,i}, R_i(t) + \Gamma_i(t)\},\ \forall\ t, \forall\ i, \quad (6)$$

where $\Gamma_i(t)$, defined in (1), is the total power received by the ith household from other cooperating households.

E. Pricing Scheme

To ensure generality, we consider location and time dependent electricity prices. The cost of the energy consumed by the ith household in $[0, T]$ is $\xi_i = \int_0^T P_i(t)\,[L_i(t) - D_i(t)]\,dt$, where $P_i(t) \geq 0,\ \forall\ t,\ \forall\ i$, is the pricing function, and $D_i(t)$ satisfies

$$D_i(t) \leq L_i(t),\ \forall\ t. \quad (7)$$

The cost of the energy consumed by the entire group of households is thus $\chi = \sum_{i=1}^{M} \xi_i$. This model generalizes pricing schemes in the discrete domain. The pricing functions $P_i(t)$'s are assumed known in advance because they are part of a demand response program where the utility sets the prices, and the consumers react by scheduling their ESDs.

III. Problem Formulation and Solution Strategy

We formulate a mathematical problem to determine the optimal energy management strategy for the system described in Sec. II. The formulation seeks to minimize χ, the cost incurred by all the households in $[0, T]$. The achieved cost savings can then be allocated to the participants following a fairness-based criterion.

A. Power Transfer Matrix

To simplify notation we define the following power transfer matrix $\Pi(t) \triangleq [\Pi_{i,j}(t)]$, where $\Pi_{i,j}(t),\ i,\ j\ \in \{1, \ldots, M\}$, defined in Sec. II-B, is the power transferred from household i to household j. Since the power exchange cannot happen simultaneously, the elements of $\Pi(t)$ must satisfy:

$$\Pi_{i,j}(t)\Pi_{j,i}(t) = 0,\ \forall\ t,\ \forall\ i \neq j. \quad (8)$$

In addition, the elements of $\Pi(t)$ are all non-negative. We can interpret the diagonal elements of this matrix as the power that the ith household transfers to itself, or said otherwise, uses locally. Hence, we can let $\Pi_{i,i}(t) = D_i(t)\ \forall\ i,\ \forall\ t$.

ISBN 978-90-827970-1-5

B. Transfer Charges

To ensure generality, we assume transfer fees proportional to the energy rates offered to the receiving household. Therefore, the cost incurred by the set of households in moving $\sum_{i=1}^{M} \Theta_i(t)$ power units across the network is:

$$\epsilon = \sum_{i=1}^{M} \rho \int_0^T P_i(t)\Theta_i(t)dt, \tag{9}$$

where $0 \leq \rho \leq 1$. The transfer fee is zero when $\rho = 0$. This fee is charged by the utility and accounts for the power loss incurred in the operation. If the utility has sufficient power delivery capacity, then the power transfer will not need to happen physically, and the operation can be recorded as an economical transaction.

C. Problem Formulation

The optimization problem can be cast in terms of the decision variables $\Pi(t)$ and the $C_i(t)$'s as follows:

$$\begin{aligned} \text{P1A:} \quad & \min_{C_1(t),\ldots,C_M(t),\Pi(t)} \quad \chi + \epsilon \\ \text{s.t.} \quad & (2),\ (4),\ (6),\ (7),\ (8) \end{aligned}$$

In P1A, the objective is the energy cost incurred by the group of facilities, plus the cost of the RE transfers that take place in $[0, T]$. Moreover, the $J_i(t)$'s and $\Pi(t)$ are connected through (3). The quantities $\Gamma_i(t)$ and $\Theta_i(t)$ were defined in terms of $\Pi(t)$ in (1). P1A is not a convex optimization problem because its objective is a functional (not a function), its decision variables are trajectories (not vectors or scalars), and it involves an infinite number of constraints, as stated in (4).

An alternative formulation can be obtained by casting the problem directly in terms of the $C_i(t)$'s, the $D_i(t)$'s, the $\Theta_i(t)$'s, and the $\Gamma_i(t)$'s. Consequently, the power transfer matrix can be obtained from (1), and (8). Hence, the resulting optimization problem is:

$$\begin{aligned} \text{P1B:} \quad & \min_{C_i(t),D_i(t),\Theta_i(t),\Gamma_i(t),\ i\ \in\ \{1,\ldots,M\}} \quad \chi + \epsilon \\ \text{s.t.} \quad & (2),\ (4),\ (6),\ (7). \end{aligned}$$

In P1B, the $J_i(t)$'s, the $D_i(t)$'s, and the $\Theta_i(t)$'s are connected through (3). Again, P1B is a non-convex optimization problem, which we relax to find an approximate solution, as explained in Sec. III-D.

D. Solution Strategy

We can use discretization to solve P1B at N equally-spaced sampling points. In the discrete domain, the decision variables become column vectors, and are denoted respectively by $\mathbf{c}_i$, $\mathbf{d}_i$, $\boldsymbol{\theta}_i$, $\boldsymbol{\gamma}_i$, $i \in \{1, \ldots, M\}$. That is: $c_i(k) = C_i(k\Delta t)$, $d_i(k) = D_i(k\Delta t)$, $\theta_i(k) = \Theta_i(k\Delta t)$, $\gamma_i(k) = \Gamma_i(k\Delta t)$, $\forall\ k$, where $k \in \{1, \ldots, N\}$ and $\Delta t > 0$ is the sampling period. We also introduce the following definition to simplify the constraint (4):

$$\mathbf{M}_D = [\alpha\Delta t\mathbf{A}_N \quad -\frac{1}{\beta}\Delta t\mathbf{A}_N \quad -\frac{1}{\beta}\Delta t\mathbf{A}_N \quad \mathbf{0}_{N,N}],$$

where $\mathbf{A}_N$ is the $N \times N$ lower triangular matrix of ones. Clearly, $\mathbf{M}_D$ is an $N \times 4N$ matrix. By using $\mathbf{M}_D$, the constraint (4) can be written compactly as follows:

$$\mathbf{0}_{N,1} \preceq \mathbf{M}_D \begin{pmatrix} \mathbf{c}_i \\ \mathbf{d}_i \\ \boldsymbol{\theta}_i \\ \boldsymbol{\gamma}_i \end{pmatrix} \preceq [\Psi_i - J_i(0)]\, \mathbf{1}_{N,1},\ \forall\ i, \tag{10}$$

where $\preceq$ denotes element-wise $\leq$. The constraints that appear in P1B can be written in the discrete domain by using matrix notation as follows:

$$\begin{pmatrix} \mathbf{I}_M \otimes \mathbf{M}_D \\ -\mathbf{I}_M \otimes \mathbf{M}_D \\ \mathbf{I}_M \otimes [\mathbf{I}_N \quad \mathbf{0}_{N,2N} \quad -\mathbf{I}_N] \\ \mathbf{I}_M \otimes [\mathbf{0}_{N,N} \quad \mathbf{I}_N \quad \mathbf{I}_N \quad \mathbf{0}_{N,N}] \\ \mathbf{1}_{1,M} \otimes [\mathbf{0}_{N,2N} \quad -\mathbf{I}_N \quad \mathbf{I}_N] \end{pmatrix} \begin{pmatrix} \mathbf{c}_1 \\ \mathbf{d}_1 \\ \boldsymbol{\theta}_1 \\ \boldsymbol{\gamma}_1 \\ \vdots \\ \mathbf{c}_M \\ \mathbf{d}_M \\ \boldsymbol{\theta}_M \\ \boldsymbol{\gamma}_M \end{pmatrix} \preceq \begin{pmatrix} \mathbf{v}_1 \\ \mathbf{r}_1 \\ \vdots \\ \mathbf{r}_M \\ \mathbf{v}_2 \end{pmatrix}, \tag{11}$$

where $\mathbf{v}_1^T = [(\Psi_1 - J_1(0))\mathbf{1}_{1,N}, \ldots, (\Psi_M - J_M(0))\mathbf{1}_{1,N}, \mathbf{0}_{1,NM}]$ and $\mathbf{v}_2^T = [q_D\mathbf{1}_{1,NM}, \mathbf{0}_{1,N}]$. The dimensions of the objects in (11) are as follows: the leftmost matrix has $4MN + N$ rows and $4MN$ columns, the vector containing the decision variables has $4MN$ elements, and the column vector at the right-hand-side has $4MN + N$ elements. If we relax the constraint (2) to

$$\sum_{i=1}^{M} \Gamma_i(t) \leq \sum_{i=1}^{M} \Theta_i(t),\ \forall\ t, \tag{12}$$

then, the optimization problem P1B can be cast in the discrete domain as a linear program by using the definition of $\mathbf{M}_D$. Introducing this relaxation will not affect the solution because a necessary[1] optimality condition is that the $\Gamma_i(t)$'s and the $\Theta_i(t)$'s must satisfy (12) with equality. Therefore, the constraint (2) will be automatically satisfied by the solution simply by enforcing (12).

IV. Numerical Results

We provide numerical results to illustrate the proposed energy management strategy. Throughout this section we consider the simulation parameters shown in Table I, where $\mathsf{minPrice} \in \mathbb{R}_+$, $\mathsf{maxPrice} \in \mathbb{R}_+$, $\mathsf{minLoad} \in \mathbb{R}_+$, $\mathsf{maxLoad} \in \mathbb{R}_+$, $\mathsf{minGen} \in \mathbb{R}_+$, $\mathsf{maxGen} \in \mathbb{R}_+$, and $\mathcal{U}(a, b)$ indicates uniform[2] distribution between a and b. Simulations results are reported using normalized quantities, which are measured in generic units. Storage capacities are measured in energy units [EU], cost in monetary units [MU], and power quantities in power units [PU].

[1] It is suboptimal to dispatch energy if it will not be used at its destination. Hence, in the relaxed formulation, the optimal strategy will satisfy (12) with equality.

[2] The uniform distribution is chosen for prices, RE generation, and load because it reflects total uncertainty given known lower and upper limits.

ISBN 978-90-827970-1-5 © EURASIP 2018

TABLE I
SIMULATION SCENARIOS

Parameter	Value
$\{T,\ \Delta t,\ M,\ J(0),\ \rho\}$	$\{23,\ 1,\ 2,\ 0,\ 0\}$
$P_i(t)$	$\sim \mathcal{U}(\mathsf{minPrice}, \mathsf{maxPrice})$
$L_i(t)$	$\sim \mathcal{U}(\mathsf{minLoad}, \mathsf{maxLoad})$
$R_i(t)$	$\begin{cases} \sim \mathcal{U}(\mathsf{minGen}, \mathsf{maxGen}), & t \in \{1, \lceil N/2 \rceil\} \\ 0 & t > \lceil N/2 \rceil \end{cases}$
$\{q_{C,i}, q_{D,i}, \Psi_i, \alpha_i, \beta_i\}$	$\{1,\ 1,\ \Psi_1,\ 1,\ 1,\ \forall\ i\}$

A. Energy Sharing Optimal Schedules

We consider the simulation parameters shown in Table I with $\mathsf{minLoad} = 1$, $\mathsf{maxLoad} = 1$, $\mathsf{minGen} = 1$, $\mathsf{maxGen} = 1$, $\mathsf{minPrice} = 0$, $\mathsf{maxPrice} = 1$, and illustrate the obtained optimal schedules in Fig. 2. As seen, the energy sharing mechanism is triggered despite having $L_1(t) = L_2(t)$ and $R_1(t) = R_2(t)\ \forall\ t$. Moreover, it is observed that a limited storage capacity prompts more frequent energy sharing operations.

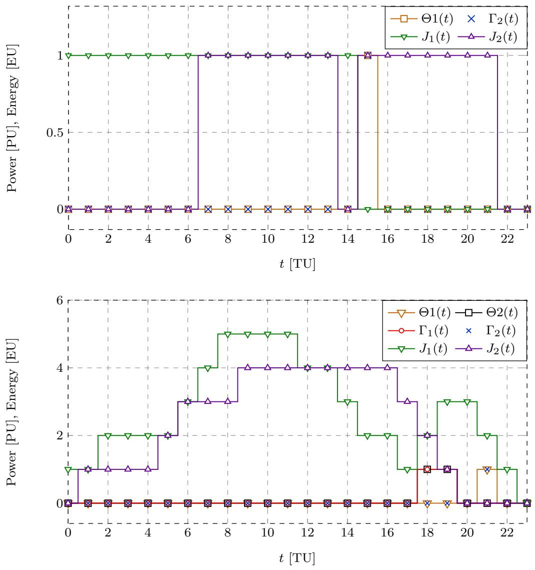

Fig. 2. Energy sharing strategy with differences across pricing functions. Top: $\Psi_1 = \Psi_2 = 1$. Bottom: $\Psi_1 = \Psi_2 = 10$.

We now consider the simulation parameters shown in Table I with $\mathsf{minLoad} = 0$, $\mathsf{maxLoad} = 1$, $\mathsf{minGen} = 1$, $\mathsf{maxGen} = 2$, $\mathsf{minPrice} = 1$, $\mathsf{maxPrice} = 1$, and illustrate the obtained optimal schedules in Fig. 3. As seen, the energy sharing mechanism is used even when there are no differences between the two pricing functions. Again, it is observed that a limited storage capacity prompts a more frequent energy sharing mechanism.

B. Performance of the Proposed Strategy

The proposed strategy can be evaluated in terms of the achievable cost savings and the RE unused due to battery overflow. Let $D_1^*(t),\ \ldots,\ D_M^*(t)$ denote the optimal dis-

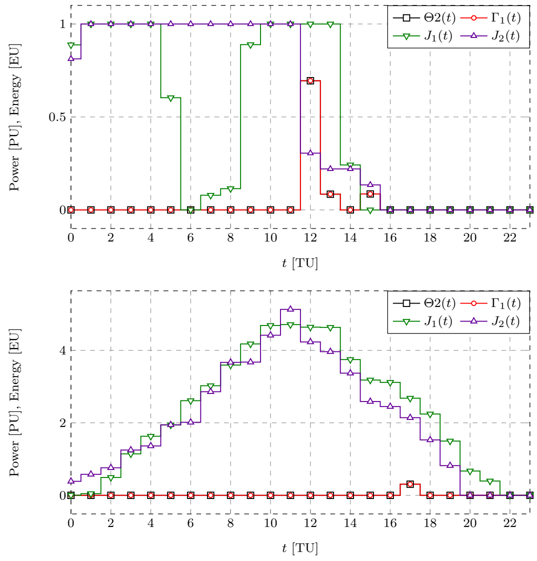

Fig. 3. Energy sharing strategy with constant pricing functions. Top: $\Psi_1 = \Psi_2 = 1$. Bottom: $\Psi_1 = \Psi_2 = 10$.

charging profiles obtained by solving P1B. Then, the total RE unused in $[0, T]$ is:

$$\mathsf{URE} = \sum_{i=1}^{M} \int_0^T \left[R_i(t) - D_i^*(t) \right] dt. \tag{13}$$

We consider the simulation scenario shown in Table I with $\mathsf{minLoad} = 1$, $\mathsf{maxLoad} = 1$, $\mathsf{minGen} = 0$, $\mathsf{maxGen} = \{1, 2\}$, $\mathsf{minPrice} = 0$, $\mathsf{maxPrice} = 1$. Then we plot the average energy cost incurred in $[0, T]$, and the average amount of RE unused, both against the storage size Ψ_i, which ranges from 1 to 10 [EU], in Fig. 4. These results were computed by averaging over ten thousand realizations. As observed, both the energy cost and the RE unused in $[0, T]$ decrease with the storage size Ψ_i, especially when the generation capacity is above the load.

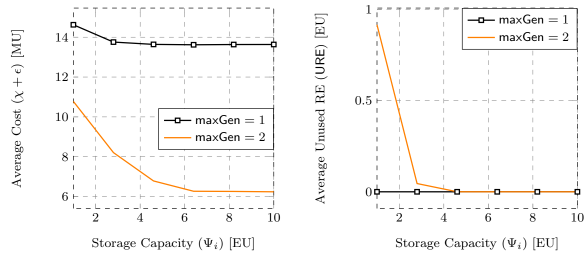

Fig. 4. Left: Average cost incurred in $[0, T]$ vs. storage capacity. Right: Average RE unused in $[0, T]$ vs. storage capacity.

We now consider the simulation scenario shown in Table I, except for $q_{C,i}$ and $q_{D,i}$, which we set as follows: $q_{C,i} = 0.2\frac{\Psi_i}{\Delta t}$, $q_{D,i} = 0.2\frac{\Psi_i}{\Delta t}$. Moreover, we let $\mathsf{minLoad} = 1$, $\mathsf{maxLoad} = 1$, $\mathsf{minGen} = 0$, $\mathsf{maxGen} = \{1, 2\}$, $\mathsf{minPrice} = 0$, and $\mathsf{maxPrice} = 1$. Then we plot the average energy cost incurred in $[0, T]$, and the average amount of RE unused, both against the storage size Ψ_i, which ranges from 1 to 10 [EU], in Fig. 5. These results were computed by averaging over ten thousand realizations. As observed, the energy cost and the RE unused in $[0, T]$ decrease consistently with the storage capacity Ψ_i. It is also seen that a storage capacity above 8 [EU] does not affect (significantly) the final energy cost. This suggests that there is a minimum storage size which ensure maximum RE utilization.

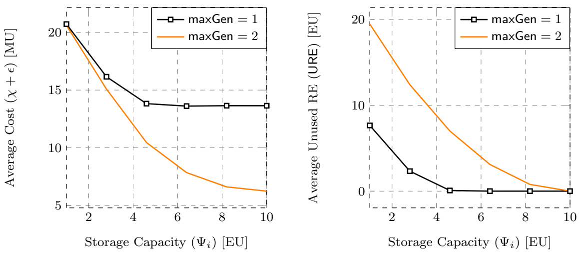

Fig. 5. Left: Average cost incurred in $[0, T]$ vs. storage capacity. Right: Average RE unused in $[0, T]$ vs. storage capacity.

V. Conclusions

We have proposed an optimization strategy for a set of households equipped with renewable energy generation and storage facilities. The households exchange renewable energy through the grid to minimize their energy cost. Transfer fees, and location and time dependent energy prices have been considered in the model. We have developed a mathematical framework to determine the optimal energy management strategy in different scenarios. We have also provided numerical results to illustrate the characteristics of the optimal strategy. Our simulations have shown that the energy sharing mechanism is used when there are differences in the pricing functions, loads, and generation profiles across participating households. Moreover, no energy sharing takes place when all the loads are above the local generation capacities at all times. The energy cost and the amount of renewable energy unused in the planning horizon have been shown to decrease as a larger storage capacity is deployed in the system.

Acknowledgement

This work was supported in part by the Academy of Finland under Grant 296849.

References

[1] P. Top *et al.*, "Observing the power grid: Working toward a more intelligent, efficient, and reliable smart grid with increasing user visibility," *IEEE Signal Processing Magazine*, vol. 29, no. 5, pp. 24–32, Sept 2012.

[2] S. C. Chan *et al.*, "Load/price forecasting and managing demand response for smart grids: Methodologies and challenges," *IEEE Signal Processing Magazine*, vol. 29, no. 5, pp. 68–85, Sept 2012.

[3] I. Atzeni *et al.*, "Cooperative day-ahead bidding strategies for demand-side expected cost minimization," in *2013 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, May 2013, pp. 5224–5228.

[4] L. Song *et al.*, "Non-stationary demand side management method for smart grids," in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, May 2014, pp. 7759–7763.

[5] S. Bahrami and V. W. S. Wong, "An autonomous demand response program in smart grid with foresighted users," in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Nov 2015, pp. 205–210.

[6] G. Ye *et al.*, "Towards cost minimization with renewable energy sharing in cooperative residential communities," *IEEE Access*, vol. 5, pp. 11 688–11 699, 2017.

[7] U.S. Energy Information Administration, "Electric power annual 2015," Tech. Rep., 2015. [Online]. Available: https://www.eia.gov/electricity/annual/

[8] M. Rastegar *et al.*, "A probabilistic energy management scheme for renewable-based residential energy hubs," *IEEE Trans. Smart Grid*, vol. PP, no. 99, pp. 1–11, 2016.

[9] T. Li and M. Dong, "Real-time joint energy storage management and load scheduling with renewable integration," in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, March 2016, pp. 3456–3460.

[10] D. Wu *et al.*, "Two-stage energy management for office buildings with workplace ev charging and renewable energy," *IEEE Trans. Transportation Electrification*, vol. 3, no. 1, pp. 225–237, March 2017.

[11] V. Pilloni *et al.*, "Smart home energy management including renewable sources: A qoe-driven approach," *IEEE Trans. Smart Grid*, vol. PP, no. 99, pp. 1–1, 2017.

[12] T. Chen *et al.*, "Energy and workload management for data centers in renewable-integrated power grid," in *2015 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, Dec 2015, pp. 513–517.

[13] J. Rajasekharan and V. Koivunen, "Optimal energy consumption model for smart grid households with energy storage," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 6, pp. 1154–1166, Dec 2014.

[14] T. C. Chiu *et al.*, "Optimized day-ahead pricing with renewable energy demand-side management for smart grids," *IEEE Internet of Things Journal*, vol. 4, no. 2, pp. 374–383, April 2017.

[15] Y. Xiang *et al.*, "Robust energy management of microgrid with uncertain renewable generation and load," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 1034–1043, March 2016.

[16] Q. Fu *et al.*, "Transition management of microgrids with high penetration of renewable energy," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 539–549, March 2014.

[17] K. Rahbar *et al.*, "Real-time energy storage management for renewable integration in microgrid: An off-line optimization approach," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 124–134, Jan 2015.

[18] Z. Zhang *et al.*, "Asynchronous distributed cooperative energy management through gossip-based incremental cost consensus algorithm," in *2013 North American Power Symposium (NAPS)*, Sept 2013, pp. 1–6.

[19] I. Stoyanova *et al.*, "Cooperative energy management approach for short-term compensation of demand and generation variations," in *2014 IEEE Int. Systems Conf. Proceedings*, March 2014, pp. 559–566.

[20] A. C. Luna *et al.*, "Cooperative energy management for a cluster of households prosumers," *IEEE Trans. Consumer Electronics*, vol. 62, no. 3, pp. 235–242, August 2016.

[21] F. Mangiatordi *et al.*, "Multi agent system for cooperative energy management in microgrids," in *2016 IEEE 16th Int. Conf. on Environment and Electrical Engineering (EEEIC)*, June 2016, pp. 1–5.

[22] K. Rahbar *et al.*, "Energy cooperation optimization in microgrids with renewable energy integration," *IEEE Trans. Smart Grid*, vol. PP, no. 99, pp. 1–1, 2016.

[23] H. Dagdougui *et al.*, "Global energy management system for cooperative networked residential green buildings," *IET Renewable Power Generation*, vol. 10, no. 8, pp. 1237–1244, 2016.

[24] W. Tushar *et al.*, "Management of renewable energy for a shared facility controller in smart grid," *IEEE Access*, vol. 4, pp. 4269–4281, 2016.

[25] N. Javaid *et al.*, "An intelligent load management system with renewable energy integration for smart homes," *IEEE Access*, vol. PP, 2017.

[26] V. Mohan *et al.*, "Microgrid energy management combining sensitivities, interval and probabilistic uncertainties of renewable generation and loads," *IEEE J. Emerging and Sel. Topics in Circuits and Systems*, vol. 7, no. 2, pp. 262–270, June 2017.

[27] Z. Zhou *et al.*, "Game-theoretical energy management for energy internet with big data-based renewable power forecasting," *IEEE Access*, vol. 5, pp. 5731–5746, 2017.

[28] M. Marzband *et al.*, "Non-cooperative game theory based energy management systems for energy district in the retail market considering der uncertainties," *IET Generation, Transmission Distribution*, vol. 10, no. 12, pp. 2999–3009, 2016.