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Peer-to-peer energy trading among smart homes

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HIGHLIGHTS

- A near-optimal energy cost optimization algorithm, named ECO-Trade, is proposed.
- The resulting trading strategy minimizes the total cost of all households.
- Results show that unrestrained peer-to-peer trading may increase the energy cost.
- Any potentially unfair cost distribution is addressed by ensuring Pareto optimality.

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ABSTRACT

This paper evaluates the impact of Peer-to-Peer (P2P) energy trading among the smart homes in a microgrid. Recent trends show that the households are gradually adopting renewables (e.g., photovoltaics) and energy storage (e.g., electric vehicles) in their premises. This research addresses the energy cost optimization problem in the smart homes which are connected together for energy sharing. The contributions of this paper is threefold. First, we propose a near-optimal algorithm, named Energy Cost Optimization via Trade (ECO-Trade), which coordinates P2P energy trading among the smart homes with a Demand Side Management (DSM) system. Our results show that, for real datasets, 99% of the solutions generated by the ECO-Trade algorithm are optimal solutions. Second, P2P energy trading in the microgrid potentially results in an unfair cost distribution among the participating households. We address this unfair cost distribution problem by enforcing Pareto optimality, ensuring that no households will be worse off to improve the cost of others. Finally, we evaluate the impact of renewables and storage penetration rate in the microgrid. Our results show that cost savings do not always increase linearly with an increase in the renewables and storage penetration rate. Rather they decrease gradually after a saturation point.

1. Introduction

The global smart home market size is expected to reach $53.45 billion by 2022 and the number of households that adopt smart home systems is forecasted to grow at a compound annual growth rate of 14.5% between 2017 and 2022 [1]. From the smart grid's perspective, smart homes are considered as nanogrids [2]. The term 'nanogrid' was first mentioned by Nordman in 2010 [3]. A nanogrid may have energy sources, e.g., photovoltaic (PV) modules, small scale wind turbines and energy storage including plug-in electric vehicles. A network of interconnected nanogrids in a neighborhood forms a microgrid [4], which enables Peer-to-Peer (P2P) energy trading among the households. This research explores the cost optimization problem in the smart homes that involves diverse energy sources, storage, and loads constrained by user preferences and the electrical properties of the participating components. It also addresses the cost minimization problem associated with P2P energy trading among the smart homes in a microgrid.

The research on P2P energy trading is still at an early stage and there is no consensus on what type of data sharing and processing infrastructure is more efficient and yields the best results. While each household can trade energy with others, it does not necessarily mean that the prosumers directly control the loads and energy sources, they may use the services of an aggregator to manage the resources [5–7]. A centralized (e.g., cloud [7]) or distributed infrastructure (e.g., blockchain [8]) may be required to process the data generated by the households. We assume that the households have already formed a microgrid with the capability of P2P trading. The proposed algorithm is developed for a centralized architecture, which requires a central processing unit/center to collect and process the information of all households. Therefore, a cloud infrastructure can be a suitable platform

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Nomenclature

Sets

H	set of timeslots where $h \in H$
I	set of appliances where $i \in I$
K	set of households where $k \in K$
U	set of uninterruptible appliances where $U \subset I$

Parameters

C_{pre}	previous cost
C_{cur}	current cost
$d_{k,i}$	disutility factor of an appliance
E_k	storage efficiency
GP_h	grid energy price
IE_k	initial storage energy level
L_k^{max}	maximum grid power limit
$MaxC_k$	maximum storage capacity
$MinC_k$	minimum storage capacity
N	number of timeslots in the scheduling time horizon
$p_{k,i}$	power consumption of an appliance
$r_{k,i,h}$	reservation time of an appliance which represents the time when the scheduler gets a request to start a specific appliance (boolean constant, $r_{k,i,h} = 1$ means that operation of the appliance is requested)
$RQ_{k,h}$	amount of generated renewable energy
SD_k	self-discharging coefficient of the storage
SP_k	required power to charge the storage
$t_{k,i}$	duration of the running time of an appliance
$\boldsymbol{x}$	final solution
$\beta_{k,i}$	maximum allowable delay of an appliance
ϵ	threshold value
ϵ_{count}	threshold counter
ϵ_{max}	maximum threshold counter limit
ϵ_{cur}	cost improvement

Variables

$BE_{k,h}$	energy used from the storage ($BE_{k,h} \in \mathbb{R}^+$)
C_k	total cost of the k-th household when it participates in microgrid energy trading ($C_k \in \mathbb{R}$)
$C_k^{NoTrade}$	total cost of the k-th household when it does not participate in microgrid energy trading ($C_k^{NoTrade} \in \mathbb{R}$)
C_{total}	total cost of all households ($C_{total} \in \mathbb{R}_0^+$)
$DS_{k,h}$	energy demand or supply of a household ($DS_{k,h} \in \mathbb{R}$, a positive value represents energy demand and a negative value represents energy surplus)
$GE_{k,h}$	energy drawn from the grid ($GE_{k,h} \in \mathbb{R}^+$)
$IC_{k,h}$	storage charging state (boolean vector, $IC_{k,h} = 1$ means the storage is in charging state)
$MQ_{k,h}$	demand or supply of microgrid energy ($MQ_{k,h} \in \mathbb{R}$, a positive value represents the minimum energy demand of the household and a negative value represents the maximum amount of energy that the household can sell to the microgrid)
$RE_{k,h}$	energy used from the renewable source ($RE_{k,h} \in \mathbb{R}^+$)
$SE_{k,h}$	energy level of a storage ($SE_{k,h} \in \mathbb{R}^+$)
$S_{k,i,h}$	appliance operation time (boolean vector, $S_{k,i,h} = 1$ means the appliance is in operation)
$US_{k,i,h}$	start time of an uninterruptible appliance (boolean vector, $US_{k,i,h} = 1$ represents the timeslot when an uninterruptible appliance starts its operation)
$\tau_{k,i}$	end time of an appliance operation ($\tau_{k,i} \in \mathbb{N}$)

Variables or Parameters

$DS_{k,h}$	energy demand or supply of a household ($DS_{k,h} \in \mathbb{R}$, a positive value represents energy demand and a negative value represents energy surplus). $DS_{k,h}$ is a variable in Module 1 and a parameter in Module 2
$ME_{k,h}$	energy traded in microgrid ($ME_{k,h} \in \mathbb{R}$, a positive value represents a buyer and a negative value represents a seller). $ME_{k,h}$ is a parameter in Module 2 and a variable in Module 3
MP_h	price of microgrid energy ($MP_h \in \mathbb{R}^+$). MP_h is a variable in Module 2 and a parameter in Module 3

to apply the optimization algorithm to process this huge smart grid data. Most of the research on demand side management assumes that the households know their energy demand and supply over the entire time horizon [9]. A household can use historical energy consumption and generation datasets to predict its future energy demand and supply [9]. Fig. 1 illustrates that the smart homes in the microgrid are connected through a bi-directional network. The energy consumption and generation data of the households is processed in a cloud by applying the proposed algorithm. All households receive the processed information from the cloud and reschedule their energy sources and loads accordingly.

One of the issues related to P2P energy trading is that it results in an unfair cost distribution among the smart homes. That is, an optimal overall solution may be quite unfair, increasing the costs of some households while reducing the costs of others. We address this unfair cost distribution problem by assuring Pareto optimality among the participating smart homes in microgrid energy trading. It means that no households will be worse off to improve the cost of others. More specifically, it ensures that the households' cost when they trade energy in the microgrid is not higher than the cost when they do not participate.

However, the aforementioned Pareto optimality feature increases the computational complexity of the optimal model [7] which means that using the resulting solution is not practical because the time complexity increases exponentially according to the increase in the problem size. Even small and relatively trivial problems can take hours to solve [7]. To overcome this limitation, we propose a near-optimal algorithm, named Energy Cost Optimization via Trade (ECO-Trade), which uses heuristics to solve the problem in lower computation time without compromising the accuracy for almost all scenarios. The

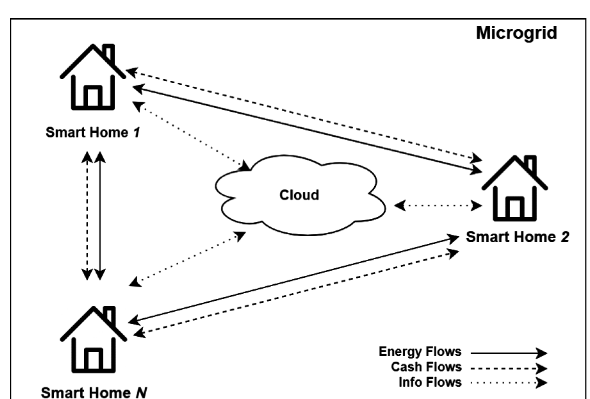

Fig. 1. Microgrid - a network of smart homes or nanogrids.

proposed algorithm aims at obtaining a socially optimal solution, i.e., maximizing the total benefits of all participating households. Unlike other methods (e.g., [10]), it does not differentiate between the households who generate surplus energy and who do not. Our results show that the solution time of the ECO-Trade algorithm is very low, mostly less than a minute, compared to the optimal model which sometimes takes hours. We also found that for real datasets, 99% of the solutions generated by the proposed algorithm are optimal solutions (global optima). Therefore, the proposed ECO-Trade algorithm is a better alternative to the optimal model considering both accuracy and solution time. Interested readers are encouraged to read our optimal solution approach to gain more insights on P2P energy trading among the smart homes [7].

Our result shows that when the smart homes are not linked together, the cost savings is low. For example, when the smart homes use the microgrid infrastructure for energy trading, they can reduce their costs by 74% compared to the scenario when they do not trade energy. Our results also show that cost savings do not always increase linearly with an increase in the renewables and storage penetration rate. Rather they decrease gradually after a saturation point. For example, the cost reduction is optimal when 50% of the households have solar panels and 100% of the households have storage.

To our knowledge, this is the first near-optimal cost optimization algorithm which considers the unfair cost distribution problem for a Demand Side Management (DSM) system coordinated with P2P energy trading. We found that P2P energy trading in the microgrid is beneficial if the households have both storage and renewables. In the presence of renewables, increased storage capacity increases cost savings until it reaches a saturation point. Similar to this, there is a threshold point after which more renewables do not aid in cost savings.

The reminder of this article is organized as follows. Section 2 identifies the research gap and discusses the significance of the proposed algorithm. Section 3 describes the ECO-Trade algorithm. Section 4 evaluates the performance of the proposed ECO-Trade algorithm. Section 5 analyzes the impact of P2P trading on cost optimization. Finally, Section 6 concludes the article addressing the contributions.

2. Literature review

This research addresses the energy cost optimization problem in the smart grid from the end-users' perspective. Early research on the smart grid considered only DSM to minimize the energy cost in a smart home. This approach optimizes the energy cost by rescheduling the loads to different times when the energy prices are comparatively low [11,12]. More recently, research integrates energy storage and renewables with DSM for cost optimization [13–15]. These contributions proposed optimization models which provide optimized schedules of the energy sources and loads. A recent paper considered energy trading among the microgrids in the smart grid [16]. However, none of these approaches considered energy trading with other households, and hence cannot minimize the energy cost of the smart homes any further.

P2P energy trading among the households is a comparatively new concept. The P2P service providers maintain the distribution network and provide metering and billing services [17,18]. These projects primarily considered the development of business models rather than optimizing energy cost coordinated with DSM. Shamsi et al. introduced an auction market in a community microgrid [19]. In this microgrid, each household trades energy with others in the presence of the grid. Liu et al. proposed an energy sharing infrastructure among the prosumers [20]. They considered the microgrid energy price as a function of the Supply and Demand Ratio (SDR) and modeled the optimization problem using bi-level programing. Tushar et al. emphasized on assuring fairness among the prosumers while selecting different pricing schemes [21]. This research aimed at obtaining socially optimal solutions, i.e., maximizing the total benefits of all participating households. Long et al. used a variant of the SDR method to ensure cost fairness among the prosumers [22]. Luth et al. analyzed the impact of energy storage systems on P2P energy trading in a community microgrid [23]. They investigated the contribution of distributed energy storage located at the customer level versus a central energy storage shared by the community. However, none of the aforementioned methods coordinate DSM with P2P trading. More specifically, these methods cannot provide a coordinated schedule of the households' loads with energy sources to maximize the benefits of P2P trading.

Energy cost optimization is typically formulated as a linear or non-linear optimization problem. Linear programming is widely used to solve linear optimization models [24–26]. The time required to solve a linear model is comparatively lower than a non-linear model. If an optimization model is non-linear but convex, it is still possible to solve within a realistic time frame [27]. However, in general, the solution times of non-linear optimization models are comparatively higher than the linear models and hence, such optimal solution approaches are not suitable to solve these problems [7]. Therefore, a number of researchers proposed approximate algorithms for this purpose [28–30]. Arabali et al. proposed a genetic algorithm-based optimization model to choose the optimal storage capacity for the smart grid [13]. Vytelingum et al. proposed a game-theoretic framework to analyze the effect of household storage on the energy price [31]. Arghandeh et al. used a gradient-based heuristic optimization model to control the community energy storage systems [32].

Table 1 presents a comparison among the methods proposed for P2P energy trading in a microgrid. It shows that Samadi et al. [33] and Zhou et al. [34] proposed similar methods to ours. They used approximate methods to implement DSM systems coordinated with P2P trading. Additionally, Zhou et al. compared the performance among the SDR, Mid-Market Rate (MMR) and Bill Sharing (BS) methods [34]. Their results show that the SDR method outperforms the others. However, none of the methods proposed in the literature evaluated the performance of their approximate algorithms with optimal methods. Therefore, we do not know the accuracy of the solutions generated by these

Table 1
Comparison between the P2P energy trading methods.

Authors	Year	Method	Solution Type	Addressed Cost Fairness Issue?	Coordinate DSM with P2P trading?	Evaluated with an Optimal Method?
Shamsi et al. [19]	2016	Dynamic Programming	Approximate	Yes	No	No
Liu et al. [20]	2017	Bi-Level Programming	Approximate	Yes	No	No
Tushar et al. [21]	2017	Game Theory	Approximate	Yes	No	No
Long et al. [22]	2018	Constrained Non-Linear Programming	Approximate	Yes	No	No
Luth et al. [23]	2018	Linear Programming	Optimal	Yes	No	N/A
Samadi et al. [33]	2016	Game Theory, Approximate Dynamic Programming	Approximate	Yes	Yes	No
Zhou et al. [34]	2018	Multiagent System	Approximate	Yes	Yes	No
Alam et al. [7]	2017	Non-Convex Mixed Integer Non-Linear Programming	Optimal	Yes	Yes	N/A
Proposed Method	2018	Bi-Linear Programming	Near-Optimal	Yes	Yes	Yes

methods and hence cannot evaluate their performance. On the contrary, in this paper, we evaluate our ECO-Trade algorithm with an optimal method [7]. Our results show that, for real datasets, the proposed algorithm provides almost optimal solutions with 99% accuracy.

To our knowledge, this work presents the first near-optimal cost optimization algorithm which considers the unfair cost distribution problem for a DSM system coordinated with P2P energy trading. Table 1 shows that most of the algorithms reported in the literature do not have the same features as ours. Therefore, a quantitative comparison with these methods is not a proper way to evaluate our algorithm. However, we still need an approach to compare our algorithm to demonstrate its effectiveness. For this reason, we initially developed an optimal model [7] which always provides exact solutions. We used this optimal model to evaluate the performance of the proposed approximate/heuristic algorithm. Table 1 also shows that the prior research rarely evaluated the accuracy of the approximate algorithms compared to optimal models. Furthermore, we analyze the results to identify the impact of P2P trading on cost optimization. Our results show that after a maximum threshold point, cost savings do not increase with an increase in the renewables and storage penetration rate.

3. The ECO-Trade algorithm

The proposed ECO-Trade algorithm follows a bi-linear programming approach. It breaks down our previously proposed optimal model (which is a non-convex mixed integer non-linear programming model [7]) into multiple Mixed Integer Linear Programming (MILP) models or modules. Each MILP model considers a convex feasible region which is smaller than the non-convex solution space. The proposed algorithm solves these MILP models until successive iterations converge to the final solution. Algorithm 1 describes the pseudocode of the proposed algorithm. Module 1 calculates the energy demand and generation of individual households. Module 2 determines the microgrid energy price. Module 3 computes the amount of microgrid energy being traded at a given price. The ECO-Trade algorithm iteratively generates the microgrid price (Module 2) and microgrid energy (Module 3) until a termination criterion is satisfied. Module 3 provides the final solution. We introduce the following variables to control the flow of the algorithm: previous cost C_{pre}, current cost C_{cur}, threshold value ϵ, threshold counter ϵ_{count}, maximum threshold counter limit ϵ_{max}, and cost improvement ϵ_{cur}. $\boldsymbol{x}$ represents the final solution.

Algorithm 1. ECO-Trade Algorithm

Input: input parameters (described in the Nomenclature section)
Output: a Pareto optimal solution: $\boldsymbol{x}$
$\epsilon_{count} \leftarrow 0$, $\epsilon_{max} \leftarrow 3$, $\epsilon \leftarrow 0.001$, $C_{pre} \leftarrow 0$
for $k = 1$ to K **do**
  solve Module 1
  $C_{pre} \leftarrow C_{pre} + C_k^{NoTrade}$
end for
$ME_{k,h} \leftarrow DS_{k,h}$
while $\epsilon_{count} \leqslant \epsilon_{max}$ **do**
  solve Module 2 ▷ Provides MP_h to Module 3
  solve Module 3 ▷ Provides $ME_{k,h}$ to Module 2
  $C_{cur} \leftarrow C_{total}$
  $\epsilon_{cur} = \left|\frac{C_{pre} - C_{cur}}{C_{pre}}\right|$
  if $\epsilon_{cur} \leqslant \epsilon$ **then**
    $\epsilon_{count} \leftarrow \epsilon_{count} + 1$
  else
    $\epsilon_{count} \leftarrow 0$
  end if
  $C_{pre} \leftarrow C_{cur}$
end while
$\boldsymbol{x} \leftarrow$ *Module 3 Solution*
return $\boldsymbol{x}$

3.1. Module 1: Initial demand and supply module

Module 1 optimizes the energy cost for the individual households when they do not participate in microgrid energy trading. It computes the initial values of energy supply and demand, $DS_{k,h}$ (defined later in (16)). Module 2 uses the values of $DS_{k,h}$ as constants in the first iteration of the ECO-Trade algorithm.

3.1.1. Objective function

If a household does not participate in microgrid energy trading, its energy cost is expressed as (1).

$$C_k^{NoTrade} = \sum_{h\in H} GP_h \cdot GE_{k,h} + \sum_{i\in I} d_{k,i}\left(\tau_{k,i} - \left(\sum_{h\in H} r_{k,i,h}\cdot h + t_{k,i} - 1\right)\right) \tag{1}$$

The objective function is defined as (2),

$$\boldsymbol{min}\ C_k^{NoTrade} \tag{2}$$

where $C_k^{NoTrade}$ is the total cost of the k-th household when it does not participate in microgrid energy trading, GP_h is the grid energy price, $GE_{k,h}$ is the amount of energy drawn from the grid, $d_{k,i}$ is the disutility factor of an appliance, and $r_{k,i,h}$ is the reservation time of an appliance which represents the time when the scheduler gets a request to start a specific appliance. The optimal solution should satisfy the following constraints.

3.1.2. Energy balance constraints

Constraint (3) ensures the balance of energy consumption and generation in each timeslot for all households. The total energy consumed by the loads should be the same as the total energy generated by the energy sources. In this constraint, the grid and renewables are energy sources and the home appliances are loads. The storage and the microgrid can be energy sources or loads based on their functionalities in each timeslot.

$$\sum_{i\in I} S_{k,i,h}\cdot p_{k,i} + IC_{k,h}\cdot SP_k = GE_{k,h} + BE_{k,h} + RE_{k,h},\ \ (k\in K,\ h\in H) \tag{3}$$

where $S_{k,i,h}$ represents the appliance operation time, $p_{k,i}$ is the power consumption of an appliance, $IC_{k,h}$ represents the storage charging state, SP_k is the required power to charge the storage, $BE_{k,h}$ is the amount of energy used from the storage, and $RE_{k,h}$ is the amount of energy used from the renewable source.

3.1.3. Stored energy constraints

In the first timeslot, storage energy is a function of initial storage energy, storage efficiency and self-discharging rate as expressed in (4).

$$SE_{k,1} = IE_k\cdot SD_k + IC_{k,1}\cdot SP_k\cdot E_k - BE_{k,1},\ \ (k\in K) \tag{4}$$

where $SE_{k,1}$ is the energy level of the storage at the 1st timeslot, IE_k is the initial storage energy level, SD_k is the self-discharging coefficient of the storage, $IC_{k,1}$ is the storage charging state at the 1st timeslot and E_k is the storage efficiency.

The stored energy in the other timeslots is a function of the available stored energy in the immediate previous timeslot, storage efficiency, and self-discharging rate, which has been expressed in (5).

$$SE_{k,h} = SE_{k,h-1}\cdot SD_k + IC_{k,h}\cdot SP_k\cdot E_k - BE_{k,h},\ \ (k\in K,\ h\in H{:}\ h\neq 1) \tag{5}$$

where $SE_{k,h}$ is the energy level of the storage at timeslot h and $SE_{k,h-1}$ is the energy level of the storage at the immediate previous timeslot.

The proposed algorithm discourages charging and discharging a storage at the same time because it will increase the energy cost. While charging the storage, due to the efficiency (E_k), we lose energy which we could have used directly to power an appliance/load or to sell, without loss.

There are 2 ways to represent storage charging. One is using discrete charging power (on/off charging using a Boolean variable). Another way is using continuous values as the storage charging power. We used the former method so that the proposed algorithm can also consider the storage of an Electric Vehicle (EV). The charging duration of an EV depends on the charging power and this on/off charging feature with fixed charging power gives the user more control over the required time to charge a storage.

3.1.4. Storage capacity constraints

Constraints (6) and (7) ensure that a storage energy should not exceed the maximum storage capacity $MaxC_k$ and should not go below the minimum energy level $MinC_k$.

$$SE_{k,h} \leqslant MaxC_k, \ \ (k \in K, h \in H) \tag{6}$$

$$SE_{k,h} \geqslant MinC_k, \ \ (k \in K, h \in H) \tag{7}$$

3.1.5. Task duration constraints

For each appliance, Constraint (8) maintains the total duration of an operation. It also ensures that the operation of an appliance can be interrupted as long as its duration of operation satisfies the required time to complete the task. For example, a dishwasher is an interruptible appliance. If it takes three hours to complete a task and has to be completed by 12 am, it does not matter what three hours we are operating the dishwasher.

$$\sum_{h \in H} S_{k,i,h} = t_{k,i}, \ \ (k \in K, i \in I) \tag{8}$$

where $t_{k,i}$ is the duration of an appliance running time.

3.1.6. Renewable energy availability constraints

Constraint (9) ensures that the energy drown from the renewables should be equal or less than the available energy $RQ_{k,h}$.

$$RE_{k,h} \leqslant RQ_{k,h}, \ \ (k \in K, h \in H) \tag{9}$$

3.1.7. Reservation time constraints

Constraint (10) specifies that an appliance operation should start after (or at) the reservation time. $\sum_{h \in H} r_{k,i,h} \cdot h$ refers to the reservation timeslot. An appliance is reserved only once in the time horizon. Therefore, the multiplication of $r_{k,i,h}$ by the corresponding timeslot h provides the reservation timeslot.

$$\sum_{h \in H} S_{k,i,h} = \sum_{h=\sum_{h \in H} r_{k,i,h} \cdot h}^{N} S_{k,i,h}, \ \ (k \in K, i \in I) \tag{10}$$

If an appliance is requested multiple times within the same time horizon, the algorithm schedules the appliance operation as if it had multiple similar appliances.

3.1.8. Relationship between the Scheduling Vector and the End Time Constraints

Constraint (11) binds $\tau_{k,i}$ with $S_{k,i,h}$. The end time of an appliance should also be the last execution time.

$$S_{k,i,h} \cdot h \leqslant \tau_{k,i}, \ \ (k \in K, i \in I, h \in H) \tag{11}$$

3.1.9. Maximum allowable delay constraints

Constraint (12) specifies that an appliance operation must be completed before (or at) the user defined maximum allowable time limit $\beta_{k,i}$.

$$\tau_{k,i} \leqslant \beta_{k,i}, \ \ (k \in K, i \in I) \tag{12}$$

3.1.10. Uninterruptibility constraints

Constraints (13) and (14) define that an uninterruptible appliance keeps running without any interruption until it completes its operation.

$$\sum_{d=0}^{t_{k,i}-1} S_{k,i,h+d} - t_{k,i} \geqslant -t_{k,i}(1 - US_{k,i,h}), \ \ (k \in K, i \in U, h = [1, N - t_{k,i} + 1]) \tag{13}$$

$$\sum_{h=1}^{N-t_{k,i}+1} US_{k,i,h} = 1, \ \ (k \in K, i \in U) \tag{14}$$

where $US_{k,i,h}$ is the start time of an uninterruptible appliance.

3.1.11. Utility grid max power limit constraints

Constraint (15) limits the power that can be drawn from the grid.

$$GE_{k,h} \leqslant L_k^{max}, \ \ (k \in K, h \in H) \tag{15}$$

where L_k^{max} is the maximum grid power limit.

3.1.12. Demand and supply constraints

Eq. (16) calculates the demand or supply of energy from the external energy sources like grid and microgrid. If the value of $DS_{k,h}$ is positive, the household has energy demand. If the value of $DS_{k,h}$ is negative, the household has energy surplus.

$$DS_{k,h} = \sum_{i \in I} S_{k,i,h} \cdot p_{k,i} + IC_{k,h} \cdot SP_k - RQ_{k,h} - SE_{k,h} - BE_{k,h} + MinC_k, \ \ (k \in K, h \in H) \tag{16}$$

3.2. Module 2: Price computation module

Module 2 computes the microgrid energy price. In this module, microgrid energy $ME_{k,h}$ is a constant and microgrid energy price MP_h is a variable.

3.2.1. Objective function

The proposed model in Module 2 is a multi-objective optimization problem which is expressed as (17).

$$min\,(C_{total}, C_1, C_2, ..., C_k) \tag{17}$$

Here, C_{total} is the total cost of all households and C_k is the total cost of the k-th household which are expressed in (18) and (19) respectively.

$$C_{total} = \sum_{k \in K} \sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{k \in K} \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \tag{18}$$

$$C_k = \sum_{h \in H} GP_h \cdot GE_{k,h} + \sum_{h \in H} MP_h \cdot ME_{k,h} + \sum_{i \in I} d_{k,i} \left(\tau_{k,i} - \left(\sum_{h \in H} r_{k,i,h} \cdot h + t_{k,i} - 1 \right) \right) \tag{19}$$

The total energy bought from the microgrid is the same as the total energy sold to the microgrid. Therefore, microgrid energy price does not have an impact on the total cost. Hence, Eq. (18) does not require the microgrid energy cost. This multi-objective optimization problem is solved by using C_{total} as the sole objective function and the remaining objective functions, C_k, are added as inequality constraints (Constraint (24) discussed later). Therefore, the objective function of Module 2 is defined as (20).

$$min\ C_{total} \tag{20}$$

The optimization model should satisfy Constraints (4)–(15) as well as the following constraints.

3.2.2. Energy balance constraints

Constraint (21) ensures that, in a specific household, total energy consumption is equal or less than the total available energy.

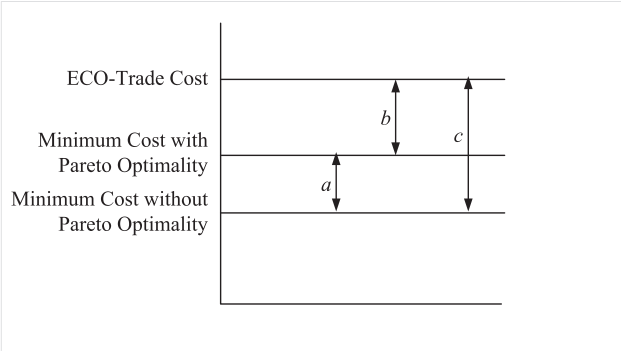

Fig. 2. Relationship between the ECO-Trade algorithm and the Optimal Models with/without Pareto Optimality.

$$\sum_{i\in I} S_{k,i,h}\cdot p_{k,i} + IC_{k,h}\cdot SP_k \leqslant GE_{k,h} + BE_{k,h} + RE_{k,h} + ME_{k,h}, \quad (k \in K, h \in H) \tag{21}$$

3.2.3. Microgrid energy price constraints

Constraints (22) and (23) define the maximum and minimum limits of microgrid energy price.

$$MP_h \geqslant 0, \quad (h \in H) \tag{22}$$

$$MP_h \leqslant GP_h, \quad (h \in H) \tag{23}$$

3.2.4. Pareto optimality constraints

Constraint (24) implements Pareto optimality. It ensues that a household cost when it participates in microgrid trading must be less than or equal to the cost when it does not participate.

$$C_k \leqslant C_k^{NoTrade}, \quad (k \in K) \tag{24}$$

3.3. Module 3: Energy computation module

The third module computes the microgrid energy, $ME_{k,h}$, using the constant microgrid prices, MP_h, provided by Module 2. The optimization model of Module 3 is similar to Module 2. The main differences are: (1) it does not require Constraints (22) and (23) because microgrid prices are constants, and (2) Constraint (21) of Module 2 is modified as Constraint (25). Module 3 also requires the following constraints.

3.3.1. Energy balance constraints

Constraint (25) ensures that, for a specific household, the total energy consumption should be the same as the total available energy.

$$\sum_{i\in I} S_{k,i,h}\cdot p_{k,i} + IC_{k,h}\cdot SP_k = GE_{k,h} + BE_{k,h} + RE_{k,h} + ME_{k,h}, \quad (k \in K, h \in H) \tag{25}$$

A negative value of $ME_{k,h}$ means the household is an energy seller at that specific timeslot. A positive value means the household is a buyer.

3.3.2. Energy balance constraints for microgrid

Constraint (26) ensures that the total energy sold in the microgrid by all households must be equal to the total energy bought from the households.

$$\sum_{k\in K} ME_{k,h} = 0, \quad (h \in H) \tag{26}$$

3.3.3. Energy constraints while trading in microgrid

Constraint (27) calculates the amount of available energy $MQ_{k,h}$ in the microgrid.

$$MQ_{k,h} = \sum_{i\in I} S_{k,i,h}\cdot p_{k,i} + IC_{k,h}\cdot SP_k - GE_{k,h} - RQ_{k,h} - SE_{k,h} - BE_{k,h} + MinC_k, \quad (k \in K, h \in H) \tag{27}$$

If a household is a seller at a timeslot, this constraint limits the maximum amount of energy that the household can sell to the microgrid. If a household is a buyer, this constraint defines the minimum energy required by the household from the microgrid.

$$ME_{k,h} \geqslant MQ_{k,h}, \quad (k \in K, h \in H) \tag{28}$$

4. Performance analysis

In this section, we compare the proposed ECO-Trade algorithm with the optimal model to evaluate its performance. We used a 64 bit Fedora 20 machine with Intel Core i7 CPU (2.67 GHz) and 12 GB RAM to collect the results. CPLEX 12.6.1.0 [35] is used to solve the problem instances.

In this paper, we consider large scenarios with real datasets. As the time complexity of the optimal model is very high, we were unable to generate the solutions for these scenarios using the model. If we exclude the non-linear constraints from the optimal model, its time complexity will decrease because in this case, the optimal model will be reduced to an MILP model. However, this optimal model will no longer ensure Pareto optimality.

The cost of the previously proposed optimal model [7] can be equal or greater than the optimal model used in this section. The relationships between these costs are expressed in Fig. 2. The minimum cost which does not consider the Pareto optimality is always equal to or less than the minimum cost that considers Pareto optimality. In Fig. 2, the difference between these 2 costs is represented by a. Instead of comparing the ECO-Trade algorithm with the optimal model with Pareto optimality [7] (the difference is b), we compare it with the optimal model without Pareto optimality (the difference is c). Here, $c = a + b$ where the value of a is either 0 or a small number. Hence, $c \geqslant b$.

We used household load datasets collected in Ottawa, Canada [36]. We collected solar irradiance for Ottawa from the National Solar Radiation Database (NSRDB) [37] which is maintained by the National Renewable Energy Laboratory (NREL) [38]. We chose Suntech STP200S-18/ub-1 as the PV module. The PV array configuration is given in Table 2. The Standard Test Conditions (STC) power rating of the PV module is 200 W. We used Tesla Powerwall as the home energy storage. The storage characteristics are given in Table 3 [39]. We used Time Of Use (TOU) energy price of Hydro Ottawa which is set by the Ontario Energy Board (OEB) [40]. Pagani et al. considered the day ahead price advertised by the wholesale market as the retail energy price for the end-user and proposed that this price can be used as Real-Time Price (RTP) [41]. Following his approach, we collected the hourly wholesale energy price advertised by the Independent Electricity System Operator (IESO) [42]. The Hourly Ontario Energy Price (HOEP) from IESO Historical Reports (2002-present) was used as RTP [43]. We consider a 24 h timeframe with 1 h time granularity. However, it is important to note that the proposed model supports any numbers of timeslots and time granularities. For the parameters and variables, we consider kWh as the unit of energy, kW as the unit of power, and cent as

Table 2
PV array configuration.

Properties	Description
PV Module	Suntech STP200S-18/ub-1 Module
Max. Power at STC	200 W
Array Tilt Angle	45.41° (Site Latitude)
Array Azimuth	180° (South Facing Array)
Number of Modules in Series	2
Number of Parallel Strings	2

Table 3
Characteristics of Tesla Powerwall [39].

Properties	Values
Power	3.3 kW
Efficiency	92%
Self-Discharging Rate	1% per day (0.042% per hour)
Minimum Energy Level	2.56 kWh (40% of max. capacity)
Maximum Energy Level	6.4 kWh

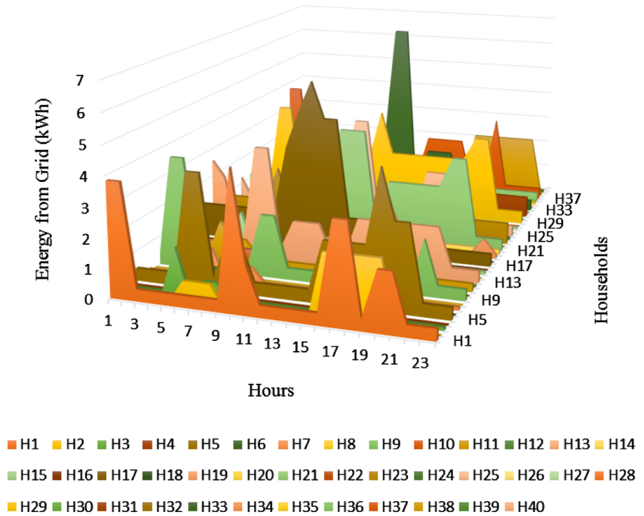

Fig. 3. Load profiles of the households.

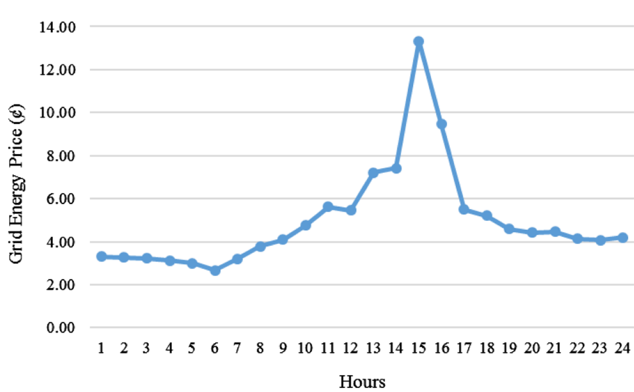

Fig. 4. Hourly Energy Price (RTP) per kWh [43].

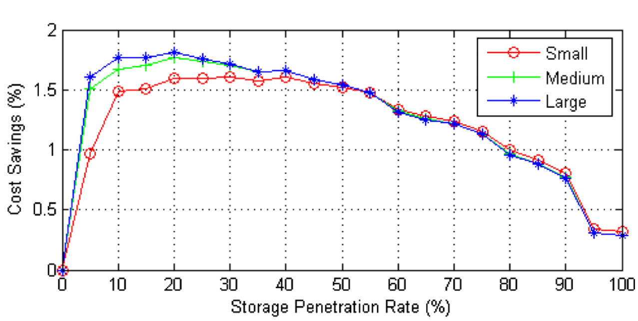

Fig. 5. Cost savings vs storage penetration rate.

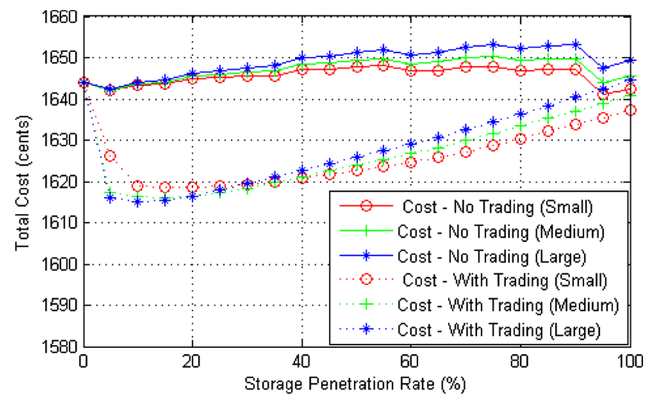

Fig. 6. Total cost vs storage penetration rate.

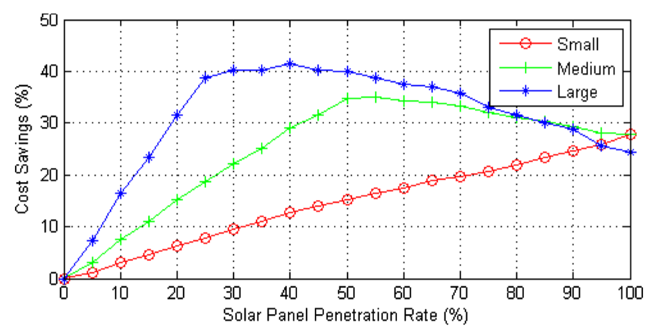

Fig. 7. Cost savings vs solar panel penetration rate.

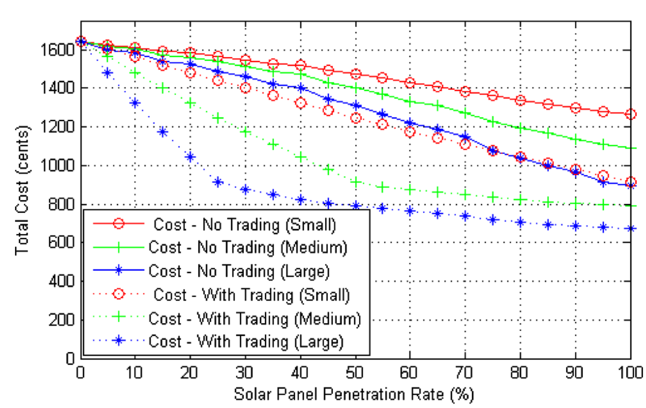

Fig. 8. Total cost vs solar panel penetration rate.

the units of cost and price. A detailed description of how these parameters were used to generate different scenarios can be found in [44].

We generated 112 different scenarios for performance analysis. The ECO-Trade algorithm terminates if the cost does not improve more than 0.1% within 3 consecutive iterations. Results show that the proposed algorithm provides optimal solutions for 99% of the scenarios. The remaining 1% of cases had a cost at most 1.8% higher than the optimal solution. The median solution time was around 4.6 s for all scenarios. For the ECO-Trade algorithm, the solution times of 90.2% of the scenarios were below 1 min. We observed that 7.1% of the scenarios took more than 2 min to solve. Therefore, we can conclude that the proposed ECO-Trade algorithm is a better alternative to the optimal model considering the trade-off between the accuracy and the solution time.

5. Impact of P2P trading on cost optimization

The ECO-Trade algorithm coordinates DSM with P2P trading, i.e., it reschedules the energy sources and loads to manage household energy generation and consumption. The cost savings reported in this section shows the benefit of DSM while the households participate in P2P energy trading among themselves. We used the same version of CPLEX solver and the same computer system which we used to collect the results described in Section 4.

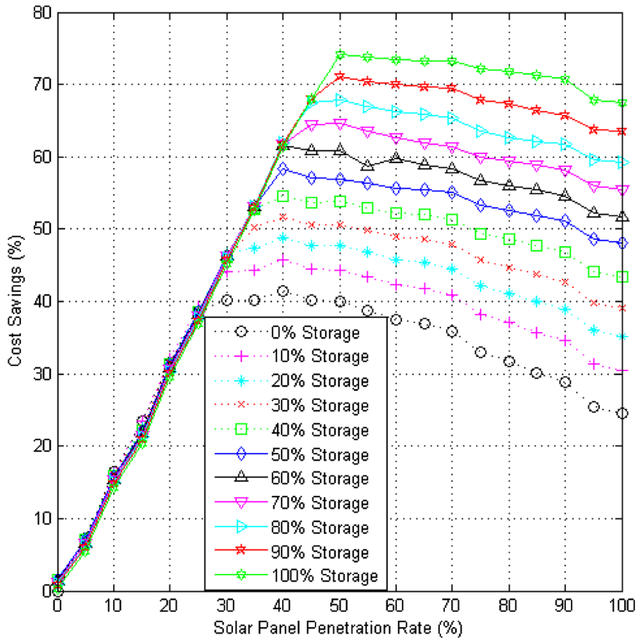

Fig. 9. Cost savings vs storage and solar panel penetration rate.

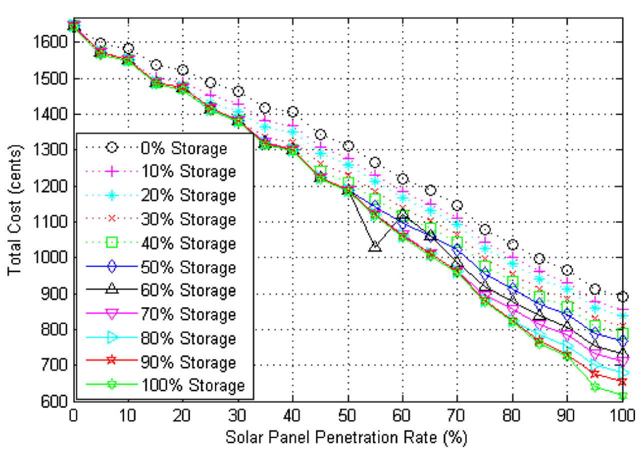

Fig. 10. Total cost vs storage and solar panel penetration rate (without microgrid trading).

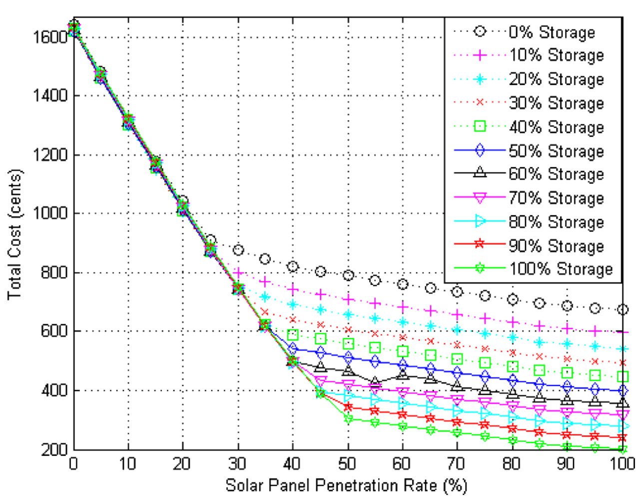

Fig. 11. Total cost vs storage and solar panel penetration rate (with microgrid trading).

5.1. Datasets

We used the same realistic datasets for household load profiles that we used previously in Section 4. We consider load profiles of 40 households as described in [44]. Fig. 3 shows the uniformly distributed household energy consumption profiles (1 h time resolution). All scenarios considered a historical summer weekday which is June 21, 2010. We used solar irradiance of that day to calculate the amount of generated solar energy. The data source is the one which we already used in Section 4. We chose Suntech STP200S-18/ub-1 (200 W) as the PV module as described in Table 2. We used three different types of solar energy generation capacities: small (2 parallel strings, each has 2 modules in series), medium (2 parallel strings, each has 4 modules in series) and large (2 parallel strings, each has 8 modules in series). We used Tesla Powerwall as the small storage as described in Table 3. We then scaled up the characteristics of the Tesla Powerwall as representative medium and large storage devices. In total, we used three different types of storage with different capacities: small (6.4 kWh), medium (12.8 kWh) and large (19.2 kWh). We used the HOEP data as RTP as described in Section 4. Fig. 4 shows the considered energy price in Ottawa on June 21, 2010 [43]. We consider a 24 h timeframe with 1 h time granularity. We allow higher delay tolerance in appliance operation by using a low disutility factor (0.001 ¢) and an appliance can be delayed up to the last timeslot. The maximum grid power limit is 100 kW per timeslot per household. We chose this high value to provide more flexible scheduling of the household loads. For example, a household may want to buy energy for another household and sell it at a lower price (we notice this may occur to maintain Pareto optimality). We are less interested in the impact of this limitation on the results, so we selected a large threshold (100 kW) that in effect means that this constraint never got triggered. For the parameters and variables, we consider kWh as the unit of energy, kW as the unit of power, and cent as the units of cost and price. A detailed description of the datasets can be found in [44].

5.2. Impact of storage on energy cost

In this section, we evaluate the impact of storage on cost savings based on the storage penetration rate in the microgrid. We increase the number of households with a storage device in the microgrid area from 0% to 100%. We use small, medium and large sizes of storage to analyze the impact of storage capacity on cost savings. Each scenario is solved once by the single household model (Module 1) which provides the total cost when the households do not trade energy. In addition, the same scenario is also solved with the ECO-Trade algorithm which provides the cost when the households participate in microgrid trading. The cost difference between these 2 solutions is used in Fig. 5 to show the cost savings for energy trading in the microgrid. Each data point in the figure represents a single scenario.

Fig. 5 shows the relationship between the percentage of households which have a storage (and no renewables) and the saved cost in the microgrid. It shows that cost savings is at a maximum when 20% of the households have an energy storage device (of any size). Beyond that point, cost savings decrease gradually. In the scenario, each household has a minimum storage energy level. This minimum energy level should be maintained: if the level drops below it, it impacts the lifespan of the storage. To maintain the energy level above this minimum energy level, each household needs to charge the storage in the first timeslots even if it is not helpful for cost minimization. It imposes energy loss due to storage charging inefficiency and increases the energy cost. Therefore, after a certain point, a higher storage penetration rate does not aid in saving more cost. It is also worth noting that energy savings are small overall, never exceeding 2%. While adding some energy storage to the microgrid overall is beneficial initially, these gains diminish as we add more storage capacity, due to the energy costs incurred by a storage device. It can be concluded that storing grid energy has insignificant impact on cost minimization because the grid energy is not cheap enough to compensate for the energy loss due to charging and self-discharging.

Fig. 6 shows the relationship between the percentage of households which have a storage and the total cost in the microgrid. It shows that having a storage device may increase the energy cost of individual households because of energy loss due to charging inefficiencies (the cost curves increase with increasing storage penetration rate). In these cases, smaller energy storage imposes less cost overhead. Hence, in the presence of microgrid trading, without renewables, cost savings from having a storage device is not significant. In the next section, we evaluate the scenarios where the households have only renewables without any storage.

5.3. Impact of renewables on energy cost

In this section, we evaluate the impact of solar panel penetration rate on energy cost minimization when the households trade energy among themselves. Generally, a storage is also installed with the installation of solar panels. However, to evaluate the impact of only the solar panels, we do not consider any storage in this section. The next section considers the scenarios with both storage and renewables.

For this case study, initially, we gradually increase the percentage of households having solar panels from 0% to 100% and solve the scenarios by the single household model (Module 1) which provides the total cost when the households do not trade energy. Then we solve the same scenarios with the ECO-Trade algorithm which provides the cost when the households participate in energy trading. The cost difference between these 2 solutions is used in Fig. 7 to show the impact of renewables on the cost savings in the microgrid. We use 3 different sizes of solar energy generation capacity to analyze the results. Each data point in the figure represents a single scenario.

Fig. 7 shows that cost savings initially increase linearly with the number of households having solar panels (but no energy storage). However, after a saturation point, cost savings decrease gradually except for the small generation capacity. After this point, more solar panels increase energy waste because the generated energy cannot all be used at that moment. Therefore, in this case, energy trading does not aid in saving costs. For the small generation capacity, it shows no energy waste because all generated energy is consumed instantaneously. The surplus energy in a certain timeslot must be traded in the microgrid in that timeslot because the households do not have storage. If the household cannot sell the surplus energy to the microgrid, it cannot minimize the cost further. Therefore, after the saturation point, the difference between the energy cost with microgrid and without microgrid starts decreasing. Compared to the scenarios in the previous section (storage but no renewables), microgrid trading achieves a significant amount of cost reduction, up to 40% in our scenarios.

Fig. 8 shows that for individual households, the total costs decrease linearly with the number of households having solar panels. For the microgrid, after a saturation point, adding more households with solar panels has little impact on cost reduction because of energy waste (for comparatively higher solar energy generation capacity). Energy waste without energy trading is higher than the energy waste with trading. This is then also reflected in the energy cost.

5.4. Impact of storage and renewables on energy cost

In this section, we evaluate the impact of storage and solar panel penetration rates on cost minimization when the households participate in energy trading. We use small storage and large PV generation capacity for all the scenarios in this section. We increase the percentage of households with storage gradually from 0% to 100%. In addition to this, for each penetration rate of the storage, we gradually increase the percentage of households having solar panels. We calculated the cost savings using the same procedure discussed in earlier sections.

Fig. 9 shows that, in the presence of energy trading, storage increases cost savings if the households have solar panels. The savings increase linearly. However, after a saturation point, cost savings decrease because of energy waste. Energy is wasted because the generated energy cannot be used or stored at that moment. Results show that microgrid energy trading can provide up to 74% cost savings when solar panels are used in combination with a storage device.

Fig. 10 shows that, without trading, the total cost decreases linearly with the increase of storage and renewables penetration rates. Fig. 11 shows that, with trading, the total cost decreases linearly for the same reason. However, for this case, after a saturation point, the total cost does not decrease significantly because of energy waste. When analyzing the data further, we noticed that energy waste without microgrid trading is higher than the energy waste with microgrid trading. It is because energy trading enables the households to trade the energy which would be wasted otherwise.

6. Conclusion

This paper investigates the impact of peer-to-peer energy trading among the smart homes in a microgrid. For this purpose, we developed a near-optimal optimization algorithm because the optimal solution approach is not practical to solve the realistic problems due to high computational complexity. Our result shows that, for real datasets, 99% of the solutions generated by the proposed ECO-Trade algorithm are optimal solutions. It also shows that the solution time of the ECO-Trade algorithm is very low (mostly less than a minute) compared to the optimal model. Another limitation of the previous research is that they failed to address the unfair cost distribution problem. These solutions may increase some households' energy cost if they participate in peer-to-peer trading. The proposed algorithm addresses this unfair cost distribution issue by ensuring Pareto optimality. We believe that this is the first near-optimal cost optimization algorithm which considers unfair cost distribution problem for a coordinated demand side management system with peer-to-peer energy trading. Previous research either considered a subset of the problem or did not consider the unfair cost distribution issue. Finally, we studied the interdependency of storage, renewables, and microgrid trading. Our results show that the cost benefits show strong correlation, where maximal cost savings are obtained at a saturation point that depends on the household loads, storage capacity and renewable energy generation capacity of a specific microgrid area. Hence, the proposed model could be useful for governments, policy makers and utilities to design programs and incentives for the households to accelerate the adoption of storage and renewables in the microgrid. We take a consumer-oriented approach, and explore ways for the end-users to avoid having to buy grid energy when this is costly. As a future extension, we could consider feed-in tariffs and how that would change the consumer or prosumer behavior.

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